FORECASTING FOREX VOLATILITY IN TURBULENT TIMES

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ABSTRACT

The present study is an attempt to evaluate the predictability of the foreign exchange volatility in thirteen countries. The data covers the period of 2005-2009. To effectively forecast the volatility in the exchange rates, a GARCH model is used. The study compares the results between crisis period and a set of normal periods. The empirical results reveal that almost all countries except Thailand witnessed non-existence of volatility shocks at least once in a three year pre-crisis period but all the sample countries had volatility shocks in the crisis period of 2008-09. This apparently indicates that forecasting can be made at least for the next day given the high degree of volatility in the crisis period. T*he paper also reveals that exchange rates tend to have persistent conditional heteroskedasticity, and hence, could be predicted with one lag term.*

JEL: C53; F31; G17

KEYWORDS: Forecasting, GARCH, Foreign exchange rates, Volatility, Financial Crisis

INTRODUCTION

Since the introduction and implementation of the floating exchange rate system in 1971, volatility has become a buzz word in the financial markets. Many countries' currencies are floating freely against each other implying the economic principles of demand and supply prevail in the foreign exchange market. The FOREX markets and their activities have evolved tremendously during past few decades. Gone are the days when foreign exchange transactions were used as part of commercial, investment and central banks. Globalization and economic integration have impacted the involvement of foreign exchange transactions by multinational corporations, hedge funds, private investors, individual investors, speculators and arbitrageurs. This has changed the shape of foreign exchange market from a traditional limited-hour operational system to 24-hour electronic-based and market-oriented mechanism. Today, this market is believed to be the largest financial market in the world with an estimated daily turnover of US\$ 3.2 trillion. According to BIS Survey 2007, turnover in traditional foreign exchange instruments such as spot, forwards, swaps etc increased by 71% and reporting dealers' turnover with both other financial institutions and non-financial customers almost doubled.

The above-mentioned dynamics have instilled a distinct feature in the foreign exchange market i.e. 'volatility'. Foreign exchange market volatility peaked in 2008, soon after Lehman Brothers collapsed. A worldwide recession followed. Though moderate volatility has always been welcomed in FOREX market circles, the recent pattern of volatility has become an issue of concern for the monetary policy makers and economists. The recent summit of G-7 nations in October in Istanbul expressed a deep concern over the unusual and abnormal behavior in exchange rates. It was noted that 'excess volatility and disorderly movements in exchange rates have adverse implications for economic and financial stability'. This is not the first time excess volatility has triggered a debate. Financial crisis and economic turbulence have been witnessed in the past from time to time, and the same issue were debated. This sparks a further discussion of why volatility clusters cannot be captured in the times of turbulence. We know volatility refers to fluctuations in a time series data due to the flow of time dependent information. It may be of concern to find out whether the past returns are able to predict the future returns in the exchange rates. While capturing volatility, one may observe that there are some calm periods with relatively small returns and some wide swings with large positive and negative returns. This is characterized as volatility clustering. If

the variance of an exchange rate series depends on the past then the series is likely to have conditional heteroskedasticity. Researchers are constantly experimenting with new ways to measure volatility in order to provide more reliable and consistent predictability in the foreign exchange markets.

Though there has been some extensive research work on the measurement and forecasting of volatility of exchange rates, most of the research attempts are related to normal economic times. Volatility patterns have been estimated during normal economic scenarios but times of turbulence have remained quite research-isolated. A renewed interest of research in this area seems inevitable as researchers would like to ascertain volatility patterns during the times of turbulence. The main objective of this paper is to examine volatility patterns in the exchange rates of developed, developing and emerging market economies especially in the current crisis period. The study uses the GARCH model to estimate volatility clustering in time series data of thirteen countries' exchange rates. The second section of the paper deals with the review of existing research literature in the area of foreign exchange volatility. Section-3 discusses the methodology and data used in this paper. Section-4 outlines the analytical part of empirical results based on methodology as discussed in section-3. The last section presents the concluding remarks.

LITERATURE REVIEW

There has been a good amount of research in the area of volatility measuring and forecasting. Some are related to developed countries while others cover some normal-state economy periods. In developed markets, the volatility structure has changed quite significantly especially in the last two decades. Long run volatility has been recorded at comparatively lower level but volatility in emerging countries like Brazil, China, India, South Africa, Russia etc currencies have fairly moderated in the recent years. Dunis, Laws, and Chauvin (2003) examine the medium-term volatility forecasting of some developed countries currencies using alternative models of forecasting. Maheu and McCurdy(2002) use nonparametric measures to analyze the time series behavior of foreign exchange volatility. According to them, the non-linear impacts in volatility should be measured taking in-sample statistics and out-of-sample forecasts. Goretti (2005) highlighted that non-linear models in financial time series analysis work better than linear models due to the fact that the latter sometimes ignore unobservable factors such as herding behavior, investors' beliefs, financial panic, and political uncertainty. Sager and Taylor(2006) clarify that the quality of short-term exchange rate models still continues to be an occupational hazard of the international financial economist as fundamental variables are poorly correlated with high frequency exchange rate movements. Sometimes models fail to record some of the variables which may cause validity of the outcomes. Takezawa (1995) evaluates information role of quote arrival in impacting intraday volatility by applying GARCH model and found that information process is time consuming. Aries, Giromini and Meissner (2006) have empirically examined the volatility of Brazilian Real, the Russian Ruble, the Chinese Yuan and the Australian Dollar concluding that these currencies are undervalued against the US$.

Hansen and Lunde (2001) have done an extensive comparison of various volatility models drawing out an inference that GARCH (1,1) model best forecast the volatility. On the contrary, Johnston and Scott (2000) have observed that GARCH models with normality assumptions do not provide a good description of exchange rate dynamics, thereby raises a question on the contribution of GARCH type models in the determination of the stochastic process. Even sometimes it was felt that there might be some differences in the outcomes of GARCH and Stochastic volatility models. Pederzoli (2006) results reveal that VaR based analysis does not support stochastic volatility model but emphasized that GARCH model could help in defining an interval forecast. Some researchers (Chowdhury and Sarno, 2004; McMillan and Speight, 2006) have used different forms of GARCH model to define intra-day volatility in the foreign exchange markets. Chowdhury and Sarno (2004) used multivariate stochastic volatility models to investigate the degree of persistence of exchange rate volatility at different frequencies while McMillan

and Speight (2006) used FIGARCH model to capture long memory dynamics in intra-day volatility. Similar work is produced by Bordignan, Caporin and Lisi (2009) in which it was mentioned that periodic patterns with long-memory behavior in conditional variance can be predicted. They tried PLM-GARCH model to examine intra-day volatility. Leon, Rubio and Serna (2005) tested the GARCH model to test time-varying volatility incorporating skewness and kurtosis and they revealed a significant presence of skewness and kurtosis. Fang (2000) work is also a remarkable contribution in time-varying volatility. He observed that there are significant day-of-week and hour-of-day seasonal effects which can best be characterized by alternative model of ARIMA-GARCH. But a recent study conducted by Vincent, Jonathan and Xuan (2009) reveals that the optimal modeling frequency volatility can be estimated based on realized volatility of 30-minute interval returns.

It may not be surprising to note that volatility is also caused by the central bank's intervention. In fact, central banks of several countries have been observed to intervene in the foreign exchange markets at times when their currencies were having unusual swings. Frenkel, Peirdzioch and Stadtmann (2005) examined the impact of monetary authorities' intervention in the exchange rate comparing Japanese intervention policy with US intervention policy, and as expected, Japanese authorities were actively respondent to the fluctuation of Yen / Dollar. Edisan, Cashin and Liang (2006) examined GARCH model to find out whether the intervention activities by the central bank influence the level of exchange rate. Their findings, though rejected that intervention consistently influence the level of exchange rate, showed that the conditional variance of the exchange rate is positively related to the magnitude of the official intervention. In the same way, Domac and Mendoza (2002) also used EGARCH model showing that both the amount and frequency of foreign exchange intervention decreased the volatility of the exchange rates. But all the time the reasons for monetary policy affecting the exchange rates are not obvious. Woglom (2003) found that the role of exchange rate in current monetary policy making is not very clear which leaves some doubts. In addition to the above mentioned factors affecting volatility, some researchers (Gau and Hua, 2007) have found that volatility is also affected by public news arrivals and unexpected volume shocks.

Some researchers have attempted to determine an appropriate volatility model in line with hedge risk objectives. The firms would like to apply a model which best defines the risk level. Mansur, Cochran and Shaffer (2007) highlighted that a firm can decide its futures position given a hedge ratio. For this purpose, ICSS-GARCH model reveals better results than standard GARCH model. In another scenario, some researchers realized that the changing pattern of volatility needs to be analyzed as it may have its impact on trade and business of multinational companies. Egert and Zumaquero (2008) carried out an extensive work measuring impact of foreign exchange volatility on export performance of some transitional east and central European countries. According to their findings, some dominating sectors like chemical and manufacturing were observed to suffer from increased foreign exchange rate volatility.

METHODOLOGY AND DATA DESCRIPTION

The main objective of this study is to evaluate the predictability of thirteen exchange rates especially in the times of turbulence. In this regard, it is important to highlight the very first contribution made by Engle (1982) who introduced autoregressive conditional heteroskedasticity (ARCH). According to the ARCH model, the variance of the dependent variable works as a function of past values of the dependent variable and independent variables. In the later stage, ARCH model was generalized by Bollerslev (1986) propounding GARCH model. The original ARCH model used the following equation:

$$r_t = \gamma_0 + \gamma_1 \sigma_t^2 + e_t + \theta_1 e_{t-1} \tag{1}$$

$$\sigma_t^2 = \omega + \alpha\, e_{t-1}^2 + \beta\, \sigma_{t-1}^2 \tag{2}$$

where α_1, αq, μ and w are the parameters to be calculated. The above mean equation (1) is written as a function of exogenous variables with an error term. Since σ_t^2 is the one-period ahead forecast variance based on past information, it is called the conditional variance. According to this equation σ_t^2 is supposed to have mean zero and variance one, and is often assumed to be normally distributed. This is a very common assumption that $\alpha 1$ and w are all positive in order to obtain positive values for the estimate of the condition variance. The (1,1) in GARCH(1,1) refers to the presence of a first-order GARCH term (the first term in parentheses) and a first-order ARCH term (the second term in parentheses). An ordinary ARCH model is a special case of a GARCH specification in which there are no lagged forecast variances in the conditional variance equation. The benefit of modeling volatility forecasting lies in the fact that variance of the errors provide more accurate time-varying intervals. This may help analyst to assess the risk of holding an asset or the value of an option. This model simply describes the characteristics of the AR(1) that the volatility in the current period is related to its past value with a white noise error term i.e. μ_t. As mentioned earlier, it is the variance which should be used as a measure of volatility and it is derived from the mean-adjusted relative log change value of the exchange rates.

With regard to data selection, since the study aims at forecasting forex volatility in times of turbulence, the most recent crisis period is chosen. The global financial crisis broke in June 2008, therefore, one year period is counted from July 1, 2008 to June 30, 2009. Indisputably, this period is the most affected period and demands a proper investigation with regard to volatility forecasting. To make this study logical, a past three-year period is also chosen in order to compare the results and draw robust conclusions. Thus the study covers a total of four-year period starting from July 1, 2005 and ending June 30, 2009. The empirical analysis considers daily changes in exchange rates. Following the IMF report which lists total twenty six countries, the present study has chosen twelve countries broadly covering developed and emerging economies, and the Euro Zone to represent the European countries. The thirteen countries include Brazil, Czech Republic, India, Korea, Mexico, Russia, South Africa, Thailand, UK, Canada, Singapore, Japan, and the Euro Zone. While choosing the countries, it is particularly taken care that the country is having either floating exchange rate system or managed float system. So the countries having other form of exchange rate systems are excluded from the study because the volatility is either restricted within a stipulated range or it is non-existent. The study uses the sample country's exchange rate against the US dollar keeping in mind the fact that these countries have significant proportion of their international business in dollar denominated currency. The exchange rates have been collected from different sources including the official website of Pacific Exchange Rate Service.

EMPIRICAL RESULTS

The daily changes in the exchange rates of twelve countries and European region currency have been compiled. The daily changes were calculated as the change in the logarithm of closing prices of the preceding day. The daily changes are calculated using the following formula:-

$$\Delta Ex_t = \ln(Ex_t) - \ln(Ex_{t-1}) \tag{3}$$

The changes in the logs of the exchange rates of the sample countries are shown through figures presented below. These figures clearly demonstrate the swings which further indicate the existence of volatility clustering.
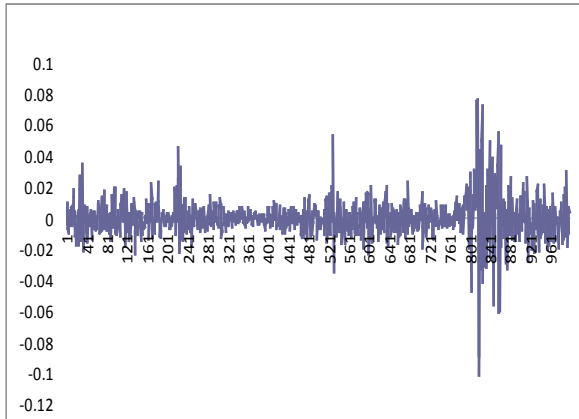
Figure 1: Fluctuation in Brazilian Real
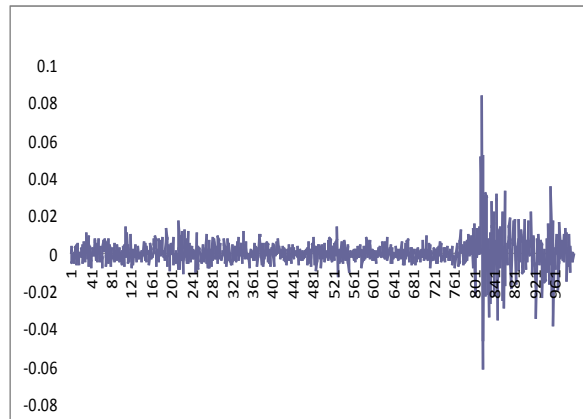

Figure 2: Fluctuation in Mexican Peso

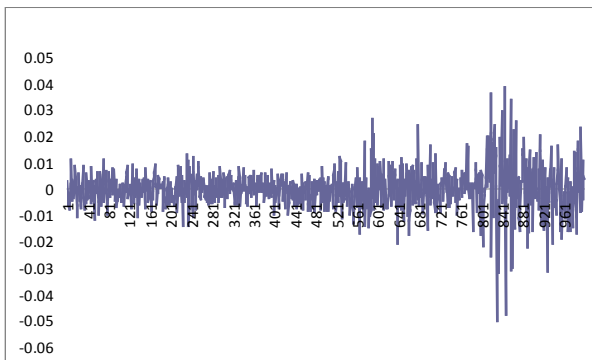

Figure 3: Fluctuation in Canadian $

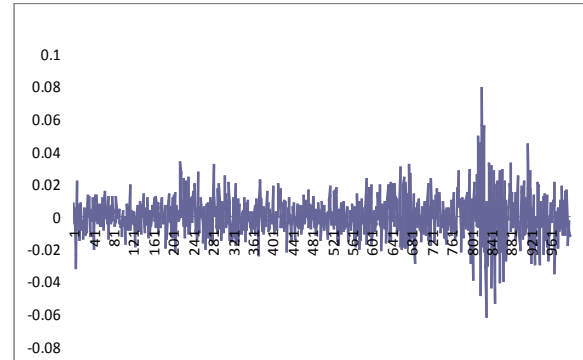Figure 4: Fluctuation in South African Rand

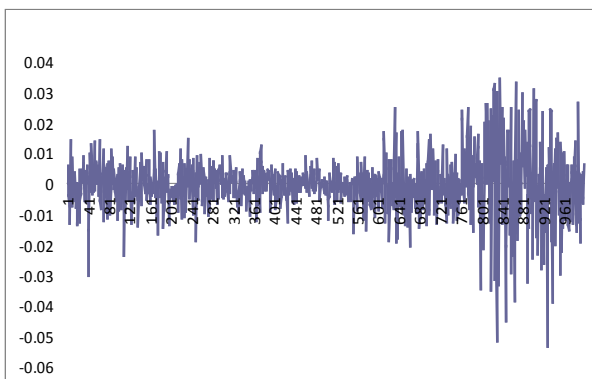Figure 5: Fluctuation in Czech Koruna
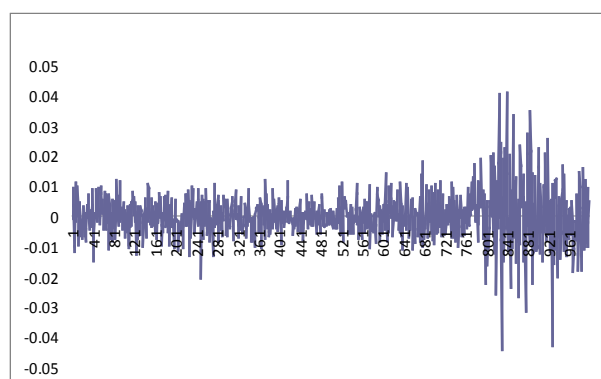

Figure 6: Fluctuation in UK Sterling
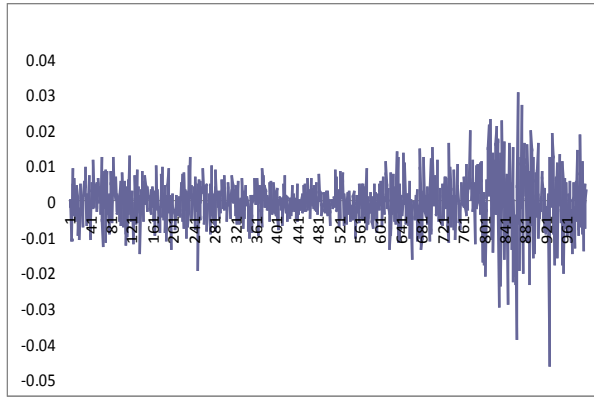
Figure 7: Fluctuation in Euro

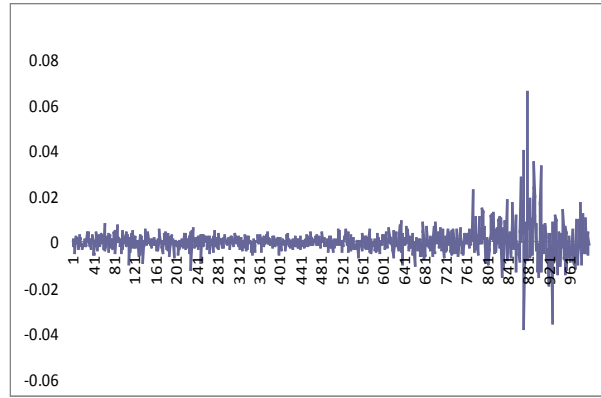Figure 8: Fluctuation in Russian Ruble
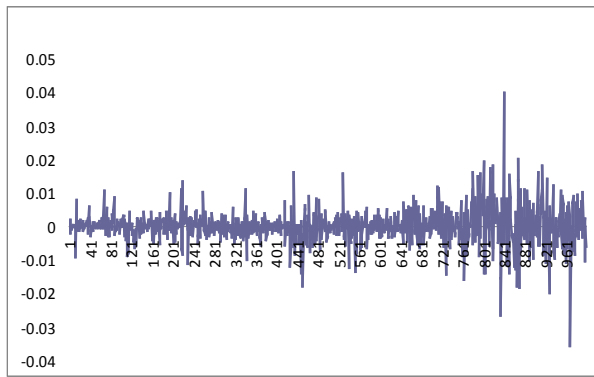

Figure 9: Fluctuation in Indian Rupee
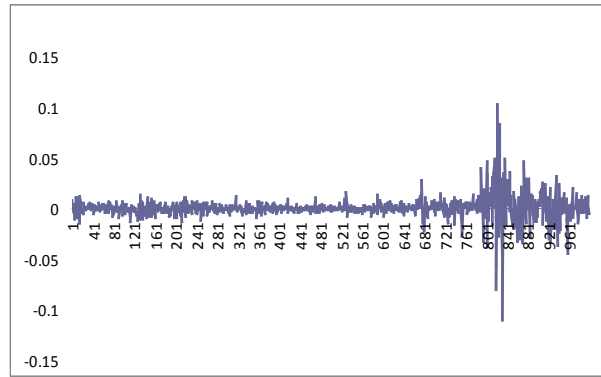

Figure 10: Fluctuation in Korean Won

Figure 11: Fluctuation in Thai Baht

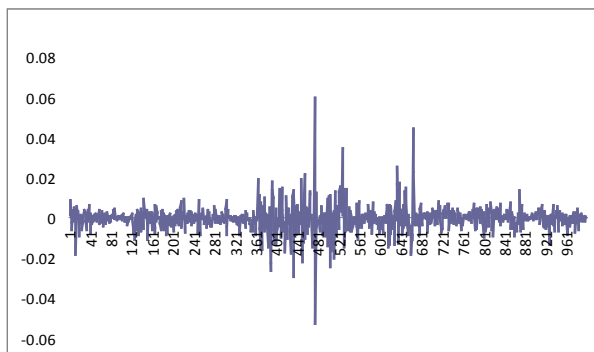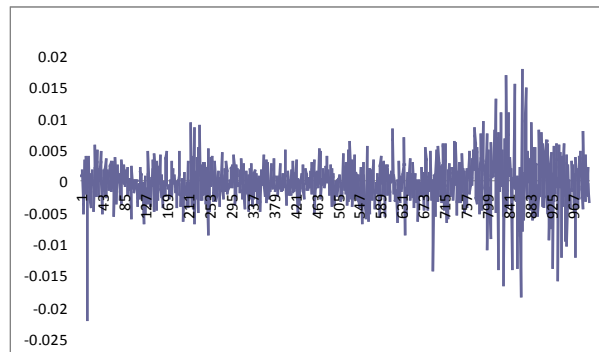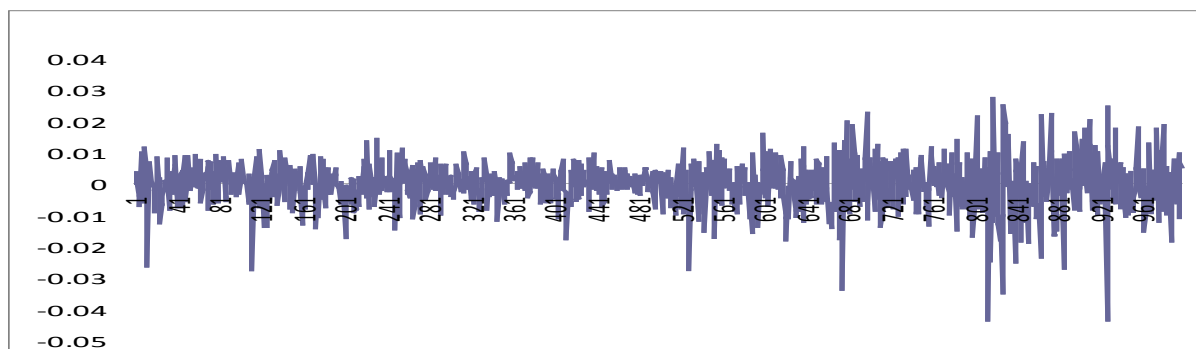Figure 12: Fluctuation in Singapore $

Figure 13: Fluctuation in Japanese Yen

All countries' exchange rates except Thai Baht could be observed to be highly fluctuating in the crisis year of 2008-09. As many as seven countries' exchange rates fluctuation turned from negative to positive into the crisis period compared to previous year indicating a very high degree of volatility. Similarly South African Rand was also seen with a very high volatility in the crisis period falling into negative zone. Since the volatility has been exorbitant in the recent past, it has posed some serious issues for the financial experts, analysts and policy makers as to how effectively it should be managed in order to contain it within limits. The Mexican peso appreciated from peso 11.364 to 10.628 to US$ registering 6.5% growth in 2005. By large, the variability of peso is quite comparable with any developed nations currencies such as Euro or Canadian Dollar during a period of 2003 to 2006. The Korean government is also taking care of exchange rate since its adoption as managed float. It has devised certain rules; important among them is 'sterilized intervention'. Dooley, Dornbusch, and Park (2002) have outlined, "changes in the composition of the central bank's assets (denominated in foreign currencies) will be relied on to moderate volatility in daily nominal exchange rates in excess of three percentage points against a basket of the dollar, euro and yen. This rule could be extended to resist cumulative movements of more than 6% in one week."

Table 1: Mean Changes in Exchange Rates (%)

	2005-06	2006-07	2007-08	2008-09
India	0.0210%	-0.0497%	0.0242%	0.0412%
Canada	-0.0425%	-0.0158%	-0.0158%	0.0551%
UK	-0.0198%	-0.0334%	0.0052%	0.0767%
Japan	0.0104%	0.0299%	-0.0568%	-0.0375%
Brazil	-0.0367%	-0.0463%	-0.0729%	0.0821%
Czech	-0.0484%	-0.0183%	-0.1319%	0.0838%
Singapore	-0.0269%	-0.0125%	-0.0450%	0.0259%
Thailand	-0.0331%	-0.0676%	0.0203%	0.0079%
Russia	-0.0278%	-0.0170%	-0.0363%	0.1153%
Korea	-0.0381%	-0.0086%	0.0525%	0.0831%
Mexico	0.0197%	-0.0105%	-0.0177%	0.0956%
S.Africa	0.0195%	0.0006%	0.0455%	-0.0055%
Euro Zone	-0.0282%	-0.0220%	-0.0582%	0.0496%

The Table 1 shows the mean changes of all the thirteen exchange rates. The outcome of this table is based on the daily log changes of the sample countries' currencies related to four-year period from 2005 to 2009. The first three years represent normal period while the last year represents crisis period. It is evident from the table that the mean changes between 2007-08 and 2008-09 are quite drastic in all countries' exchange rates except Japanese yen. Indian currency volatility shot up to 0.0412% in the year 2008-09 from previous year's level of 0.0242%. British pound also could not remain away from such high volatility which was recorded at 0.0767% in the crisis year compared to 0.00522% in 2007-08. Fluctuations can be observed to be more than double in case of India, Brazil, South Africa and Europe.
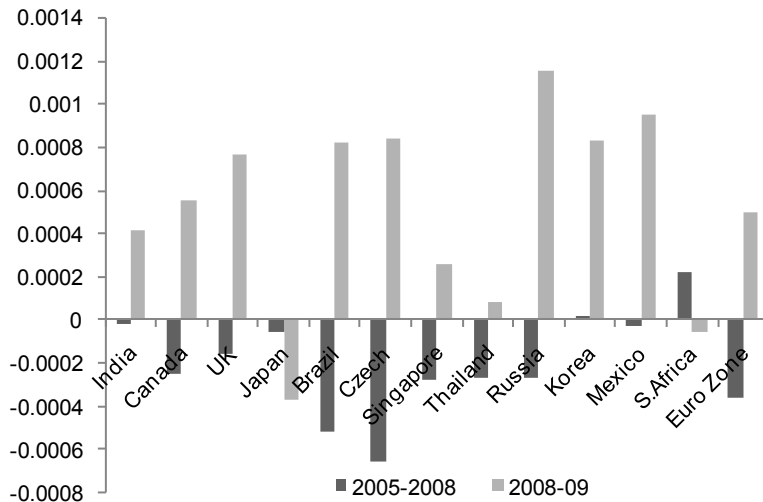
Figure 1: Average Daily Fluctuation (%)

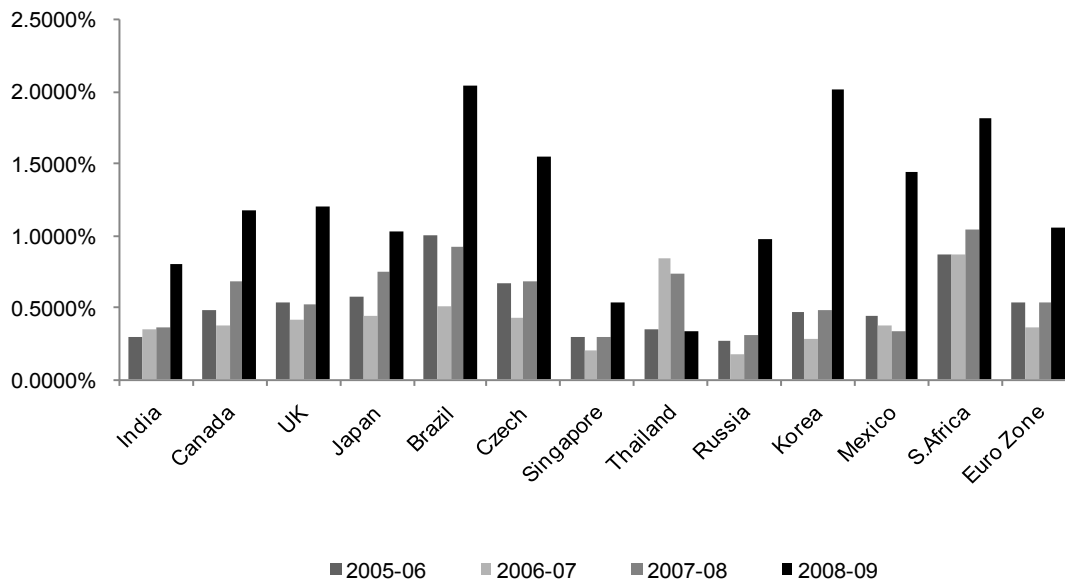Figure 2: Exchange Rate Volatility (%)

Figure 1 is a clear indication of pre-crisis and crisis period mean variability in thirteen exchange rates. One interesting fact can be noted from the above Figure that almost all the exchange rates' (except Korea

and South Africa) average fluctuation in the period 2005-2008 is found to be negative and most of them turned positive in the crisis period of 2008-09. More importantly, the average daily fluctuations can be seen at very high rate in the crisis period. In most cases, it remained in the range of 0.06% to 0.11%.

Figure 2 demonstrates volatility in the exchange rates. As mentioned earlier, this volatility is construed to be variance of all the thirteen countries time series. The analysis of statistical results indicates that standard deviations have been quite high in the crisis period in case of Brazil and Korea which were a little more than 2%-level. Canada, UK, Japan, Czech, Mexico, South Africa, and Euro Zone have shown standard deviations of >1%. However, countries like Singapore, Thailand, and Russia registered a moderate standard deviation of <1% mark. Indian currency seems to have the least degree of risk volatility as it recorded 0.08% standard deviation. On yet another note, eight exchange rates are observed to have negative skewness while India, UK, Russia, Mexico, and South Africa had positive skewness in the crisis period. The Jerque-Bera function is used to indicate whether the changes in the exchange rates are normal or not. An equally mix result can be observed looking at the data.

Table 2: GARCH Results

		2005-06	2006-07	2007-08	2008-09
India	ARCH(1)	0.1875	0.1002	0.0685	0.0044
	GARCH(1)	0.4073	0.8673	0.8871	0.9513
Canada	ARCH(1)	0.1364	-0.0566	0.1333	0.0659
	GARCH(1)	-0.1427	0.8622	0.4846	0.9197
UK	ARCH(1)	-0.0382	-0.0298	-0.0511	0.0460
	GARCH(1)	1.0160	0.6852	1.0214	0.9423
Japan	ARCH(1)	-0.0251	0.0292	0.0592	0.0223
	GARCH(1)	0.7422	0.9083	0.8678	0.9433
Brazil	ARCH(1)	0.1779	0.1128	0.2230	0.1990
	GARCH(1)	0.6997	0.8582	0.7263	0.8239
Czech	ARCH(1)	-0.0092	0.0215	0.0316	0.0445
	GARCH(1)	0.7538	0.9434	0.9579	0.9329
Singapore	ARCH(1)	0.0203	-0.0563	-0.0551	0.0388
	GARCH(1)	0.6692	0.9117	1.0120	0.9401
Thailand	ARCH(1)	0.1087	0.0996	0.3371	0.1244
	GARCH(1)	0.8740	0.9278	0.6861	0.8216
Russia	ARCH(1)	-0.0366	-0.0825	-0.0314	0.0649
	GARCH(1)	1.0122	0.7693	1.0234	0.9160
Korea	ARCH(1)	0.1243	0.0293	0.2186	0.2564
	GARCH(1)	0.7711	0.1754	0.7100	0.7444
Mexico	ARCH(1)	0.1198	0.0496	0.2382	0.2307
	GARCH(1)	0.7493	0.9080	-0.2997	0.8059
S.Africa	ARCH(1)	0.0377	0.0099	0.0535	0.1076
	GARCH(1)	0.9309	0.5604	0.8993	0.8649
Euro Zone	ARCH(1)	-0.1767	-0.0146	-0.0262	0.0305
	GARCH(1)	0.0156	1.0083	1.0202	0.9540

Table 2 presents the outcome of GARCH model. The results are based on the variance which is basically considered as a measure of volatility and is derived from the mean-adjusted relative log change value of the exchange rates. As mentioned in the preceding sections, GARCH model is used to test whether there appears to be volatility in the given set of series; and if found so; then the forecasting will hold. In this study, GARCH (1,1) is used to show that when the sum of ARCH and GARCH coefficients ($\alpha + \beta$) equals to one, there will be persistence of volatility shocks and hence, volatility can be forecast for the next day.

If the pre-crisis period is analyzed, it becomes evident that volatility shocks could not be captured in certain cases. For example, Canada witnessed non-existence of volatility shocks in 2005-06 and 2007-08 while almost all other countries except Thailand witnessed non-existence of volatility shocks at least once in a three year pre-crisis period. But this study emerged with an interesting observation that all the sample countries had volatility shocks in the crisis period of 2008-09. This apparently indicates that due to high degree of volatility in the crisis period, forecasting can be made at least for the next day.

CONCLUDING REMARKS

The current study has objectively focused on the volatility patterns in the exchange rate of thirteen countries with specific reference to the current crisis period. It describes the persistence of volatility clustering in the time series data of thirteen countries applying the GARCH model. The volatility is perceived to be a critical issue especially for those countries which have shifted from fixed exchange rate regime to floating exchange rate regime.

All the countries' exchange rates except Thai Baht are highly volatile in the crisis year of 2008-09. As many as seven countries' exchange rates volatility turned from negative to positive in the crisis period compared to the previous year indicating a very high degree of volatility. But South African Rand is seen with a very high volatility in the crisis period but falling into negative zone from the positive volatility in the preceding year. Indian currency volatility shot up to 0.0412% in the year 2008-09 from previous year level of 0.0242%. British pound also could not avoid high volatility which was recorded at 0.0767% in the crisis year compared to 0.00522% in 2007-08. Almost all the exchange rates' (except Korea and South Africa) average volatility in the period 2005-2008 are negative and most turned positive in the crisis period of 2008-09. Since the volatility has been exorbitant in the recent past, it poses some serious issues for the financial experts, analysts and policy makers as to how effectively it should be contained.

The results of the GARCH model are quite encouraging especially when the pre-crisis period is analyzed. Surprisingly, the volatility shocks could not be captured in certain cases. For example, Canada witnessed non-existence of volatility shocks in 2005-06 and 2007-08 while almost all other countries except Thailand witnessed non-existence of volatility shocks at least once in a three year pre-crisis period. But this study emerged with an interesting observation that all the sample countries had volatility shocks in the crisis period of 2008-09. This apparently indicates that due to high degree of volatility in the crisis period, forecasting can be made at least for the next day. In conclusion, this paper reveals that exchange rates have persistent conditional heteroskedasticity, and hence, could be predicted with one lag term.

The study objectively evaluates the predictability of volatility patterns in exchange rates in times of turbulence. However, it has certain limitations. Further investigations might consider more lag terms to determine the predictability in the exchange rate volatility. Further studies, might also cover more crisis periods, to gain additional insights.

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