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Essays on Exchange Rate Volatility

By

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This thesis is the result of author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

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Abstract

This thesis explores a number of aspects of time series modelling of exchange rate volatility. After having reviewed the main modelling approaches used in the existing literature, the first key chapter investigates the best models for forecasting the volatility of daily exchange rate returns for a number of countries, including new results for a selection of developing countries. The superior performance of the FIGARCH model, noted in the recent literature, is confirmed in the case of industrialised countries, but the IGARCH model results in substantial gains in in-sample estimation and out-of-sample forecasting performance when dealing with developing countries.

The next essay investigates exchange rate volatility co-movements and spillovers before and after the launch of the Euro. This study has the advantage of a longer sample period than the most comparable papers. Key results are that the dominance of the Deutsche mark in volatility transmission was succeeded by the dominance of the Euro following its launch, in that both exert unidirectional and persistent spillovers on the sterling, the Swiss franc and the Japanese yen. Further, there is evidence of greater stability in financial markets after the launch of the Euro in that conditional variances, covariances and correlations in exchange rate returns declined significantly.

Finally the thesis turns to assessing the impact of official central bank interventions (CBIs) on exchange rate returns, their volatility and bilateral correlations. By exploiting the recent publication of intervention data by the Bank of England, this study is able to investigate interventions by a total number of four central banks, while the previous studies have been limited to three (the Federal Reserve, Bundesbank and Bank of Japan). The results of the existing literature are reappraised and refined. In particular, unilateral CBI is found to be more successful than coordinated CBI. The likely implications of these findings are then discussed.

Chapter 1

Introduction

1.1 Background

Since the fall of the Bretton Woods system in 1973 and the adoption of flexible exchange rates, exchange rate volatility has become a central issue and concern for various groups of agents including policy makers, central banks, academics and individual investors among others. It is widely accepted that high levels of exchange rate volatility can be extremely detrimental for economies as they impede international investment flows, adversely affect international trade, can lead to currency crises and the fall of financial systems. Several currency crisis episodes such as the European Monetary crisis in the 1992-93, the Mexican's Peso crisis in 1994 and the Asian crisis of 1997-98, offer gruesome examples.[1]

The adoption of flexible exchange rates was accompanied by exchange rate volatility and this gave rise to various theoretical attempts to explain and predict the nature of the latter.[2] However, the empirical literature has long reached a consensus that macroeconomic fundamentals cannot explain exchange rate movements in the short-run (see, for instance, Meese and Rogoff, 1983, Mussa 1990). When confronted with real data, these theoretical models seem to provide some explanations about exchange rate movements in the long-run. Nonetheless, the dynamics of high

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[1] For studies investigating currency crisis episodes in the 1990's, see, for instance, Eichengreen and Wyplosz, (1993) and Buiter, Corsetti and Pesenti (1998a, 1998b) on the European Monetary crisis of 1992-93; Sachs, Tommell and Velasco (1996) and Calvo and Mendoza (1996) on the Mexican peso crisis of 1994; and International Monetary Fund (1997, 1998), Corsetii, Pesenti and Roubini (1999a, 1999b), Mishkin (1999) and Radelet and Sachs (1998) on the Asias crisis of 1997-98.

[2] See for instance, Sarno and Taylor (2002) for a comprehensive discussion of theoretical exchange rate determination models.

frequency exchange rates (daily or intradaily) cannot be explained by macroeconomic fundamentals (see, for instance, Andersen and Bollerslev, 1998b, Andersen et al., 1999, 2001 and 2003).

Assessing the optimal way of capturing and forecasting the times series dynamics of exchange rates is of great importance. Good predictions allow policy makers and others to form good expectations and minimize the deleterious effects of exchange rate volatility. Modelling the empirical regularities of high frequency exchange rate returns series, aside from macroeconomic fundamentals, captured by volatility clustering, skewness and kurtosis was not possible until the advent of Autoregressive Conditional Heteroskedasticity (ARCH) modelling in 1982. The ARCH model was introduced by Engle (1982) and there have been considerable further developments both in univariate and multivariate context.[3]

There have been numerous applications of these models in modelling financial data, including estimating and forecasting exchange rate returns and/or volatility (see Bolerslev, Chou and Kroner, 1992; Poon and Granger, 2003 for a survey). However, few of these applications have focused on daily exchange rate volatility modelling and forecasting in developing countries. Applications have mainly focused on major industrialised countries, such as the USA, EU, UK and Japan, since these countries are the most active participants in the global financial markets.[4] Nonetheless, developing countries' financial linkages with the global financial markets have risen significantly in recent decades. For instance, Mauro et al., (2006) report that in 1870-1913 capital flows to developing countries were 1.084 billion US dollars whereas in 1993 and 2003 they were 1979 and 3973 billion US dollars, respectively. This dramatic increase in capital flows to developing countries (even when corrected for

[3] See Teräsvirta (2009) for a survey of univariate models of conditional heteroskedasticity and Bauwens, Laurent and Rombouts (2006) for a survey on multivariate ones.

[4] The BIS's Triennial Central Bank Survey on Foreign Exchange and Derivative Market Activity in 2007 reports that, from April 2004 to April 2007, the average daily turnover of the US dollar and the Euro accounted for 86.3% and 37%, respectively, of all transactions (spot and forward transactions. The Japanese yen, the British Pound and the Swiss franc follow the euro with average daily turnovers of 16.5%, 15% and 6.8%, respectively. The reason the % shares exceed 100% is because two currencies are involved in each transaction hence, the sum of the % shares of individual currencies used in the BIS report totals 200%.

inflation) creates new challenges for risk management, policy-making or even the distorting nature of speculation in developing countries' currencies. Chapter 3 examines whether the volatility models used widely in previous studies of industrialised countries perform equally well in terms of in-sample and out-of-sample performance when applied to daily data for developing countries.

In any case, there is no consensus view on the most appropriate modelling approach to adopt in dealing with financial series; including exchange rate returns/volatility (see, for instance, Angelidis and Degiannakis, 2008). A typical approach is for the researcher to examine various competing models and evaluate their relative performance in in-sample and out-of-sample contexts.

Although there are some winners from currency speculation associated with high exchange rate volatility, currencies that exhibit low and stable exchange rate volatility create the basis for the prosperity of the financial markets as a whole, as they attract flows from other countries thus, facilitating international trade. In addition, countries with high exchange rate volatility may be motivated to join countries with low exchange rate volatility that are relatively insulated from shocks arriving from other markets (also known as spillovers), by adopting their currency (see for instance, Pesenti and Tille, 2000).

The creation of the Euro in 1999 has set new standards for the stable development of the financial markets. After a tumbling introduction ten years ago, which was followed by a considerable loss of value in the first couple years, and pessimistic initial predictions in terms of its sustainability, the Euro is currently a well-established and independently strong currency (see chapter 4).[5] The common monetary policy conducted in the Euro Area by the European Central Bank has ensured a record of consistently low inflation in the Euro Area over most of the Euro's life.[6] With EU expansion more countries are joining or signalling an

[5] From the period of 4.01.1999 (valued at 0.847€/$) to 25.10.2000 (where it reached a peak of 1.207€/$) the Euro depreciated by 42.45% against the US dollar. Whereas, from 25.10.2000 to 22.04.2008 (where it reached a minimum of 0.626€/$) appreciated by 48.14%. Currently the Euro is being traded at around 0.78€/$. Source: Bank of England's database.

[6] The CPI percentage change has remained below 2% since 2002. Source: IMF – IFS database.

intention to join the Euro area (conditional on the fulfillment of the Maastricht Treaty prerequisites) as they realise the benefits of a single currency.

Chapter 4 investigates whether volatility in a market is being transmitted to other markets (also known as spillovers) in the pre- and post- euro periods in order to assess the magnitude of markets' interdependence.

Nonetheless, there have been occasions of central bank official interventions in the foreign exchange markets, unilateral or in coordination, with the aim of influencing exchange returns and/or volatility. Two well known agreements for the initiation of such interventions are the Plaza Agreement and the Louvre Accord. The Plaza Agreement was signed on September 22, 1985 by the G5 countries (specifically, France, West Germany, Japan, UK and US) in order to induce a depreciation of the US dollar. The Louvre Accord was signed on February 22, 1987 by the G6 countries (specifically, the G5 previously mentioned plus Canada[7]) to promote stability in financial markets. Even though the theoretical literature suggests several channels through which official central bank interventions (CBIs hereafter) could influence exchange returns and volatility in the intended direction, the evidence from the empirical literature on the impact of official CBIs on exchange returns and volatility shows that intervention has been counterproductive. Specifically, there is evidence that CBIs have no effect on exchange returns and increase their volatility.[8] Chapter 5 tries to fill this lacuna by introducing, new available data and methodologies, where appropriate, and comparing and contrast with the existing literature.

Providing a reappraisal of previous findings and closing some gaps in the existing literature are the ultimate objectives of this thesis.

1.2 Overview

This thesis deals with a number of topics in the field of exchange rate volatility. It addresses various models of exchange rate volatility to analyze issues such as the

[7] Italy was also an invited member in the Louvre Accord, however, declined to finalize the agreement.
[8] See Sarno and Taylor (2001) for a theoretical and empirical survey on the impact of CBIs.

optimal method of exchange rate volatility forecasting, and the need to capture volatility comovements and spillovers, and the impact of central bank interventions on exchange rate returns, their volatility and bilateral correlations. In the following, a detailed description of each chapter is provided.

Chapter 2 introduces the salient features of short-term movements in exchange rate returns and motivates models of exchange rate volatility and the forecast evaluation criteria that will be employed in this thesis.

Chapter 3 evaluates the performance of various univariate models, described in Chapter 2, to estimate and forecast exchange rate volatility of a range of nominal bilateral exchange rates against the US dollar in developing and industrialised countries. A key question is whether the volatility models used widely and successfully in previous studies of industrialised countries perform equally well in terms of in-sample and out-of-sample performance when applied to daily data for developing countries. The empirical literature on forecasting daily exchange rate volatility in developing countries is rather silent. Chapter 3 tries to address this gap by employing the various conditional heteroskedasticity models described in chapter 2, to assess their forecasting performance. The main results of the empirical analysis are summarized as follows. In line with the empirical literature, it is found that, in the case of industrialised countries' exchange returns series, modelling both long memory and volatility clustering properties results in substantial gains in out-of-sample forecasting performance compared to modelling the short memory and volatility clustering properties. The Fractionally Integrated Generalized Auto-Regressive Conditional Heteroskedasticity (FIGARCH) model is found to fit the data best among the alternatives, and to provide superior forecasting performance, as indicated by various evaluation criteria. On the other hand, when modelling developing countries' return series, the Integrated-GARCH (IGARCH) model is found to be superior in both in-sample estimation and out-of-sample forecast evaluation.

Chapter 4 addresses an important aspect of the introduction of the euro by analyzing and comparing exchange rate volatility comovements and spillovers among the major financial markets before and after its introduction. The results of the empirical analysis show that significant volatility spillovers and comovements across the four exchange rates exist, but their magnitude has declined significantly since the introduction of the euro. These findings suggest that the launch of the euro itself coincided with greater stability in the global financial markets. Moreover, the results show that Deutsche Mark (or Euro after 1999) is the dominant currency in volatility transmission, as its volatility affects all other markets' volatility, and exerts an unidirectional spillover on the British pound, Swiss franc and Japanese yen volatility. However, an additional finding is that British pound has become the least volatile currency against the US dollar in the group since the launch of euro. On this basis alone, replacing the British pound with the Euro might be inadvisable. Nevertheless, as already pointed out by Malik (2005) and many others, exchange rate volatility is just one feature of the many that have to be considered before making any conclusive argument as to whether UK should replace pound with euro or not.

Chapter 5 investigates the impact of official central bank interventions on exchange returns, their volatility and spillovers. This investigation is based on the impact of the G4 officially announced CBIs rather than solely relying on the impact of the G3 CBIs that has been thoroughly examined by the literature. The addition of information from a fourth central bank provides the opportunity to investigate coordinated interventions by up to three central banks, which has never previously been assessed. In common with the existing literature, the results demonstrate that CBIs intensify exchange rate correlations. However, under the G4 assessment, unilateral CBIs are shown to have a significant impact on returns and, in minor cases, reduce volatility. In addition, the impact of coordinated bilateral interventions is less clear than the existing literature has suggested and we find that coordination between three central banks tends to coincide with increased volatility. The latter results lead us to question the conclusions of earlier studies and caution against the belief that coordinated intervention is necessarily beneficial.

Chapter 6 provides an overall conclusion along with the implications and suggestions for further research.

Chapter 2

Exchange rate returns, volatility modelling and forecasting

2.1 Introduction

The main purpose of this chapter is to explain the salient features of short-term moments in exchange rate returns and to motivate the models of exchange rate volatility and their forecast evaluation criteria (in relation to the literature) that will be employed in this thesis. This chapter is organised as follows. Section 2.2 describes the features of exchange rate returns series while, section 2.3 presents the various models employed in the following three chapters, that have been applied in exchange rate volatility modelling and forecasting, both in univariate (section 2.3.1) and multivariate (section 2.3.2) frameworks, along with their empirical justification and their extensions. Finally, section 2.4 presents the various forecast evaluation criteria used to assess these models' forecasting performance.

2.2 Characteristics of exchange rate returns

A large number of studies have documented the key characteristics of exchange rate, and its higher moment, series. According to these studies, the raw spot exchange rate series is generally found to be non-stationary. For example, Baillie and Bollerslev (1989) among others conclude that free floating nominal exchange rates are best described as non-stationary, also known as integrated of order 1 or I(1), processes, based on the Augmented Dickey Fuller (ADF) and Phillips and Perron (PP) tests for unit roots. By obtaining the first differences of exchange rates, returns become stationary series and standard time series analysis is applicable. A widely used transformation that will render exchange rates series stationary is the first natural logarithmic differences of nominal exchange rate as given by the following equation:

$$\Delta \ln S_t = \ln(S_t) - \ln(S_{t-1}) \qquad (2.1)$$

where S_t denotes the nominal exchange rate at period t (the number of units of domestic currency required to buy one unit of foreign currency). Hereafter, the use of the exchange returns term will refer to the one obtained based on equation (2.1).

Extensive studies that have employed daily observations of exchange returns clearly find them to be heteroskedastic; i.e. they are characterized by periods of relative tranquillity followed by periods of more turbulent volatility, also known as volatility clustering (dating at least to Mandelbrot, 1963 and Fama, 1965). Such a phenomenon can be easily detected through the application of the Ljung and Box (1978) portmanteau tests for high order of serial correlation in squared returns. For instance, Hsieh (1988) uses daily data of five countries' nominal exchange rates against the US dollar and finds that the null hypothesis of no serial correlations in squared returns is rejected.

Another established key feature of exchange rate returns is their fat tailed distribution. That is, the probability density function of exchange rate returns appears to be leptokurtic, so is more peaked at the centre and has fatter tails compared to that of the normal distribution. Numerically, the kurtosis coefficient which is expressed as:

$$K = \frac{E[(\Delta \ln S_t - \mu)^4]}{\sigma^4} \qquad (2.2)$$

(where μ is the mean, σ the standard deviation of exchange returns, E is the expected value operator and $\Delta \ln S_t$ is defined by equation (2.1)) is found to be significantly greater than 3.[9]

[9] The kurtosis coefficient of a normally distributed variable equals to 3.

In addition, exchange rate returns tend to be slightly skewed, which is not consistent with their being normally distributed. Skewness is a measure of (a)symmetry. A distribution of a variable is said to be symmetric if it looks the same to the right and left of the centre point. The value of skewness of a normally distributed variable which is defined as:

$$SK = \frac{E\left[(\Delta \ln S_t - \mu)^3\right]}{\sigma^3} \qquad (2.3)$$

equals to zero. Negative values of skewness in nominal exchange rate returns indicate that data are skewed to the left referring to an appreciation of the currency, whereas positive values of skewness indicate that data are skewed to the right referring to a depreciation of the currency.[10] Since the exchange rate returns series exhibits significant skewness and kurtosis, the normality assumptions are clearly not met. Hence, alternative distributions have to be used as a basis for modelling higher moments of exchange rate returns, such as the Student-t, skewed Student-t or the Generalized Error distribution (rather than the normal distribution) which take into account the phenomenon of leptokurtosis and skewness in the probability density function.

In order to successfully model exchange rate returns it is important that the key characteristic of the data are captured by the various models under consideration. Modelling the empirical regularities of exchange rate returns series such as volatility clustering, skewness and kurtosis was not possible until 1982. Contributory to such modelling has been the Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by Engle (1982) and its further developments (e.g. among others the GARCH, EGARCH and FIGARCH). There have been numerous applications of these models to modelling financial data including estimating and forecasting exchange rate returns (see Bolerslev, Chou and Kroner, 1992; Poon and Granger, 2003 for a survey). However, there is no unanimous view on the most appropriate modelling approach to adopt in dealing with financial series (see Angelidis and Degiannakis, 2008). A typical approach a researcher has to adopt is to examine

[10] The exchange rate is defined as the number of units of domestic currency required to buy one unit of foreign currency.

various competing models and evaluate them, both in in-sample and out-of-sample performance. In the remainder of this chapter, several conditional heteroskedasticity models and their forecast evaluation criteria are presented.

2.3 Models of exchange rate volatility forecasting

According to the theoretical and empirical literature (see below) various models are capable of capturing daily exchange rate volatility and which are used in volatility forecasting. One can split these models into univariate and multivariate frameworks.

2.3.1 Univariate models of exchange rate volatility

On univariate framework one can split the various models into two main categories: the models able to capture short memory dependencies in exchange rate volatility and models able to capture long memory dependencies in exchange rate volatility. These models are discussed in sections 2.3.1.1 and 2.3.1.2. In addition, realized volatility models from both these two categories are presented in section 2.3.1.3.[11] The realized volatility models differ from the other two in the way the squared returns are calculated. Realized volatility models use the sum of squared returns of a higher frequency as a proxy for actual volatility rather than ex post squared returns of the same frequency. For further discussion, see below.

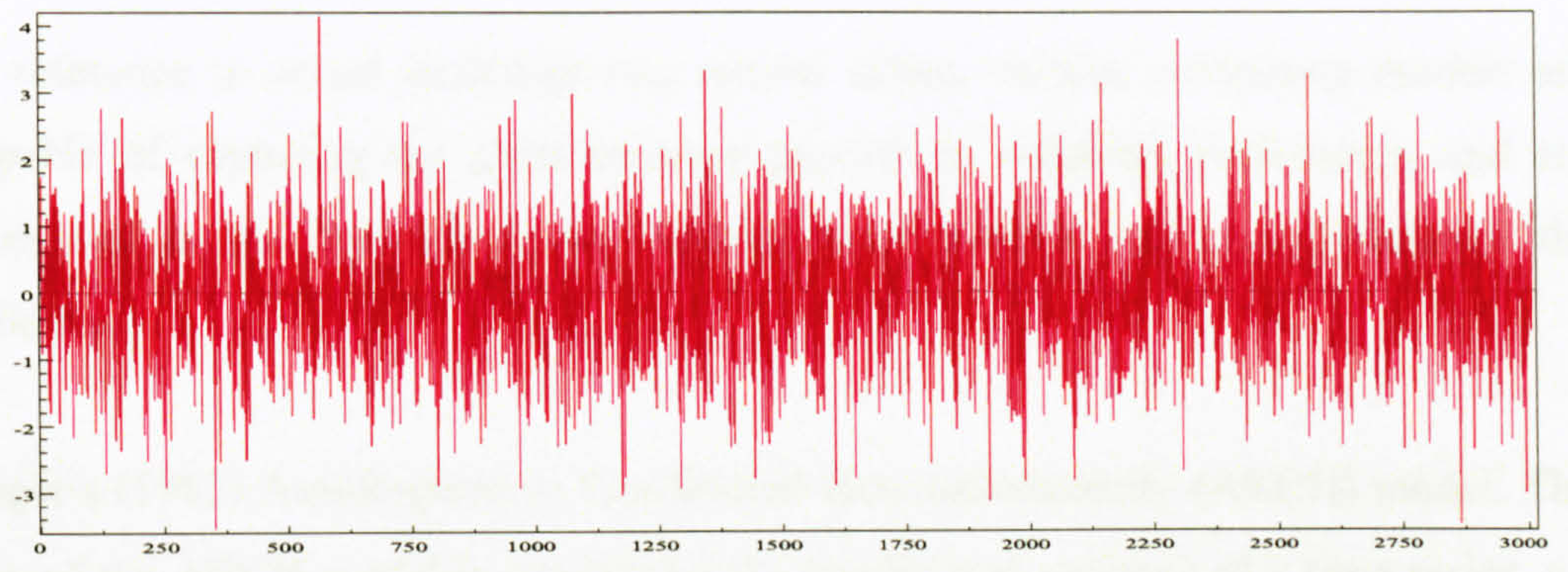
2.3.1.1 Models able to capture the short memory process in volatility persistence

A large amount of empirical evidence has documented the short memory process in the volatility persistence of daily exchange rate returns series (see Vilasuso 2002, among others). A stationary time series process y_t with mean μ and autocorrelation function ρ_j exhibits short memory or weak dependence, if $\lim_{n\to\infty}\sum_{j=-n}^{n}|\rho_j|<\infty$.

[11] However, the realized volatility models are not applied in this research because of the lack of higher frequency data availability for developing countries.

In order to decide whether time series (in our case exchange rate returns, $\Delta \ln S_t$) exhibit short memory process, a careful examination in the plotted series, $\Delta \ln S_t$ and the autocorrelation function (ACF) of squared series, $(\Delta \ln S_t)^2$, is needed. One would expect a time series to exhibit short memory if the plot of this series has the following form:

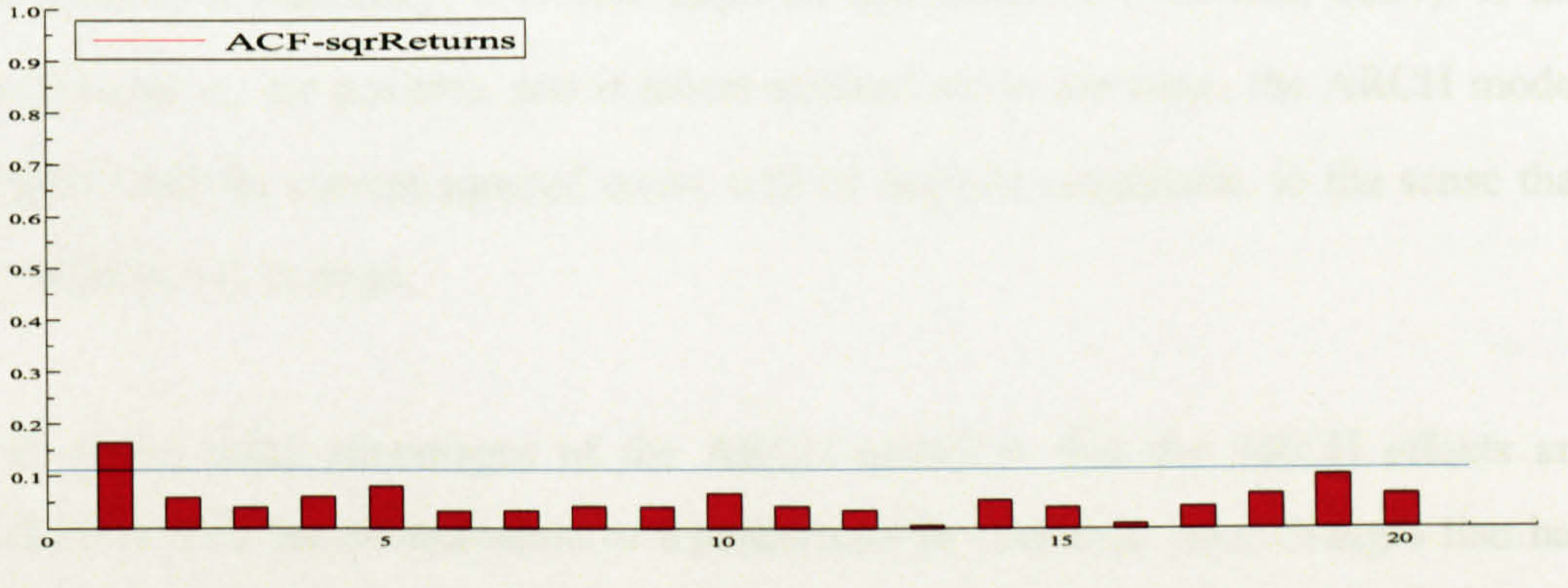
Figure 2.1: Plot of artificially generated short memory returns series



According to Figure 2.1, the time series reverts quite quickly to its mean and is uniformly distributed.

The plot of the ACF of the artificially generated squared return series, which is shown in figure 2.2, is also quite revealing of a short memory process:

Figure 2.2: ACF of artificially generated short memory squared returns series



The autocorrelations from this figure are not persistent and die out very fast. Specifically, after 1 lag the autocorrelation coefficients of the squared returns are insignificant since, they lie inside the insignificant level defined by $2/\sqrt{n}$, where n is the number of points of the time series being analysed (shown by the horizontal line in the figure). That is, events from the distant past have a negligible effect on the present. Hence, plots of this kind may serve as a starting point in terms of distinguishing whether a time series exhibits short or long memory process.

In reference to actual exchange rate returns series, various competing models are capable of capturing the short memory process in volatility persistence, and are discussed in the following part. Among these models one can distinguish the following.

Engle's (1982) AutoRegressive Conditional Heteroskedasticity (ARCH) model. The aim of the ARCH model is to estimate the conditional variance of a time series y_t, $Var\langle y_t | y_{t-1}\rangle = \sigma_t^2$ as an autoregressive (AR) process which can be written as:

$$\sigma_t^2 = h_t^2 = \delta + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \ldots + \alpha_q\varepsilon_{t-q}^2 + \omega_t = \delta + \alpha(L)\varepsilon_{t-1}^2 + \omega_t \qquad (2.4)$$

where ω_t is a white noise and $\alpha(L)$ is a lag polynomial of order $q-1$. One restriction that must be fulfilled is that the conditional variance is positive. To ensure that the conditional variance is positive, δ should be greater than zero and the coefficients in $\alpha(L)$ must be greater or equal than zero. In addition, to ensure that the process is stationary, it is also required that $\alpha(q) < 1$ (Verbeek, 2004). If the coefficients α_i are positive, and if recent squared errors are large, the ARCH model predicts that the current squared errors will be large in magnitude, in the sense that its variance σ_t^2 is large.

One of the main advantages of the ARCH model is that the ARCH effects are consistent with the phenomenon of leptokurtosis in exchange rates changes that has been documented by a number of studies (see, among others, McFarland, Pettit and Sang, 1982; So, 1987). While Engle's (1982) ARCH model is undoubtedly one of the major contributions in financial econometrics, it is rarely used in the area of forecasting exchange rate volatility. That is because long lags are often required in the conditional variance specification which renders the estimation intractable. For instance, Hsieh (1988) using daily data on five currencies against the US dollar, finds that an ARCH(12) model is needed to capture most of the nonlinear stochastic dependencies. Furthermore, in other studies, a fixed lag structure is imposed in order to avoid the problem of negative variance parameter estimates in the ARCH specification (see for instance Engle and Kraft, 1983). This is due to the fact that exchange rates changes are often characterized by a higher order autoregression process in the conditional variance rather than that captured by the ARCH process. Specifically, the squares of exchange rate changes appear to be highly serially correlated, a feature which cannot be captured by the ARCH model, since its estimation does not include any lags of the conditional variance. In this research, the ARCH model will be one of the competing models, although we do expect to find the inclusion of a large number of lags to be necessary in the ARCH specification.

Since the ARCH process might not capture some of the stylized facts in the exchange rate return series, Bollerslev (1986) extended the ARCH model to allow the error variance to depend on its own lags as well as lags of the squared error. In other words, his extension allows the conditional variance to follow an Auto Regressive Moving Average (ARMA) process, which can be specified as:

$$\begin{aligned}\sigma_t^2 = h_t^2 &= \delta + \alpha_1\varepsilon_{t-1}^2 + \ldots + \alpha_q\varepsilon_{t-q}^2 + \beta_1\sigma_{t-1}^2 + \ldots + \beta_p\sigma_{t-p}^2 + \omega_t \\ &= \delta + \sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2 + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^2 + \omega_t = \delta + a(L)\varepsilon_{t-1}^2 + \beta(L)\sigma_{t-1}^2 + \omega_t\end{aligned} \qquad (2.5)$$

where $\alpha(L) = \alpha_1 L + \alpha_2 L^2 + \ldots + \alpha_p L^q$ and $\beta(L) = \beta_1 L + \beta_2 L^2 + \ldots + \beta_p L^p$ are lag polynomials. According to Engle and Bollerslev (1986) if we define the surprise in the squared innovations as $\upsilon_t \equiv \varepsilon_t^2 - \sigma_t^2$ then the GARCH(1,1) process can be rewritten as:

$$\varepsilon_t^2 = \delta + (\alpha + \beta)\varepsilon_{t-1}^2 + \upsilon_t - \beta\upsilon_{t-1} \qquad (2.6)$$

which shows that the squared errors follow an ARMA(1,1) process. While the error υ_t is uncorrelated over time, it does exhibit heteroskedasticity. Furthermore, the root of the autoregressive part is $\alpha+\beta$, so stationarity requires that $\alpha+\beta<1$ (Verbeek, 2004 op. cit, p.299). The GARCH(p,q) process can be defined by:

$$\sigma_t^2=\delta+\sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2+\sum_{j=1}^{p}\beta_j\sigma_{t-j}^2 \qquad (2.7)$$

where the conditional variance is a linear function of a constant, q lags of the past squared error terms and p lags of the past squared conditional variances. The necessary conditions needed to ensure that the conditional variance σ_t^2 is strictly positive are the following: $\delta>0,\ \alpha_i\geq 0,\ \beta_j\geq 0,\ i=1,2,\ldots,p\ j=1,2,\ldots,q$. The weak stationarity of this model is assured by:

$$\sum_{i=1}^{q}\alpha_i+\sum_{j=1}^{p}\beta_j<1. \qquad (2.8)$$

The GARCH(1,1) model, in general terms, seems to perform very well in terms of tracking the short-run dependencies in volatility and explaining the characteristics of the financial times series such as exchange rate returns (Hansen and Lunde, 2005).

The empirical applications of the GARCH models in exchange rates return series is ample. In two papers of Hsieh (1989a and 1989b) it is shown that the GARCH(1,1) model outperforms the ARCH(12) model estimated in Hsieh (1988). A number of other studies including Taylor (1986) and McCurdy and Morgan (1988) have reached similar conclusions. West, Edison and Cho (1993) using weekly exchange rate data find that the GARCH(1,1) specification has a tendency to surpass alternative specifications and they state that *"... an investment advisor whose only specialized tool is the GARCH may be as worthy of her as hire as are professionals currently on Wall Street"*. The success of the GARCH model, in the field of exchange rate returns, compared to the ARCH model derives from the more parsimonious lag structure being able to successfully capture the dependencies in the higher-order conditional moments. The GARCH model will be among the competing models in this research.

Another extension of the GARCH model is the Exponential GARCH (EGARCH) model introduced by Nelson (1991). The EGARCH model allows for an asymmetric response to a shock, meaning that good news has a different impact to bad news on volatility. The EGARCH can be defined by:

$$\log \sigma_t^2 = \omega + [1-\beta(L)]^{-1}[1+\alpha(L)]g(z_{t-1}) \qquad (2.9)$$

Where $g(z_t)$ depends on various aspects. According to Nelson (1991, p. 351) "*to accommodate the asymmetric relation between stock return and volatility changes ... the value of $g(z_t)$ must be a function of both the magnitude and the sign of z_t*". For that reason he defines the function $g(z_t)$ by:

$$g(z_t) = \underbrace{\theta_1 z_t}_{sign\ effect} + \underbrace{\theta_2 \left[|z_t| - E|z_t|\right]}_{magnitude\ effect} \qquad (2.10)$$

Because the level z_t is included, the EGARCH model is asymmetric as long as $\theta_1 \neq 0$. When $\theta_1 < 0$, positive shocks ('good news') generate less volatility than negative shocks ('bad news'). When $\theta_1 > 0$, negative shocks ('bad news') generate less volatility than positive shocks ('good news') (Verbeek, 2004 op. cit, p.300).

The empirical evidence of the successful performance on EGARCH models in stock returns is voluminous (see for instance Nelson, 1991). The documented negative correlation between current stock returns and future volatility has a plausible economic explanation suggested by Black (1976) known as the 'leverage effect'. The leverage effect means that a drop in equity value would increase the debt-to-equity ratio, therefore raising the riskiness of the firm as marked by an increase in future volatility. As a result, the future volatility will be negatively related to the current stock return. A similar justification is not obvious for exchange rate returns. The empirical evidence on EGARCH models in the area of exchange rate returns is questionable.

Balaban (2004) finds that the EGARCH model outperforms the GARCH model, although the difference is negligible. He argued that there is no theoretical rationale for asymmetries in exchange rate returns, unlike stock returns, and suggests that the reported asymmetry may be attributed to the unexplained characteristics of the data. In a similar context, Bollerslev, Chou and Kroner (1992) argue that the EGARCH model is less likely to capture asymmetries of the conditional variance given the twosided nature of the foreign exchange market. This argument is also supported by Kisinbay (2003) who finds evidence of asymmetry in stock returns but not in foreign exchange returns.

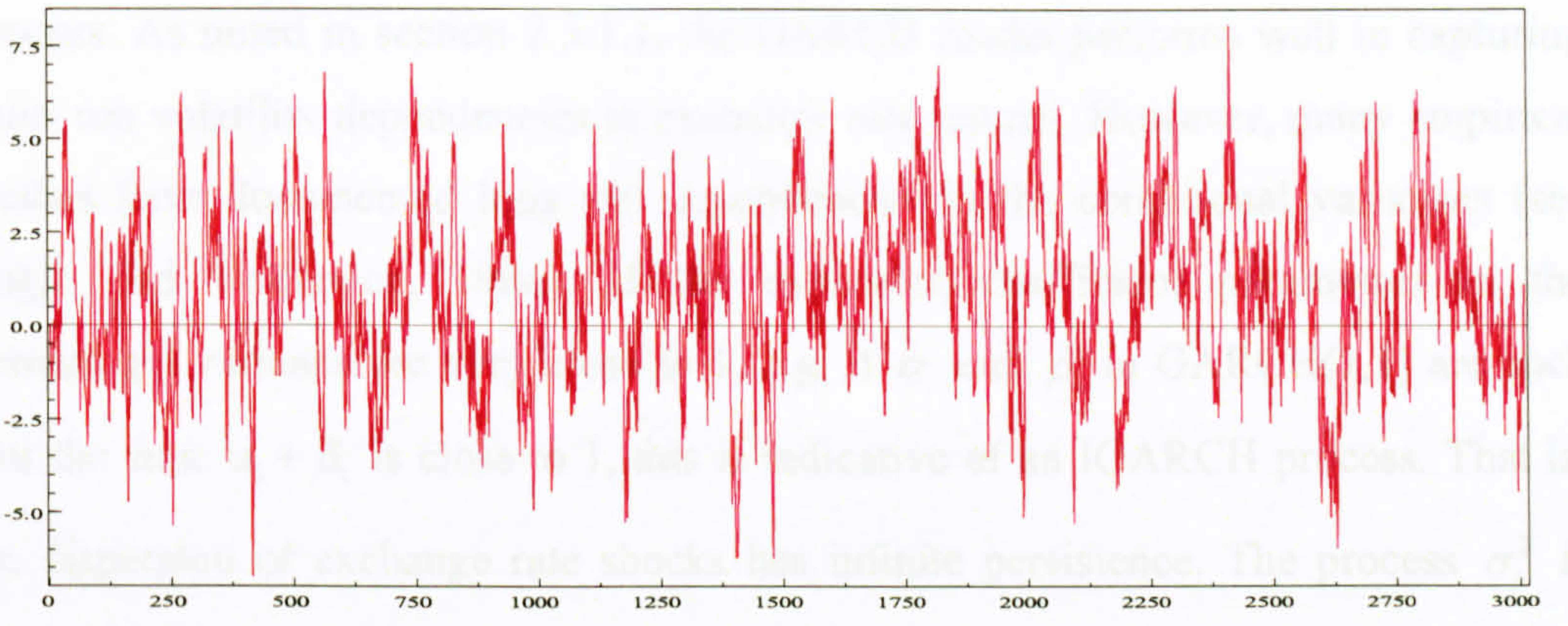
Since the empirical evidence of the EGARCH model on exchange rate returns is ambiguous, the EGARCH will be one of the competing models employed in this research.

2.3.1.2 Models able to capture the long memory process in volatility persistence.

The existing literature offers considerable evidence of long memory processes in volatility persistence of exchange rate returns series (Ding, Granger and Engle, 1993; Dacorogna et al., 1993; Baillie & Bollerlsev and Mikkelsen 1996; Chortareas et al., 2007, among others). Various definitions of long memory process are available. According to McLeod and Hipel (1978) and many others, given a discrete time series process y_t with autocorrelation function ρ_j at lag j, the process contains long memory if the quantity $\lim_{n\to\infty}\sum_{j=-n}^{n}\left|\rho_j\right|$ is nonfinite. This means that the autocorrelation function decays at a hyperbolic, rather than exponential, rate as the lag increases. In other words, the rate of decay towards zero is much slower for a long memory process, implying that current observations retain some "memory" of the distant past.

In order to decide whether time series (in our case exchange rate returns, $\Delta \ln S_t$) exhibit long memory process, again, a careful examination in the plotted series, $\Delta \ln S_t$, and the autocorrelation function (ACF) of squared series, $(\Delta \ln S_t)^2$, is needed. One would expect a time series to contain long memory if the plot of a series has a similar form as that in Figure 2.3:

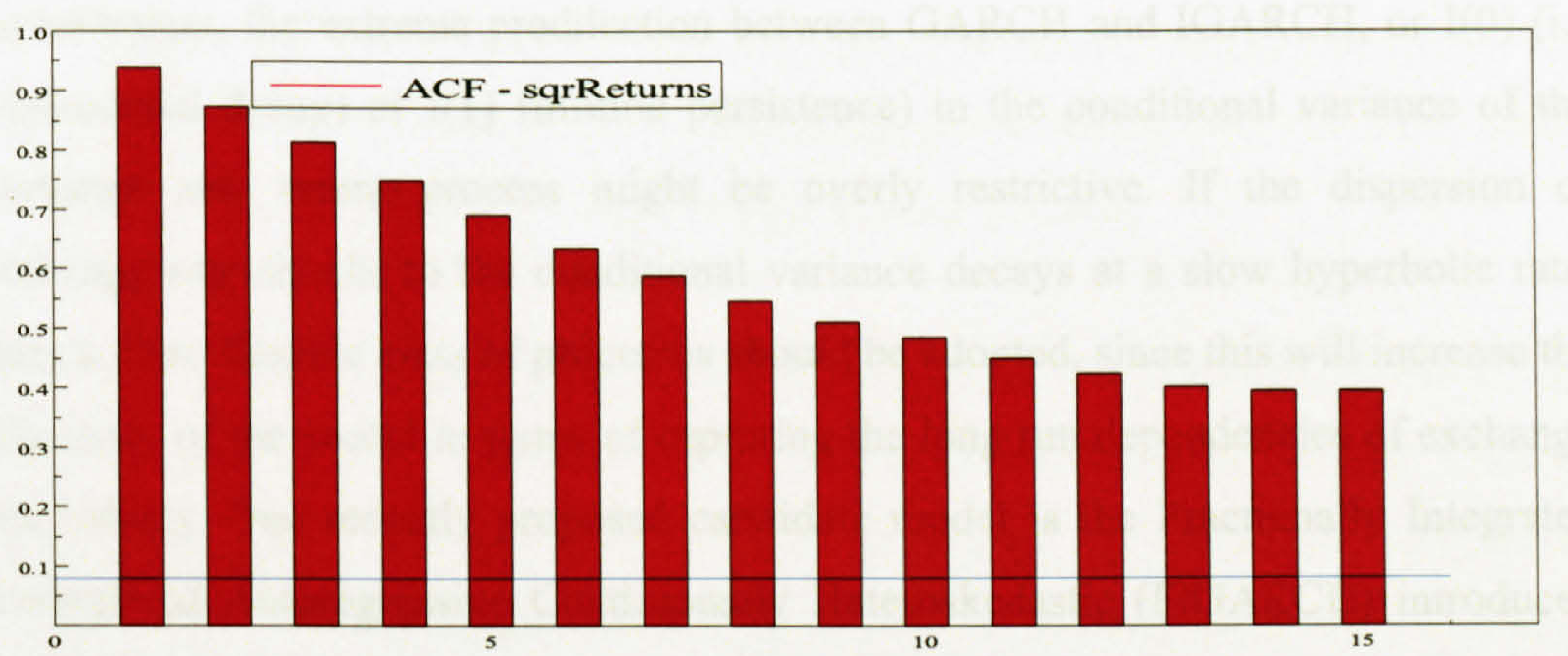
Figure 2.3: Plot of artificially generated long memory returns series



That is, (i) there are persistent departures from the mean and (ii) mean reversion takes place but only slowly.

The plot of the ACF which is shown in Figure 2.4 is also quite revealing of a long memory process.

Figure 2.4: ACF of artificially generated long memory squared returns series



The autocorrelations from Figure 2.4 are very persistent and die out at a slow hyperbolic rate as opposed to the quick decay which is found for a short memory process. In addition, significant correlations exist even between observations that are widely separated in time. That is, a shock to the series has a long-lasting impact, even though it eventually dissipates. Hence, plots of this kind may again serve as a starting point in terms of distinguishing whether a time series exhibits a short or long memory process. Various models are capable of capturing their long memory process. As noted in section 2.3.1.1, the GARCH model performs well in capturing short run volatility dependencies in exchange rate returns. However, many empirical studies have documented long run dependencies in the conditional variances (see Engle and Bollerslev, 1986). If the estimated coefficient parameters in the conditional variance are very close to 1, e.g. if α and β in GARCH(1,1) are such that the sum $\alpha_1 + \beta_1$ is close to 1, this is indicative of an IGARCH process. That is, the dispersion of exchange rate shocks has infinite persistence. The process σ_t^2 is strongly stationary but not covariance stationary.

Many studies that use daily data have reached the conclusion that the volatility is highly persistent and tends to be well approximated by an IGARCH process (see e.g., Bollerslev 1987, McCurdy and Morgan 1988, Baillie and Bollerslev 1989, and Hsieh 1989b). As a result, the IGARCH is going to be one of the rival models examined in this research.

Nevertheless, the extreme predilection between GARCH and IGARCH, or I(0) (i.e .exponential decay) or I(1) (infinite persistence) in the conditional variance of the exchange rate return process might be overly restrictive. If the dispersion of exchange rate shocks to the conditional variance decays at a slow hyperbolic rate, then, a more flexible class of processes should be adopted, since this will increase the efficiency of the model in terms of capturing the long run dependencies of exchange rate returns. One recently proposed candidate model is the Fractionally Integrated Generalized Autoregressive Conditionally Heteroskedastic (FIGARCH) introduced by Baillie, Bollerslev and Mikkelsen (1996). The FIGARCH model incorporates a lag polynomial term of the form $(1-L^d)$, for non-integer d, and thereby allows a long memory process in the conditional variance. If the actual autocorrelations in conditional variance decay more slowly (at a hyperbolic rate) than is compatible with the usual short-range dependent specifications, such a model might be expected to perform relatively well at longer horizons for exchange rate returns. The FIGARCH extends the GARCH model by allowing a term of the form $(1-L^d)$, defined by:

$$(1-\phi(L))(1-L)^d \varepsilon_t^2 = \omega + (1-\beta(L))(\varepsilon_t^2 - \sigma_t^2)$$
$$or \qquad (2.11)$$
$$\sigma_t^2 = \omega^* + \left\{1 - \left[1-\beta(L)\right]^{-1} \phi(L)(1-L)^d\right\} \varepsilon_t^2$$

where the constant is now defined as $\omega^* = \omega\left[1-\beta(L)\right]^{-1}$ and $d \in (0,1)$.

The empirical evidence of FIGARCH process in exchange rate returns is well documented. Baillie, Bollerslev and Mikkelsen (1996) used daily DM/US dollar spot exchange rate data and found evidence of a FIGARCH formulation of the conditional variance process, rather than a GARCH or IGARCH. Primarily, this reflected a slow hyperbolic rate of decay in the effect of a shock to the conditional variance. Vilasuso (2002) examined daily observations of the nominal exchange rates of six industrialized countries the Canadian dollar, French Franc, German mark, Italian lira, Japanese yen and British pound all against the US dollar, for the period of 1979-1997. He evaluated the performance of GARCH, IGARCH and FIGARCH models in terms of out-of-sample forecast accuracy. For each currency, the FIGARCH model was preferred both for its ability to capture the salient features of exchange rate volatility and to produce more accurate forecasts. The Mean Square Error (MSE) and the Mean Absolute Error (MAE) forecast criteria generated by the FIGARCH model were found to be superior at 1, 5 and 10 day forecast horizon.

Davidson (2004) proposed a generalized version of the FIGARCH model the Hyperbolic GARCH (HYGARCH) model. This model can generate long memory without 'behaving oddly' when *d*, the parameter of fractional integration, approximates 1. When *d* approaches to one, then the memory parameter, measured by $-\delta$ in equation (2.2) of his paper, is discontinuous, jumping to $-\infty$ (see Davidson, 2004 for further discussion). The HYGARCH model is given by the following equation:

$$\sigma_t^2 = \omega[1-\beta(L)]^{-1} + \{1-[1-\beta(L)^{-1}\phi(L)\{1+\alpha[(1-L)^d]\}\}\varepsilon_t^2 \qquad (2.12)$$

Interestingly, the HYGARCH nests the FIGARCH when $\alpha = 1$, or equivantly when $\log(\alpha) = 0$, and the process is stationary when $\alpha < 1$, or equivantly when $\log(\alpha)<0$, in which case the GARCH component observes the usual covariance stationarity restrictions (see Davidson, 2004).

The limited existing research shows that the HYGARCH model performs well. Davidson (2004) finds that, when evaluated on 10 daily dollar exchange rate returns, the HYGARCH model cannot be rejected in favour of the GARCH and IGARCH models according to the log-likelihood values. That is, hyperbolic convergence of squared returns is not rejected as the estimated parameter α in equation (2.12) is statistically significant less than one. Since the empirical evidence of HYGARCH on exchange rate returns is promising but limited to date, this model is going to be among the competing models in this research.[12]

2.3.2 Multivariate models of exchange rate volatility

On multivariate framework one can split the various models into three main approaches for constructing multivariate conditional heteroskedasticity models: i) direct generalizations of the univariate GARCH model of Bollerslev (1986), ii) linear combination of univariate GARCH models and iii) conditional correlation models. In the remainder, only the models employed in this thesis will be presented.[13]

One of the models employed in this thesis, which falls in the first approach mentioned above, is the Full-BEKK[14] GARCH model proposed by Engle and Kroner (1995). This model can capture the exact direction of comovements and spillovers between n series' volatility (where $n > 1$), in our case, exchange rate volatility. That is, it allows the investigation of the impact of innovations and volatility persistence of a market in that particular market and the examination of cross-innovations and cross-volatility persistence. Being more specific, we examine how innovations and

[12] Other extensions of the GARCH models have been taken into account in this research such as the FIEGARCH of Bollerslev and Mikkelsen (1996) and the FIAPARCH of Tse (1998) but the results where not supporting thus, not presented in this research. These results can be provided from the author upon request.
[13] For a survey of the available multivariate GARCH models and their extensions, see Bauwens, Laurent and Rombouts (2006).
[14] The acronym comes from the conjoint work of Baba, Engle, Kraft and Kroner.

volatility persistence in one market affects that particular markets and other markets, as well as the direction of spillovers.

The Full-BEKK model of Engle and Kroner (1995) is defined as:

$$y_t = \mu_t(\theta) + \varepsilon_t, \text{ where } \varepsilon_t | \Omega_{t-1} \sim N(0, H_t)$$
$$H_t = C'C + \sum_{i=1}^{q} \sum_{k=1}^{K} A_i' \varepsilon_{t-i} \varepsilon_{t-i}' A_i + \sum_{i=1}^{p} \sum_{k=1}^{K} B_i' H_{t-i} B_i \qquad (2.14)$$

where $y_t = (y_{it} \ldots y_{nt})'$ is a $nx1$ vector of series, $\mu_t(\theta) = (\mu_{it}, \ldots, \mu_{nt})'$ is the conditional $nx1$ mean vector of y_t, H_t is the conditional variance matrix of y_t, C is a lower triangular matrix, and A and B are nxn matrices. The conditional mean vector of y_t can be specified as an ARMA process according to:

$$\Psi_i(L)(y_{it} - \mu_{it}) = \Theta_i(L)\varepsilon_t$$
$$\mu_{it} = \mu_i + \sum_{j=1}^{n_1} \delta_{ji} \chi_{j,t}, \qquad (2.15)$$

where L is the lag operator, $\Psi_i(L) = 1 - \sum_{j=1}^{n} \psi_{ij} L^j$ and $\Theta_i(L) = 1 - \sum_{j=1}^{s} \theta_{ij} L^j$.

The Full-BEKK model described in equation (2.14) is more general as it involves a summation over K terms. Whenever $K > 1$, an identification problem arises, as there are several parameterizations that yield the same representation of the model. The Full-BEKK contains $((p+q)Kn^2)2 + n(n+1)/2$, thus obtaining convergence may therefore be difficult because the previous equation is not linear in parameters. Since, numerical difficulties are so common in the estimation of the Full-BEKK model, it is typically assumed that $p = q = K = 1$ in applications of the Full-BEKK. In this thesis is also assumed that $K = 1$ and thus, the Full-BEKK is defined as:

$$H_t = C'C + \sum_{k=1}^{K} A_i' \varepsilon_{t-i} \varepsilon_{t-i}' A_i + \sum_{k=1}^{K} B_i' H_{t-i} B_i \qquad (2.16)$$

This model ensures the positive semi-definiteness of the conditional variance-covariance matrix by construction.

The coefficients of A and B matrices in (2.16) are of interest since they indicate the innovations in markets and the persistence (or the rate of the decay) of news in markets, respectively. Specifically, the diagonal coefficients of A and B matrices capture the own innovation and own volatility persistence effects of each market, respectively, whereas, the off-diagonal coefficients capture the cross-innovation and cross-volatility persistence (or spillovers) between exchange markets, respectively. The coefficients of the lower triangular $C'C$ matrix (of constants) are of no interest and their matrix decomposition is used only to ensure positive definiteness of H_t.

Even though the Full-BEKK model is very useful when investigating volatility spillovers, it is rarely applied for more than 4 variables because as the number of variables increases, the number of estimated parameters increases exponentially. For instance, with $n = 2$ variables the number of estimated parameters for a full BEKK equals 11 but with $n = 4$ and $n = 5$ equals to 42 and 65, respectively.

Other flexible multivariate GARCH specifications have been developed to account for many variables, such as the Constant Conditional Correlation (CCC) proposed by Bollerslev (1990) and the Dynamic Conditional Correlation (DCC) proposed by Engle (2002).[15] Those two models fall into the category of nonlinear combinations of univariate GARCH models.

The CCC model of Bollerslev (1990) is defined as:

$$\begin{aligned} & y_t = \mu_t(\theta) + \varepsilon_t, \text{ where } \varepsilon_t \left|\Omega_{t-1} \sim N(0, H_t)\right. \\ & \varepsilon_t = H_t^{1/2} u_t, \text{ where } u_t \sim N(0, I) \\ & H_t = D_t R D_t = (\rho_{ij} \sqrt{h_{iit} h_{jjt}}) \end{aligned} \qquad (2.17)$$

where y_t can be defined as in equation (2.14), H_t is the conditional variance-covariance matrix, $D_t = diag(h_{iit}^{1/2} ... h_{nnt}^{1/2})'$ is a diagonal matrix of square root conditional variances, where h_{iit} can be defined as any univariate GARCH-type

[15] A similar specification of the DCC model has been proposed by Tse and Tsui (2002).

model, and $R=(\rho_{ij})$ is a symmetric positive definite matrix with $\rho_{ii}=1,\forall i$ that contains the constant conditional correlations ρ_{ij}.

The CCC model of Bollerslev (1990) in its simplest form has a GARCH(1,1) specification for each conditional variance in D_t:

$$h_{iit}=\omega_i+\alpha_i\varepsilon_{i,t-1}^2+\beta h_{ii,t-1}\ i=1,2,...,n. \qquad (2.18)$$

This model contains $n(n+5)/2$ parameters. The positive definiteness of H_t is ensured if and only if all the n conditional variances are positive and R is positive definite. The unconditional variances are easily obtained, as in the univariate case, but the unconditional covariances are difficult to calculate because of the nonlinearity in the second equation of (2.17).

The CCC model is based on the assumption that correlations remain constant over time, which is a rather unrealistic in many empirical financial applications (e.g. see Longin and Solnik (1995) and Sheady (1997)). Having estimated the CCC model of Bollerslev (1990), one can apply two tests for constant conditional correlations of Tse (2000) and Engle and Sheppard (2001) to check whether correlations remain constant over time or not. In the former test, the null hypothesis, which is that conditional correlations remain constant over time, is specified as:

$$H_0: h_{ijt}=\rho_{ij}\sqrt{h_{iit}h_{jjt}}, \qquad (2.19)$$

where the conditional variances are GARCH-type models and the alternative hypothesis is that conditional correlations are time-dependent and specified as:

$$H_a: h_{ijt}=\rho_{ijt}\sqrt{h_{iit}h_{jjt}} \qquad (2.20)$$

This test statistic is an LM statistic which under the null is asymptotically χ^2 distributed with $n(n-1)/2$ degrees of freedom.

In the constant correlation test of Engle and Sheppard (2001), the null hypothesis is specified as:

$$H_0: R_t=\bar{R}\ \forall t \qquad (2.21)$$

And the alternative is specified as:

$$H_a : vech(R_t) = vech(\bar{R}) + \beta_1^* vech(R_{t-1}) + ... + \beta_p^* vech(R_{t-p}) \quad (2.22)$$

The test is easy to employ as H_0 entails that the coefficients in the regression $X_t = \beta_0^* + \beta_1^* X_{t-1} + ... \beta_p^* X_{t-p} + u_t^*$ are equal to zero, where $X_t = vech^u(\hat{z}_t \hat{z}_t' - I_N)$, $vech^u$ is like the vech operator but it only selects the elements under the main diagonal, $\hat{z}_t = \hat{\bar{R}}^{-1/2} \hat{D}_t^{-1} \hat{\varepsilon}_t$ is the N x 1 vector of standardized residuals (under the null), and $D_t = diag(h_{11t}^{1/2} ... h_{nnt}^{1/2})$.

The second competing model employed in this thesis is the DCC model of Engle (2002). The specification of the DCC is similar to the CCC; however, the coefficients in the correlation matrix under the DCC specification are time-varying.

The DCC model of Engle (2002) is defined as:

$$\begin{aligned} y_t &= \mu_t(\theta) + \varepsilon_t, \text{ where } \varepsilon_t | \Omega_{t-1} \sim N(0, H_t) \\ \varepsilon_t &= H_t^{1/2} u_t, \text{ where } u_t \sim N(0, I) \qquad (2.23) \\ H_t &= D_t R_t D_t \end{aligned}$$

where y_t and $\mu_t(\theta)$ are defined as above, H_t is the conditional variance-covariance matrix and $D_t = diag(h_{iit}^{1/2} ... h_{nnt}^{1/2})'$ is a diagonal matrix of square root conditional variances, where h_{iit} can be defined as any univariate GARCH-type model. The main and important difference from the CCC, is that here R_t is the $t \times \left(\frac{n(n-1)}{2} \right)$ matrix containing the time-varying conditional correlations defined as:

$$R_t = diag(q_{11,t}^{-1/2} ... q_{nn,t}^{-1/2}) Q_t diag(q_{11,t}^{-1/2} ... q_{nn,t}^{-1/2}). \qquad (2.24)$$

where $Q_t = (q_{ij,t})$ is a nxn auxiliary symmetric positive definite matrix given by:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u_{t-1}' + \beta Q_{t-1} \qquad (2.25)$$

where $u_t = (u_{1t} u_{2t} ... u_{nt})'$ is the $nx1$ vector of standardized residuals, $\bar{Q}$ is the nxn unconditional variance matrix of u_t, and α and β are nonnegative scalar parameters satisfying $\alpha + \beta < 1$.

The DCC model can be estimated through a 1-step or 2-step procedure. In the case of the 1-step procedure, both the individual conditional variances and the conditional correlation matrix are being constructed simultaneously. Whereas, in the case of the 2-step procedure, the individual conditional variances are specified as univariate GARCH processes, in the first step and in the second step the standardized residuals from the first step are used to construct the conditional correlation matrix. The latter procedure is often used as it overcomes certain numerical difficulties often arising in estimating multivariate GARCH models (such as the estimation of many parameters simultaneously, where is difficult to ensure convergence and the positive definiteness of the covariance matrix)

A drawback of the DCC model is that it does not distinguish the direction of spillovers because it generates a conditional correlation matrix for which each element is a single ratio. That is, even though the DCC produces estimates of the correlation coefficients between variables, it does not quantify which variable (Granger-) causes the other. For instance, having found a significant estimated correlation coefficient between the EUR and the GBP volatility, one cannot distinguish whether the EUR volatility granger causes the GBP volatility or the opposite. In order to overcome this drawback, we employ robustness checks, whenever appropriate (for instance, in chapter 4, the Full-BEKK is employed in addition to the DCC, along with impulse responses to check for the direction/duration of transmission of shocks among markets).

2.4 Evaluation of forecasts

Since international transactions are usually settled in the near future, exchange rate changes forecasting is extremely important to evaluate the benefits and risks associated with the international environment. One of the most important issues in forecasting is whether, the model, from which forecasts will be produced, is correctly specified. There exists a general consensus that, well estimated models produce more accurate forecasts than incorrectly specified ones (see, for instance, Diebold and

Lopez, 1996). Hence, the choice of a correctly specified model, able to capture the volatility of exchange rates is a crucial matter.

In order to decide on a forecast method, we need a way to choose which one, among the models discussed in the previous sections, is most suitable. The main objective of building well defined volatility models is to perform more accurate future volatility forecasts. There are various competing methods of forecasting performance. This section discusses some of the most commonly used measures to evaluate the forecasting performance of the various volatility models. A model might provide a good fit to a series, y_t, in the sample used to estimate the parameters, but this need not translate to good forecast performance. An out-of-sample comparison involves using the first part of a sample to estimate the parameters of the models and saving the latter part of the sample to gauge its forecasting ability. Furthermore, out-of-sample volatility forecasts can be produced for 1-day ahead or for k-day ahead forecast horizon, where $k \geq 2$. According to the empirical evidence, forecasting accuracy decreases as the forecast horizon increases, in other words, as k increases (Diebold and Lopez, 1996; Christoffersen and Diebold, 1997).

The most widely used evaluation criteria of forecasting accuracy are: The Mincer and Zarnowitz (1969) regression based test. According to this test, the true (or realized) volatility[16] is regressed on a constant and forecast volatility:

$$\sigma_{squared\_returns,t+1} = \alpha + \beta\hat{\sigma}_{forecast,t+1} + \varepsilon_t \qquad (2.26)$$

Then, the R^2 (goodness-of-fit) from this regression is used for the assessment of the predictability of several models. The model with the largest R^2 indicates that the true volatility can be appropriately explained by the forecast one, and that has the most powerful forecast ability. In addition, the estimated parameters of α and β of a well specified model should be equal to zero and 1, respectively. This approach has been widely used in exchange rate volatility forecasting evaluation (see, for

[16] We use daily squared returns as a proxy for true or realized volatility.

instance, Anderson and Bollerslev 1998a; Balaban, 2004; Martens, Chang and Taylor, 2002 and Pong, Shackleton, Taylor and Xu, 2004).

Another forecasting evaluation criterion is the forecast encompassing test. The idea behind the forecast encompassing test is to test whether a competing forecast contains additional information that is not contained in the base model. In such a case, the combined forecast will perform better than either forecast alone. If the interest is focused on checking whether one forecast contains information incremental to another forecast, then the test is performed by estimating the true volatility on the forecasts from two different models and is defined by:

$$\sigma_t = \alpha + \beta_1 F_{1,t} + \beta_2 F_{2,t} + \varepsilon_t \qquad (2.27)$$

where $F_{1,t}$ is the forecast attained from the first model and $F_{2,t}$ the forecast attained from the second model. If $\beta_2 = 0$, there is no incremental predictive information of the second model and thus, it is said that $F_{1,t}$ encompasses $F_{2,t}$. However, if $\beta_2 > 0$ then the competing forecast, $F_{2,t}$, contains information that $F_{1,t}$ does not and therefore, it is said that $F_{1,t}$ does not encompass $F_{2,t}$. The null hypothesis that $\beta_2 = 0$, can be tested using a standard regression test.

Moreover, consider the following loss function:

$$e_{t+1} = \sigma_{t+1} - \hat{\sigma}_{t+1} \qquad (2.28)$$

where $\hat{\sigma}_{t+1}$ denotes a prediction of future volatility and σ_{t+1} denotes actual volatility in period t, using the parameter estimates from the various competing models, discussed above, over $[0,T]$. This loss function is used to gauge the forecasting accuracy of various models in the criteria discussed below.

One simple criterion of volatility forecast performance is the Mean Error. The Mean Error measure of bias is defined by:

$$ME = \frac{1}{T}\sum_{t=1}^{T} e_{t+1,t} \qquad (2.29)$$

In order to decide which of the various competing models produces more accurate forecasts, a comparison of the Mean Error among these models is required. The model with the minimum ME is preferred in terms of forecasting accuracy. However, the ME is rarely applied because its simplicity.

The most widely used accuracy measure in the forecasting literature is the Mean Square Error (MSE) (see for instance, Vilasuso, 2002). The MSE for a sample size T is a quadratic loss function and defined by:

$$MSE = \frac{1}{T}\sum_{t=1}^{T} e_{t+1,t}^{2} \qquad (2.30)$$

This loss function is again used to measure forecast accuracy. The model with the minimum MSE is preferred.

Another extension is the Mean Absolute Error criterion. The MAE is the average of the absolute forecast errors, defined by:

$$MAE = \frac{1}{T}\sum_{t=1}^{T} \left| e_{t+1,t} \right| \qquad (2.31)$$

If we compute MAE for two or more forecasting methods, then again, the model with the smallest value of MAE is preferred.

The Root Mean Square Error (RMSE) is defined by:

$$RMSE = \left(\frac{1}{T}\sum_{t=1}^{T} e^{2}{}_{t+1,t} \right)^{1/2} = \sqrt{\frac{1}{T}\sum_{t=1}^{T} e^{2}{}_{t+1,t}} \qquad (2.32)$$

This is essentially the sample standard deviation of forecast errors. If we compute RMSE for two or more forecasting methods, then again, we prefer the one with the smallest value of RMSE.

The Heteroskedasticity Adjusted Mean square Error (HRMSE) compares true volatility with the forecasted value and calculates the forecast error according to:

$$HRMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T} \left(1 - \frac{\hat{\sigma}_{forecast,t,t+1}}{\hat{\sigma}_{realized,t,t+1}} \right)^{2}} \qquad (2.33)$$

A smaller HRMSE denotes that forecast is closer to the true volatility and the corresponding model is superior. This criterion is found to perform better when the true volatility is proxied by higher frequency data than that used to compute the forecasts (see, Andersen et al., 1999).

Nevertheless, the model with the smaller forecast error does not necessarily mean that is significantly superior to other models. This is because the difference between two forecasts might be insignificantly different from zero. That is why Diebold and Mariano (1995) suggest an equal accuracy test among two forecasting models. They denote a loss function e.g. for the MSE let f(.) be the loss function and $f(e_{t1})$ and $f(e_{t2})$ are two forecast error series which arise from two rival models. Then the loss differential is defined by $d_t = f(e_{t1}) - f(e_{t2})$. The H_0 hypothesis indicates that forecast accuracy among the two rivals models are equal, which means that $E[f(e_{t1})]=E[f(e_{t2})]$ or $d_t = 0$. The alternative hypothesis H_a indicates that the two rival models have no equal forecast accuracy, and the one with the smaller loss is significantly superior to the other. The DM statistic is defined by:

$$DM=\frac{\bar{d}}{\sqrt{\hat{V}(\bar{d})}}. \qquad (2.34)$$

where $V(\bar{d})=\mathrm{cov}(d_t, d_{t-j})$ and $\hat{V}(\bar{d})$ is a consistent estimate of the asymptotic (long-run) variance of $\sqrt{T}\bar{d}$. The long-run variance is used in the statistic because the sample loss differentials are serially correlated for $h > 1$. The DM test statistic, according to the central limit theorem, will have an asymptotic standard normal distribution under the H_0 hypothesis.

Harvey, Leybourne and Newbold (1997) proposed an adjusted DM test statistic (HLN), because they argue that, for finite samples, the normal distribution can be a poor approximation, and the test statistic might be biased depending on the degree of serial correlation among forecast errors. The HLN adjusted DM test, which improves small sample properties, is defined by:

$$HLNDM = \sqrt{\frac{T+1-2h+h(h-1)/T}{T}}DM. \qquad (2.35)$$

where h is the number of days ahead used. The test statistic is then compared with the t-Student distribution with $(T-1)$ degrees of freedom. According to Harris and Sollis (2003), the HLNDM performs much better at all forecasts horizons if the forecast errors are auto-correlated or have non-normal distributions.

Hansen (2005) introduced a Superior Predictive Ability (SPA) test which is able to evaluate the performance of several alternative models. This is not the case for the DM test, which makes a comparison from only two rival models. Specifically, the SPA can select from up to 6 models, among a large number of competing models, which is the most significant model, best model, model with a performance relative to 25%, 50%, and 75% of the benchmark model and the worst model. That is, the SPA test shows the rank of the models evaluated at the same time. Furthermore, the SPA evaluates whether the same outcomes can be attained from more than one sample, by the use of a bootstrap procedure. The author states that a target (benchmark) model is selected and the question of interest is whether any alternative forecast is better than the target (benchmark) forecast. In the SPA test, forecasts are evaluated by a predetermined loss function. Specifically, let $\mathrm{L}(\mathrm{Y}_t, \hat{\mathrm{Y}}_t)$ denote the loss if one had made the prediction, $\hat{\mathrm{Y}}_t$, when the realized value turned out to be Y_t. The performance of the model k, relative to the benchmark model (at time t), can be defined as $\mathrm{X}_k(\mathrm{t})=\mathrm{L}(\mathrm{Y}_t, \hat{\mathrm{Y}}_{0t})-\mathrm{L}(\mathrm{Y}_t, \hat{\mathrm{Y}}_{kt})$, where $k=1,...,l$ and $t=1,...,n$. The question of interest is whether any of the models $k=1,...,l$ are better than the benchmark model. To analyze this question Hansen formulated the testable hypothesis that the benchmark model is the best forecasting model. This hypothesis can be expressed parametrically as $\mu_k=\mathrm{E}\left[X_k(t)\right]\leq 0$ where $k=1,...,l$. Since a positive value of μ_k corresponds to model k being better than the benchmark, one needs to test the hypothesis that $H_0:\mu_k \leq 0$ under the following test statistic:

$$T_n^{sm}=\max_k \frac{n^{1/2}\overline{X}_k}{\hat{\sigma}_k}, \qquad (2.36)$$

where $\overline{X}_k=\frac{1}{n}\sum_{t=1}^{n} X_k(t)$ and $\hat{\sigma}_k=\hat{V}ar(n^{1/2}\overline{X}_k)$.

In the following chapters we employ the models previously discussed along with their forecasting performance assessment, wherever appropriate, to investigate a number of aspects of time series modelling of exchange rate volatility.

Chapter 3

Estimation and Forecasting of Nominal Exchange rate volatility in Developing and Industrialised Countries

3.1 Introduction

A key question this chapter addresses is whether the volatility models used widely and successfully in previous studies of industrialised countries perform equally well in terms of in-sample and out-of-sample performance when applied to daily data for developing countries. While the empirical literature on modelling forecasting daily exchange rate volatility in industrialised countries is ample, in developing countries it is rather sparse.[17] This chapter tries to address this gap by employing various conditional heteroskedasticity models, described in chapter 2, and assessing their forecasting performance.

Our motivation to focus on the forecasting performance of various exchange rate volatility models in developing versus industrialized countries for daily data derives from the fact that a number of studies document far greater exchange rate volatility in developing as opposed to industrialized countries. For instance, Devereux and Lane (2003) having an extensive sample of 158 countries (23 industrialised and 135 developing) find that monthly exchange rate volatility in developing countries, measured by the standard deviation of the first logarithmic differences of bilateral exchange rates, is almost 2.5 times greater than that in industrialised countries. In a

[17] An excellent review of volatility forecasting is given in Poon and Granger (2003).

similar framework in a study of Hausmann, Panizza & Rigobon (2006) it is found that exchange rate volatility in developing countries is approximately three times greater than that in industrialised countries. Employing panel estimation techniques for 74 industrialised and developing countries on annual data for the period between 1980-2000, they show that this difference in volatility could not be explained by the fact that developing countries are more likely to face larger shocks (such as shocks to terms of trade, GDP growth and inflation shocks), by the experience of recurrent currency crises or by a different elasticity of exchange rate volatility with respect to these. Employing ARCH models they showed that part of the difference in the exchange rate volatility between developing and industrialised countries could be explained by differences in persistence of the exchange rate volatility itself. This suggests that capturing the differential dynamics is of great importance.

A common feature of these studies, as many others, is the use of low frequency (monthly or annual data) rather than daily data. The purpose of using such low frequency data derives from the fact that studies attempt to explain exchange rate volatility using macro data (such as gross domestic product, inflation and exports) which in the best cases are available for monthly data and not for daily data. However, it has been argued that dynamics of exchange rate returns and volatility (such as microstructure effects) can be best described by the use of high-frequency data such as daily or even intra-daily data (see, for instance, Andersen and Bollerslev, 1998b, Andersen et al., 1999, 2001 and 2003). What ultimately this chapter tries to address is whether there are better ways to capture and forecast daily exchange rate volatility in developing countries and compare the results with those for industrialised countries, not focusing on explaining longer horizon exchange rate returns or volatility in the two groups of countries, which is left for further research.

A further motivation for focusing on developing countries' daily exchange rate volatility derives from the fact that developing countries' financial linkages with the global economy have risen significantly in recent decades. Although industrialised countries are the most active participants in the financial globalization process, developing (primarily middle-income) countries have also started to participate, often attracting FDI and other financial flows from the industrialised countries. According to Mauro, Sussman and Yafeh (2006) in 1870-1913 the capital flows to developing countries were 1.084 billion US dollars whereas in 1993 and 2003 they were 1979 and 3973 billion US dollars, respectively. This dramatic increase in capital flows to developing countries, even when corrected for inflation, creates new challenges for policymakers and for various other agents.

International financial globalization is assumed, by its proponents, to be one of the main channels through which countries can reduce macroeconomic volatility and promote economic growth (Prasad et al., 2003). However, financial globalization can also carry risks. One well known risk is that financial globalization can cause financial crises. Indeed the process of globalization appears to have been accompanied by increased vulnerability to crises. Crises such as these affecting Asia and Russia in 1997-98, Brazil in 1999, Ecuador in 2000, Turkey in 2001, Argentina in 2001, and Uruguay in 2002 are examples that have captured worldwide interest.

Despite the risks associated with financial globalization, the potential benefits for developing countries can be plentiful. According to Prasad et al., (2003) potential benefits include the reduction in the cost of capital, transfers of technology from advanced to developing countries, the development of domestic financial sectors and improvements in both macroeconomic policies and institutions. Predominantly, it is argued that these benefits are induced by the competitive pressures or the discipline effect of globalization. Nonetheless, globalization creates new challenges for policymakers. One key challenge is to manage financial globalization in such a way that countries can take full advantage of the opportunities, while reducing the potential downside risks. This is important as financial globalization is likely to intensify over time, driven by agents seeking the perceived benefits. In this process of financial globalization, exchange rate volatility plays a key role. The better forecasting or understanding of the movements of exchange rate may help the policy makers to conduct a suitable monetary policy which will in turn achieve its desired objectives of price stability and higher economic activity. Hence, it is of great importance to check whether the established volatility models, already employed extensively in industrialised countries, perform equally well in developing countries.

If the dynamics of bilateral exchange rate movements appear to follow different patterns in industrialised countries and in developing, but similar patterns within each group, this might have implications for policy-makers, foreign exchange market participants and individual agents in each of these groups. For instance, in a recent paper of Ganguly and Boucher Breuer (forthcoming), where supporting evidence of the previous argument is found, the higher exchange rate volatility in developing than in industrialised countries can be explained by institutional differences with respect to central banks and national treasuries. Thus, policy makers could intervene by making central banks more transparent, less corruptive, and autonomous from governments' role in monetary policy (which was the case e.g. in Lesotho during the 1990s).

The key findings of this chapter are as follows. The superior performance of the FIGARCH model, noted in the recent literature, is confirmed in the case of industrialised countries, but the IGARCH model results in substantial gains in in-sample estimation and out-of-sample forecasting performance when dealing with developing countries. Even under a Value-at-Risk assessment, the above results are strengthened.

The remainder of the chapter is organized as follows. Section 3.2 describes the data and methodology employed. Section 3.3 presents the empirical results of the in-sample estimation and out-of-sample performance. Section 3.4 assesses the Value-at-Risk performance of these models and section 3.5 concludes. [18]

3.2 Data and Methodology

The data used here consist of daily observations of eight spot exchange rates against the US dollar from November 11, 1993 to December 31, 2001 obtained from Oanda

[18] For a literature review on modelling and forecasting exchange rate volatility see chapter 2.

and the Bank of England database, totalling 2069 observation.[19] Specifically, the countries under consideration are: the Japan (JPY), Norway (NOK), Switzerland (CHF), UK (GBP), Botswana (BWP), Chile (CLP), Cyprus (CYP) and Mauritius (MUR). The choice of these particular industrialised countries was based on industrialised countries with the highest trading volume on foreign exchange returns. According to the Bank of International Settlements the JPY, NOK, CHF and the GBP account for 85% of all foreign exchange rate transactions.[20] Our sample runs to 2001 so we avoid including countries that adopted the Euro (such as the DM) as the launch of the euro may indirectly distort our results since the currencies involved were locked to the euro in 1999. In the case of developing countries, the choice of four countries is based on the fulfillment of the following conditions: developing countries i) with daily nominal exchange rate data that are included in the sample of Devereux and Lane (2003) and ii) that have not fixed their currency with the US dollar,[21] our base currency, throughout our sample. iii) Another condition, on which our choice is based, is the availability of daily data in developing countries.[22] After a careful inspection, the developing countries that fulfilled the above two conditions were: Botswana, Chile, Cyprus, Kuwait, Mauritius and Morocco. Since our analysis in this chapter involves a restricted sample of four industrialised and four developing countries, we need a way to reduce the above sample of developing countries to four. The choice of the four developing countries to pursue our analysis was based on the condition that countries are widely dispersed in distance, in order to check whether our results can be generalised.[23] The four developing countries that fulfilled all the above conditions are: Botswana, Chile, Cyprus and Mauritius.

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[19] Ultimately would be preferable to use intra-daily data but since exchange rate data in developing countries exist only for daily data, we focus on daily data for both these groups of countries.

[20] The reason the of such a high percentage is because two currencies are involved in each transaction hence, the sum of the % shares of individual currencies used in the BIS report totals 200%.

[21] That is, countries with flexible or intermediate exchange rate arrangements based on the Levy-Yeyati and Sturzenegger (2005) de facto classification rather than the IMF's de jure classification. In addition, one can clearly see in the upper left panel of Figures 3.6 – 3.9 that exchange rate returns for these four developing countries are not constant throughout the sample.

[22] The earliest exchange rate data that could be obtained in developing countries are spanning from the beginning of November 1993.

[23] The location of countries selected range from South America to the eastern Mediterranean and the coast of south Africa.

Weekends, Christmas, Easter and bank holidays have been excluded from the sample, since during these periods transactions are non existent or very limited so their inclusion would distort the estimation procedure.

Our approach is to model the conditional mean and variance of exchange returns simultaneously.[24] However, prior to analyzing the models in the conditional variance specification we have to consider the conditional mean specification. We begin with an Autoregressive Moving Average Model (ARMA). Several studies have shown that the dependent variables, such as exchange rate returns, may exhibit significant autocorrelation between observations separated in time. According to Cuthbertson (1996) and others, any stationary time series y_t (in our case, exchange rate returns) can be approximated by a mixed Autoregressive Moving Average (ARMA) process of order (p,q), that is ARMA(p,q):

$$\begin{aligned} &y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_{t-q} \varepsilon_{t-q} \\ &or \\ &\phi(L) y_t = \theta(L) \varepsilon_t \end{aligned} \qquad (3.1)$$

where $\phi(L)$ and $\theta(L)$ are polynomials in the lag operator:

$$\begin{aligned} \phi(L) &= 1 - \phi_1 L - \phi_2 L^2 - \phi_3 L^3 - \ldots - \phi_p L^p \\ \theta(L) &= 1 + \theta_1 L + \theta_2 L^2 + \theta_3 L^3 + \ldots + \theta_q L^q \end{aligned} \qquad (3.2)$$

and ε_t is the disturbance term with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_s) = 0,\ \forall\ t \neq s$.In order to satisfy necessary conditions for stationarity, the roots of $\phi(L)$ and $\theta(L)$ must lie outside the unit circle.

Various specifications of the ARMA(p,q) model are going to be examined, prior to modelling the conditional variance simultaneously with the conditional mean. To identify the lags of ϕ_p and θ_q, we use a preliminary procedure. In the first step we estimate (3.1) by Maximum Likelihood (ML) or we estimate just an Autoregressive (AR) or Moving Average (MA) process by Least Squares (LS). In the second step we square the residuals of the first step and estimate by LS in order to make a

[24] All estimation was carried out using the OxMetrics interface and G@RCH 4.0 econometric package.

preliminary decision on appropriate lag length in the conditional variance. The second regression is basically used for the identification of ARCH errors. The choice of the appropriate number of lags for each of the equations will be made with the help of over-fitting tests on the residuals and the AIC (Akaike Information Criteria), SBC (Schwarz Bayesian Criteria) and HQC (Hannan-Quinn Criteria) information criteria. The model with the minimum AIC, SBC and HQC criteria will be suggested. The use of these three types of information criteria is for robustness reasons. However, this approach is simply used to identify the size of ϕ_p and θ_q and our final suggestion of the appropriate lag length will be made after modelling the conditional mean and the conditional variance equations simultaneously, for the six volatility models, by the use of the tests and criteria previously discussed.

The analysis is based on univariate equations for the eight exchange rate series and employing six conditional heteroskedasticity models, specifically the ARCH, GARCH, EGARCH, IGARCH, FIGARCH and HYGARCH model that were formulated on chapter 2.

The in-sample estimation period is from 8/11/1993 to 29/12/2000, totalling 1806 observations. The covariance matrix of the estimates is computed with the Quasi-Maximum Likelihood (QML) method. In addition, the optimization method of the QML procedure is done primarily under the standard QML approach that uses the quasi-Newton method of Broyden, Fletcher, Goldfarb and Shanno (BFGS). When no convergence by this conventional BFGS optimization algorithm is made, an alternative optimization algorithm, the Simulated Annealing (SA) algorithm of Goffe, Ferrier and Rogers (1994) for optimizing non-smooth functions with possible multiple local maxima, will be used. Some of the unpleasant possibilities that the BFGS algorithm may face during estimation according to Cramer (1986, p. 77) are: i) the algorithm may not converge in a reasonable number of steps, ii) it may head toward infinitely large parameter values, or even loop through the same point time and again and iii) it may have difficulty with ridges and plateaus. When faced with such difficulties, the researcher might have to use different starting values to overcome them. Last but not least, Goffe, Ferrier and Rogers (1994, p. 66) state that *"even if the algorithm converges, there is no guarantee that it will have converged to a global, rather than a local, optimum since conventional algorithms cannot distinguish between the two"*. In order to overcome such difficulties the algorithm of Goffe, Ferrier and Rogers (1994) is applied[25] that explores the function's entire surface and tries to optimize the function while moving both uphill and downhill. This means that it is largely independent of the starting values, often a critical input in conventional algorithms. Moreover, it can escape from local optima and go on to find the global optimum by the uphill and downhill moves.

For the first five models we make use of the Student-t Distribution and for the HYGARCH model the skewed-Student-t Distribution, as it was also used by Davidson (2004).[26] The Student-t and the skewed-Student-t distributions are used since they take into account the phenomenon of leptokurtosis and skewness in the probability density function as opposed to the normal distribution.

In terms of forecasting performance, 253 observations ranging from 2/01/2001 to 31/12/2001 are used as the out-of-sample period for the forecast evaluation. The 253 out-of-sample volatility forecasts will be produced for the one-step ahead daily forecast horizon. In order to produce 253 daily volatility forecasts the procedure is repeated 253 times and estimated recursively. The accuracy of exchange rate volatility forecasts is evaluated by some of the most commonly used criteria. These contain the Mincer and Zarnowitz's (1969) regression based test, the Mean Square Error (MSE) and the Superior Predictive Abilitity (SPA) test developed by Hansen (2005).

In the case of the regression based test, the test is conducted for each model separately. For a given model's forecast to be unbiased, the estimated parameters α and β from equation (2.26) should be equal to zero and one, respectively. In

[25] The SA algorithm is applied only if there is no convergence under the conventional BFGS. algorithm. In our research, since no convergence is obtained in the case of developing countries, the SA algorithm is used.

[26] The HYGARCH model has been estimated also under a Student-t distribution but the skewed-Student-t was preferred as the log-likelihood value was greater for the later. The AIC, SBC and HQC also suggested the later. The estimation results under the Student-t are not presented but can be provided upon request.

addition, the R^2 (goodness-of-fit) of this regression is used as a measurement of predictive power of the various models considered. The model with the largest R^2 indicates that the true volatility (which is proxied by squared returns) can be appropriately explained by the forecast volatility, and therefore has the most powerful forecasting ability. We use as a proxy of true volatility the daily squared ex-post returns to conduct this test.

The second and most widely used accuracy measures in volatility forecasting literature is the MSE. This criterion has been widely and successfully used in many studies of exchange rate volatility forecasting (see, for instance, Vilasuso, 2002 and Balaban, 2004). There exist many other forecast evaluation criteria, such as the ME and MAE described in chapter 2. All these out-of sample criteria including the MSE argue that the model with the smallest forecast error is preferred. However, they do not imply whether the model with the smallest forecast error is significantly superior to the other models or not. For instance, the difference among two forecast methods could be insignificantly different from zero. In order to be able to evaluate whether a difference is in fact significant or not Diebold and Mariano (1995) proposed an equal accuracy test (DM test) (see chapter 2).

However, when the interest of the researcher is to test the significance of superiority of one model against m models (where $m>2$) the DM test seems inappropriate. Even if calculated, it is time consuming since the test has to be applied $\frac{m(m-1)}{2}$ times to evaluate m rival models. For instance, if one wants to find the significantly superior model among 10 rivals models, one has to calculate 45 seperate DM tests $\frac{10(10-1)}{2}=45$ times.

In order to overcome this drawback, Hansen (2005) introduced a Superior Predictive Ability (SPA) test that permits evaluation of the performance of all alternative models simultaneously. The SPA test evaluates whether the same outcomes can be attained from more than one model, by the use of a bootstrap procedure (see Hansen, 2005). Specifically, a target model is selected by one of the evaluation criteria and the question of interest is whether any alternative forecast is better than the target forecast. In the SPA test, forecasts are evaluated by a predetermined loss function. According to Hansen (2005), the choice of the loss function could be one among the one specified by the MAE and MSE.

In our analysis which deals with various volatility models and their forecast accuracy evaluation, the SPA test[27] will be preferred from the DM test, since it is able to evaluate the performance of several alternative volatility models simultaneously. In addition, the SPA test will be calculated with the choice of the loss function specified by the MSE.[28]

The criterion of model selection for each of the six GARCH-type models is based on in-sample and out-of-sample diagnostic tests. These include the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), Hannan-Quinn Criterion (HQC), Shibata Criterion (SC), log-likelihood values, Box-Pierce statistics on both raw (Q) and squared (Q^2) standardized residuals and Engle's LM ARCH test for the presence of further ARCH effects. Under the Student-t or Skewed-Student-t distribution, the model with the minimum AIC, SBC, HQC, SC, maximum log-likelihood values and which passes the *Q-*, *Q-squared* and the LM ARCH test simultaneously, in the case of in-sample model selection, is adopted. In the case of out-of-sample selection, the model with the smallest forecast error of the various tests is adopted.

3.3 Empirical Results

3.3.1 Descriptive Statistics

Tables 3.1 and 3.2 provide the summary statistics of exchange rate returns (calculated according to equation 2.1) for each of the eight currencies against the US

[27] Many thanks to P. R. Hansen for providing the Ox code of the SPA test.
[28] Other loss functions, described in chapter 2, have been employed without any change in the results. These results are not presented but can be provided upon request.

dollar ($\Delta \ln S_t$) in industrialised and developing countries, respectively. We can see from tables 3.1 and 3.2 that the estimated excess kurtosis[29] is positive and statistically significant for each of the eight exchange returns. This indicates that daily exchange rate returns are heavy-tailed. In other words, this means that a sample from such distribution tends to contain extreme values and such a distribution is said to be leptokurtic. Hence, the use of the Student-t or Skewed-Student-t distribution seems more appropriate since these are able to account for fat-tails. Bollerslev (1987), Hsieh (1989b) and Baillie and Bollerslev (1989) among others have shown that these distributions perform better in terms of capturing the higher observed kurtosis. In addition, we can observe that the excess kurtosis in each of the four developing countries' returns is greater than that in industrialised countries' ones. In the case of industrialised countries, the excess kurtosis ranges from 1.73, for the UK (GBP/USD), to 6.01 for Japan (JPY/USD). Whereas, in developing countries ranges from 7.46, for Cyprus (CYP/USD), to 44.27, for Chile (CLP/USD). This is consistent with the idea that developing countries are more prone to extreme episodes, such as currency/financial crises, than industrialised countries are.

Another feature of Tables 3.1 and 3.2 is that the value of skewness in industrialised countries is negative and statistically significant whereas, in developing countries it is positive and statistically significant. This implies that appreciations are more probable in industrial countries and depreciations in developing countries.

Moreover, Tables 3.1 and 3.2 which also report the Jarque-Bera normality test show that the test statistic is far beyond the critical value which implies that we strongly reject the null hypothesis that returns are normally distributed. Hence, instead of the normal (Gaussian) distribution we are going to concentrate on the estimation of the various models under a Student-t or Skewed-Student-t distribution since they take into account the phenomenon of leptokurtosis and skewness in the probability density function as opposed to the normal distribution.

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[29] The excess kurtosis is defined as: $K = \frac{E\left[(y-\mu)^4\right]}{\sigma^4} - 3$. A distribution with positive excess kurtosis is said to have heavy tails, implying that the distribution puts more mass on the tails of its support than a normal distribution does.

Table 3.1: Descriptive statistics - Industrialised countries

	CHF/USD	JPY/USD	GBP/USD	NOK/USD
Minimum	-0.0386	-0.0662	-0.0246	-0.0499
Maximum	0.0302	0.0341	0.0227	0.0380
Mean	5.7929e-005	9.155e-005	7.087e-006	0.0001
Standard Deviation	0.0068	0.0075	0.0047	0.0058
Skewness	-0.434 [0.00]**	-0.765 [0.00]**	-0.136 [0.01]*	-0.496 [0.00]**
Excess Kurtosis	2.248 [0.00]**	6.010 [0.00]**	1.730 [0.00]**	5.277 [0.00]**
JB Normality Test	498.2 [0.00]**	3299 [0.00]**	263.0[0.00]**	2169 [0.00]**
ARCH 1-2	29.71 [0.00]**	52.02 [0.00]**	4.840 [0.01]**	222.3 [0.00]**
ARCH 1-5	14.90 [0.00]**	22.61 [0.00]**	5.491 [0.00]**	88.87 [0.00]**
ARCH 1-10	8.260 [0.00]**	15.78 [0.00]**	3.600 [0.00]**	44.59 [0.00]**
Q(5)	2.129 [0.83]	11.00 [0.05]	10.82 [0.06]	12.80 [0.03]*
Q(10)	9.912 [0.45]	17.38 [0.07]	14.87 [0.14]	19.88 [0.03]*
Q(20)	21.00 [0.40]	37.60 [0.01]**	32.28 [0.04]*	28.52 [0.10]
$Q^2(5)$	87.54 [0.00]**	144.6 [0.00]**	27.82 [0.00]**	421.1 [0.00]**
$Q^2(10)$	108.3 [0.00]**	231.6 [0.00]**	39.20 [0.00]**	428.6 [0.00]**
$Q^2(20)$	165.3 [0.00]**	322.5 [0.00]**	76.79 [0.00]**	432.4 [0.00]***

Notes: The numbers in the parentheses and brackets are t-statistics and *P*-values respectively. All values are computed using OxMetrics and G@RCH. Q and Q^2( ) is the Ljung-Box *Q*-statistics of order 5, 10, 20 on the raw and squared returns respectively. * Significant at 5%; ** Significant at 1%.

Table 3.2: Descriptive statistics - Developing countries

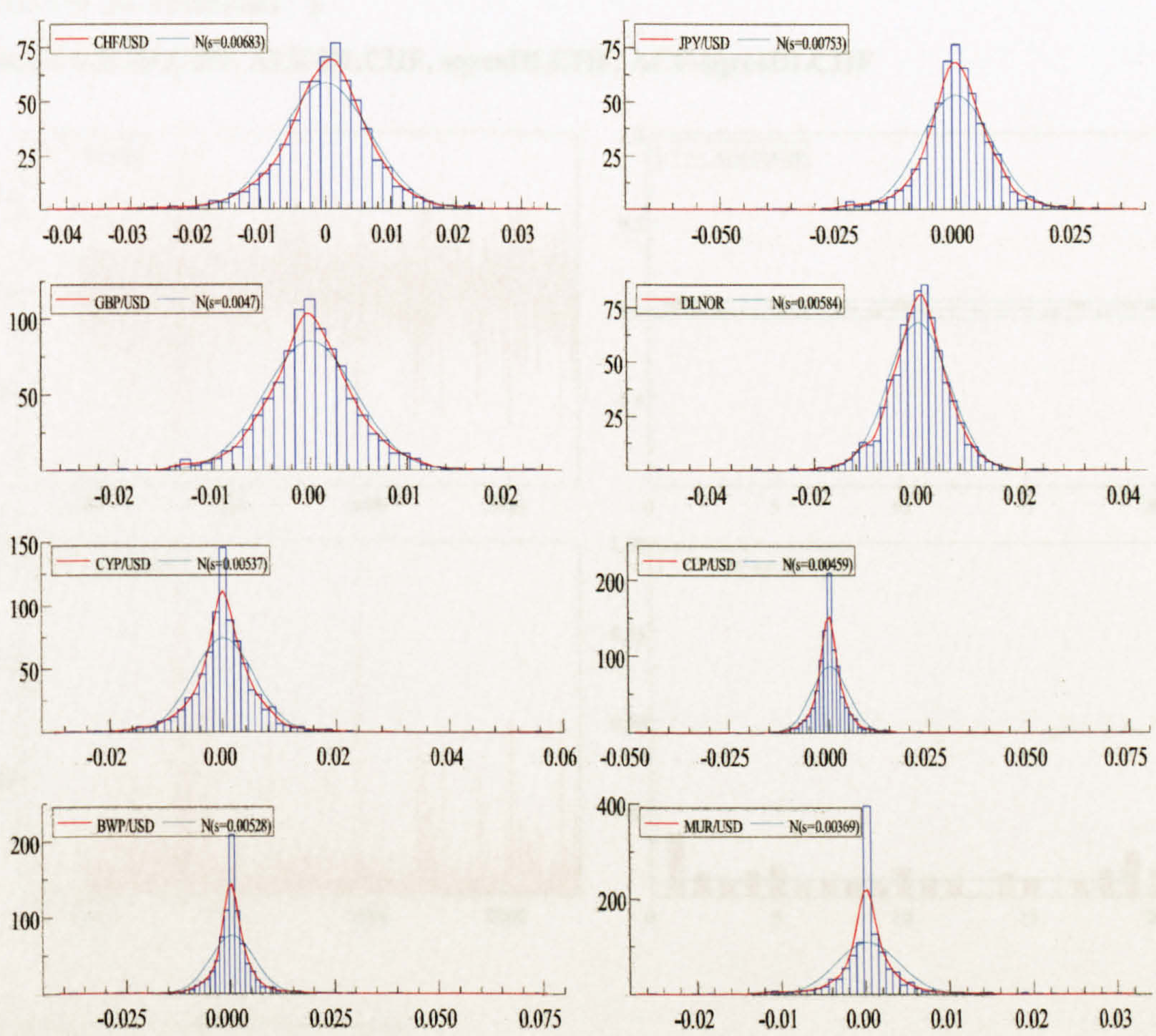
	CYP/USD	BWP/USD	CLP/USD	MUR/USD
Minimum	-0.027509	-0.038329	-0.046232	-0.024876
Maximum	0.055115	0.073553	0.073225	0.029836
Mean	0.00012034	0.00044093	0.00024122	0.00023843
Standard Deviation	0.0053665	0.0052807	0.0045869	0.0036893
Skewness	0.281 [0.00]**	1.663 [0.00]**	1.805 [0.00]**	0.595 [0.00]**
Excess Kurtosis	7.46 [0.00]**	28.66 [0.00]**	44.27 [0.00]**	10.16 [0.00]**
JB Normality Test	4796 [0.00]**	71396 [0.00]**	1.69e+5[0.00]**	8968 [0.00]**
ARCH 1-2	2.109 [0.12]	39.03 [0.00]**	48.86 [0.00]**	118.0 [0.00]**
ARCH 1-5	1.957 [0.08]	19.75 [0.00]**	19.84 [0.00]**	50.09 [0.00]**
ARCH 1-10	1.452 [0.15]	10.06 [0.00]**	10.63 [0.00]**	27.73 [0.00]**
Q(5)	6.231 [0.28]	29.78 [0.00]**	31.84 [0.00]**	135.0 [0.00]**
Q(10)	8.887 [0.54]	45.16 [0.00]**	37.83 [0.00]**	151.3 [0.00]**
Q(20)	21.68 [0.36]	55.02 [0.00]**	59.69 [0.00]**	212.0 [0.00]**
$Q^2(5)$	11.00 [0.05]	133.0 [0.00]**	111.2 [0.00]**	340.9 [0.00]**
$Q^2(10)$	17.89 [0.06]	147.5 [0.00]**	121.1 [0.00]**	433.7 [0.00]**
$Q^2(20)$	36.66 [0.01]*	155.5 [0.00]**	132.3 [0.00]**	876.0 [0.00]**

Notes: The numbers in the parentheses and brackets are t-statistics and *P*-values respectively. All values are computed using OxMetrics and G@RCH. Q and Q^2( ) is the Ljung-Box *Q*-statistics of order 5, 10, 20 on the raw and squared returns respectively. * Significant at 5%; ** Significant at 1%.

In addition, Tables 3.1 and 3.2 provide evidence of ARCH effects in all eight exchange rate returns series (apart from CYP/USD), since the ARCH LM test which test the null hypothesis of no ARCH effect in the residuals is rejected up to 10 lags. However, the Ljung-Box statistic provides evidence of serial correlation in the standardized squared CYP/USD returns for 20 lags and thus, higher order dependence.

Figure 3.1 plots the density functions of the daily returns of industrialised and developing countries. Also shown, by a dashed/green line, in each subplot is the normal probability density function evaluated by using the sample mean and standard deviation of the eight exchange rate returns. These subplots indicate that the normality assumption is questionable for all daily exchange rate returns. The empirical density function has a higher peak around its mean, but fatter tails than that of the corresponding normal distribution.

Figure 3.1: Density function of returns - Industrialised & Developing countries



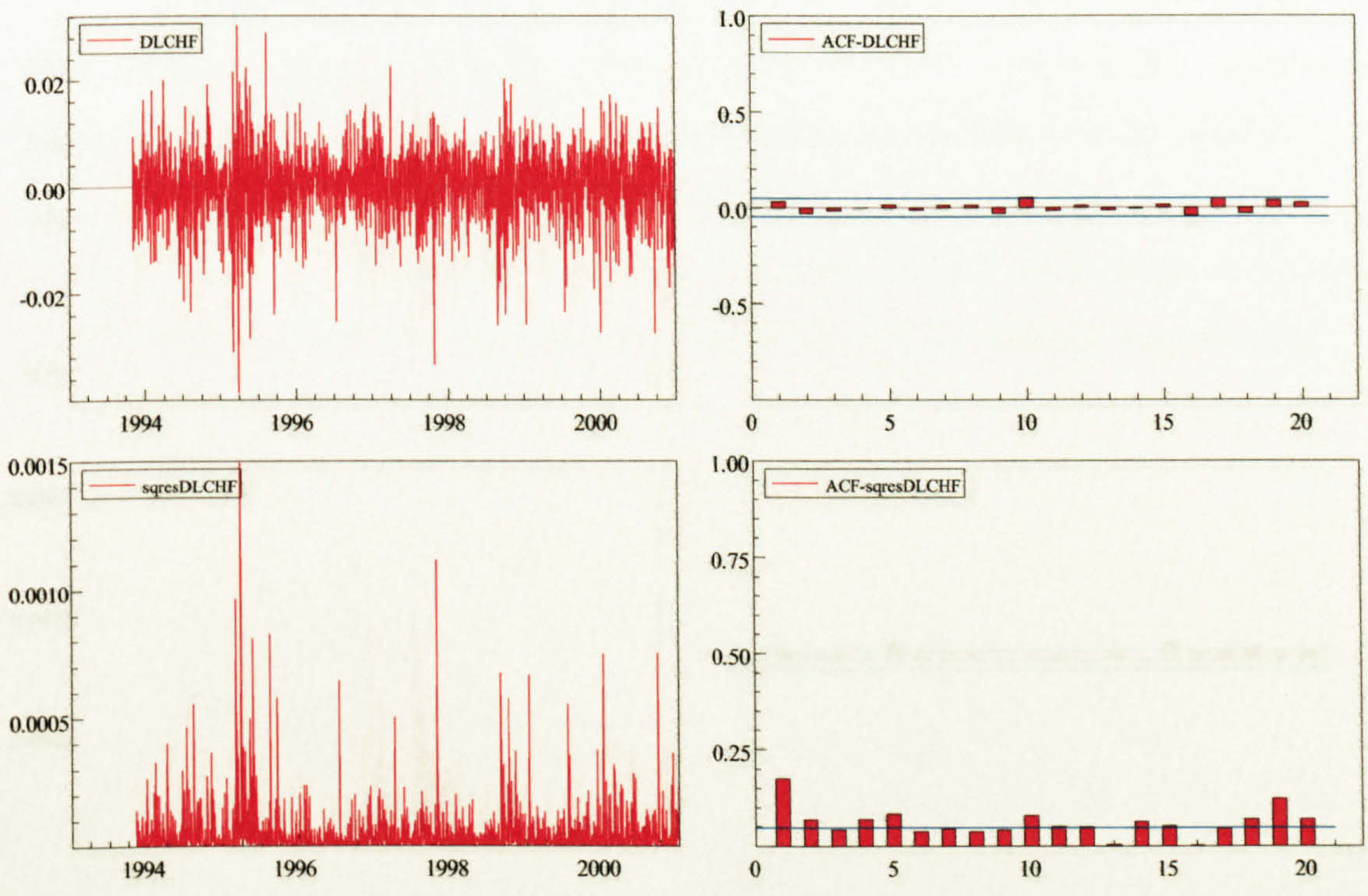
3.3.2 In-Sample Estimation results

In this section we present the in-sample estimation results for the ARCH, GARCH, EGARCH, IGARCH, FIGARCH and HYGARCH models (described in detail in chapter 2) in order to explain the models' fit. Sections 3.4.2.1 and 3.4.2.2 present these results in industrialised and developing countries, respectively.

3.3.2.1 Industrialised Countries

According to our preliminary approach for the conditional mean specification of the CHF/USD, JPY/USD, GBP/USD and the NOK/USD return series, we found p and q lags of equation (3.1) to be 1 and 0 [or AR(1)], 3 and 0 [or AR(3)], 3 and 0 [or AR(3)] and 0 and 0 (or a random walk NOK/USD exchange rate) respectively. This is also supported from the autocorrelation functions (ACF) of returns in the upper right panel of Figures 3.2, 3.3, 3.4 and 3.5, respectively (and also from the overfitting tests on the residuals[30]).

Figure 3.2: DLCHF, ACF-DLCHF, sqresDLCHF, ACF-sqresDLCHF



[30] These tests are not presented but can be provided upon request.

Figure 3.3: DLJPY, ACF-DLJPY, sqresDLJPY, ACF-sqresDLJPY

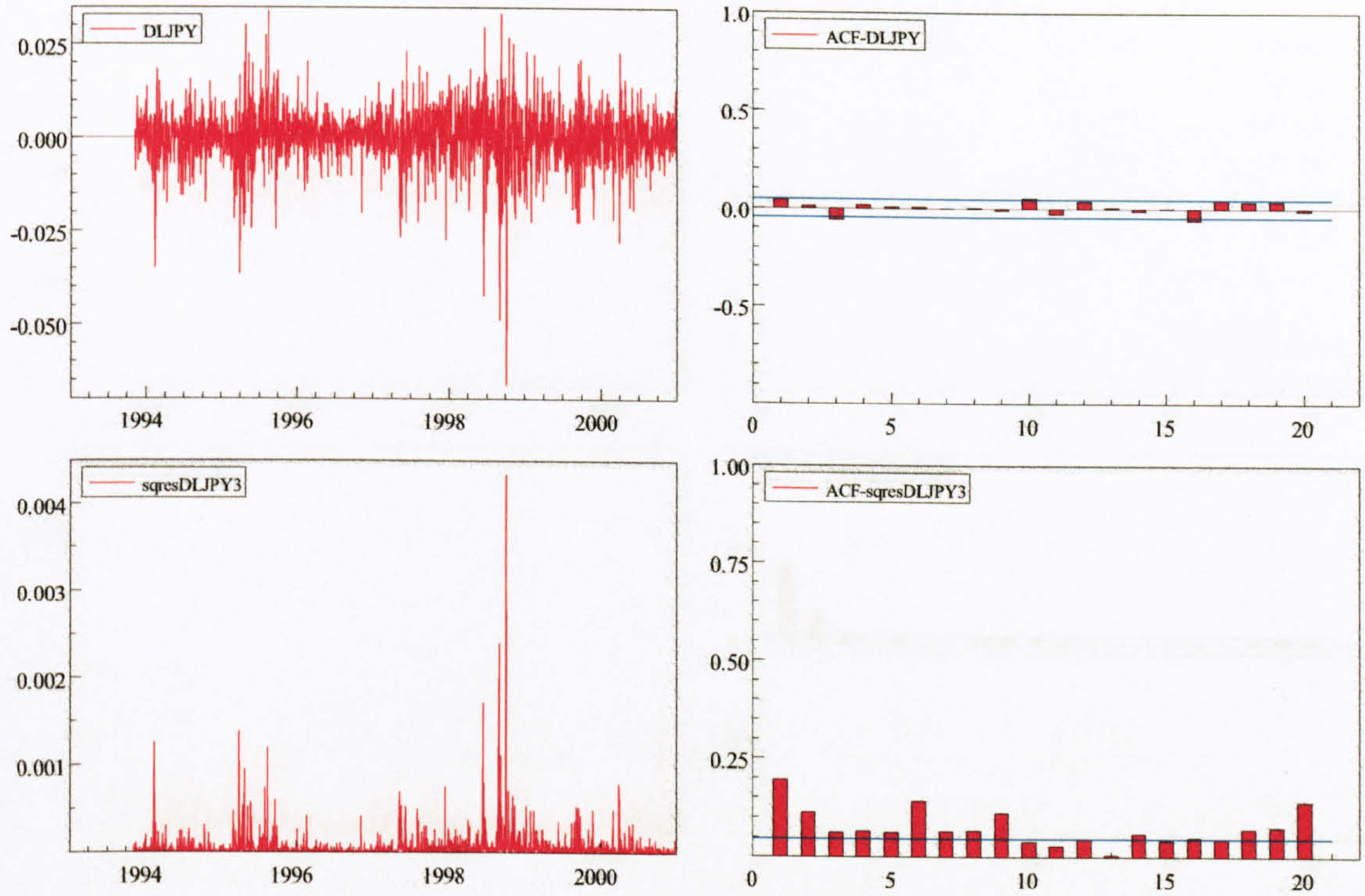


Figure 3.4: DLGBP, ACF-DLGBP, sqresDLGBP, ACF-sqresDLGBP

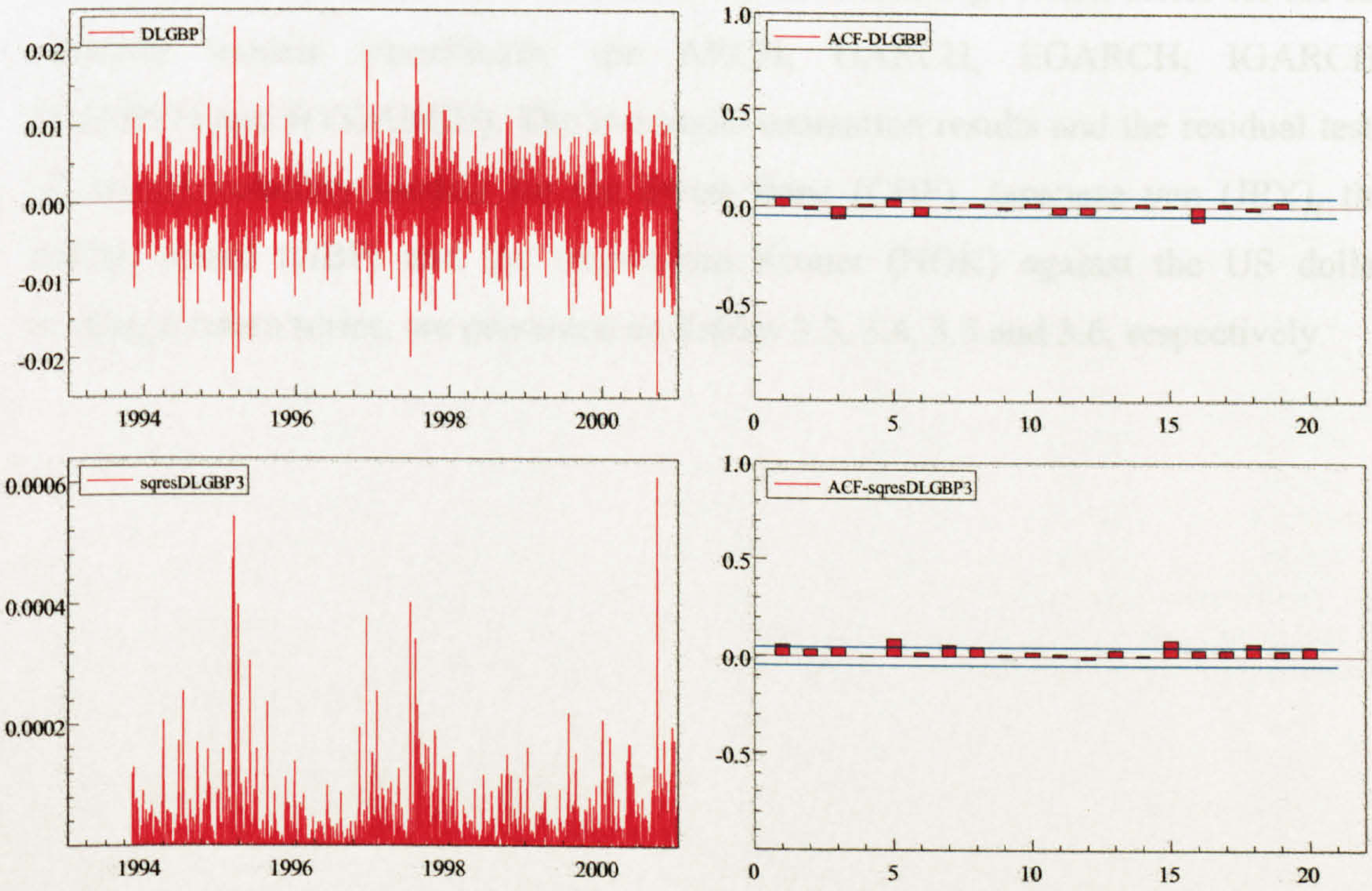
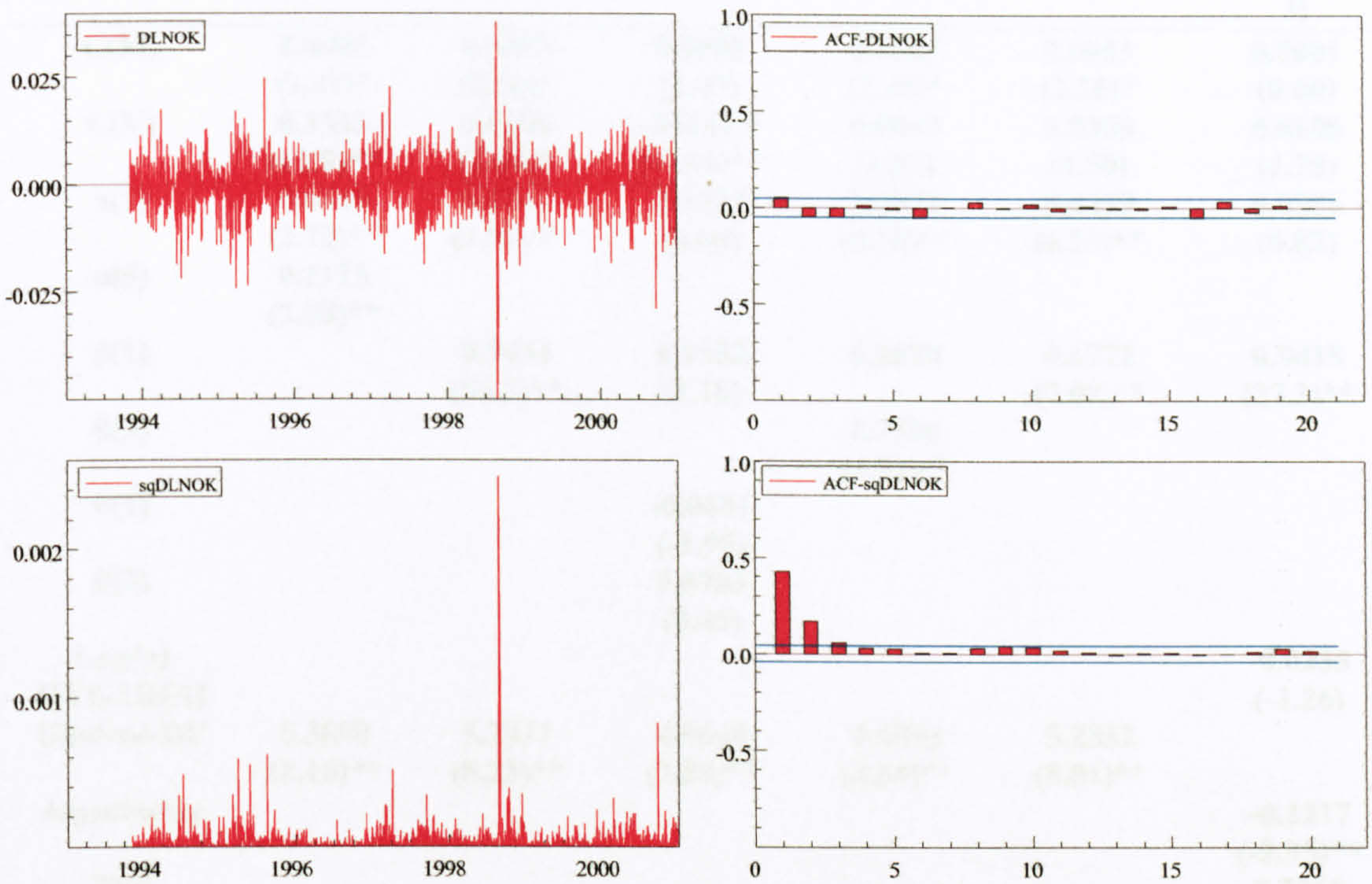


Figure 3.5: DLNOK, ACF-DLNOK, sqresDLNOK, ACF-sqresDLNOK



Having applied this preliminary approach we continue the analysis by modelling both the conditional mean and variance of the four exchange return series for the six volatility models (specifically the ARCH, GARCH, EGARCH, IGARCH, FIGARCH and HYGARCH). The in-sample estimation results and the residual tests of the six volatility models for the Swiss franc (CHF), Japanese yen (JPY), the British pound (GBP) and the Norwegian Kroner (NOK) against the US dollar exchange return series, are presented on Tables 3.3, 3.4, 3.5 and 3.6, respectively.

Table 3.3: In-sample Estimation Results for CHF/USD - 08.11.1993-29.12.2000

	ARCH	GARCH	EGARCH	IGARCH	FIGARCH	HYGARCH
C(M)	0.0003	0.0003	0.0003	0.0003	0.0003	0.0001
	(2.47)*	(2.30)*	(1.85)	(2.38)*	(2.26)*	(0.60)
C(V)	0.3333	0.0106	-93161.9	0.0043	0.0300	0.0105
	(12.9)**	(2.06)*	(-7.66)**	(1.63)	(1.50)	(1.38)
a(1)	0.0845	0.0347	1.3322	0.0674	0.4459	0.0506
	(2.72)**	(3.91)**	(0.86)	(3.70)**	(6.23)**	(0.82)
α(5)	0.1115					
	(2.78)**					
β(1)		0.9434	0.1552	0.1820	0.6772	0.9415
		(56.5)**	(1.18)		(7.09)**	(27.3)**
β(2)				0.7506		
				(2.52)**		
θ(1)			-0.0601			
			(-1.95)			
θ(2)			0.0763			
			(0.45)			
Log(α) HYGARCH						-0.0235
						(-1.26)
Student-DF	5.3890	5.2877	4.9640	4.6893	5.2352	
	(8.16)**	(8.23)**	(7.89)**	(8.34)**	(8.01)**	
Asymmetry						-0.1217
						(-3.95)**
Tail						5.5760
						(8.03)**
d					0.2978	0.9746
					(2.60)**	(13.4)**
Log-Lik	6547.55	6554.52	6535.41	6551.87	6553.04	6562.53
AIC	-7.2420	-7.2530	-7.2297	-7.2501	-7.2503	-7.2586
SBC	-7.2177	-7.2378	-7.2084	-7.2349	-7.2321	-7.2343
HQC	-7.2330	-7.2474	-7.2218	-7.2445	-7.2436	-7.2496
Shibata	-7.2421	-7.2531	-7.2297	-7.2501	-7.2503	-7.2587
ARCH 1-5	0.3891	1.4760	6.4549	0.6545	0.5080	0.6618
	[0.86]	[0.20]	[0.00]**	[0.66]	[0.77]	[0.65]
ARCH 1-10	0.5577	1.0407	4.1649	0.59975	0.5955	0.5923
	[0.85]	[0.41]	[0.00]**	[0.82]	[0.82]	[0.82]
Q(10)	9.5572	11.6468	11.4093	12.2569	11.0526	11.3970
	[0.48]	[0.31]	[0.33]	[0.27]	[0.35]	[0.33]
Q(20)	19.6559	19.9922	23.4712	19.5103	19.4224	19.5262
	[0.48]	[0.46]	[0.27]	[0.49]	[0.50]	[0.49]
Q^2(10)	5.8989	10.4365	51.2161	6.2156	6.1383	6.1036
	[0.32]	[0.24]	[0.00]**	[0.52]	[0.63]	[0.64]
Q^2(20)	18.3565	16.9959	90.4803	11.5100	11.9433	11.7344
	[0.24]	[0.52]	[0.00]**	[0.83]	[0.85]	[0.86]

Notes: The numbers in the parentheses and brackets are t-statistics and p-values respectively. All values are computed using OxMetrics and G@RCH package. Q( ) and Q^2( ) is the Ljung–Box Q-statistics of order 5, 10, 20 on the raw and squared standardized residuals respectively.* Significant at 5%; ** Significant at 1%.

Table 3.4: In-sample Estimation Results for JPY/USD - 08.11.1993-29.12.2000

	ARCH	GARCH	EGARCH	IGARCH	FIGARCH	HYGARCH
C(M)	0.0004	0.0003	0.0003	0.0003	0.0004	0.0003
	(2.65)**	(2.60)**	(2.36)*	(2.61)**	(2.71)**	(1.77)
AR(1)	0.0112	0.0112	0.0077	0.0108	0.0102	0.0097
	(0.48)	(0.49)	(0.44)	(0.48)	(0.44)	(0.42)
AR(2)	-0.0251	-0.0214	-0.0184	-0.0217	-0.0224	-0.0249
	(-1.03)	(-0.95)	(-0.96)	(-0.97)	(-0.95)	(-1.09)
AR(3)	-0.0475	-0.0459	-0.0454	-0.0451	-0.0468	-0.0464
	(-2.06)*	(-2.06)*	(-3.09)	(-2.05)*	(-2.05)*	(-2.04)*
C(V)	0.2262	0.0075	-42320	0.0048	0.4728	0.0190
	(6.89)**	(1.69)	(-302)**	(1.66)	(3.57)**	(0.95)
α(1)	0.1000	0.0547	0.4598	0.0591	0.3021	0.3164
	(2.42)*	(3.31)**	(1.37)	(3.18)**	(2.34)*	(2.56)*
α(9)	0.0684					
	(2.31)*					
β(1)		0.9351	0.8349	0.9409	0.5637	0.5901
		(44.3)**	(29.9)**		(3.92)**	(3.85)**
θ(1)			-0.0672			
			(-2.35)*			
θ(2)			0.2285			
			(3.90)**			
Log(α) HYGARCH						0.0304
						(0.26)
Student-DF	4.4546	4.5964	4.4287	4.2269	4.9315	
	(9.50)**	(8.98)**	(10.0)**	(9.85)**	(10.3)**	
Asymmetry						-0.0501
						(-1.56)
Tail						4.7626
						(9.00)**
d					0.3349	0.3417
					(5.41)**	(2.59)**
Log-Lik	6448.18	6457.77	6422.42	6456.65	6459.08	6460.06
AIC	-7.1242	-7.1426	-7.1012	-7.1424	-7.1429	-7.1418
SBC	-7.0786	-7.1183	-7.0708	-7.1212	-7.1156	-7.1083
HQC	-7.1074	-7.1336	-7.0900	-7.1346	-7.1328	-7.1295
Shibata	-7.1244	-7.1427	-7.1013	-7.1425	-7.1430	-7.1419
ARCH 1-5	0.4070	0.7083	0.2132	0.6641	0.5079	0.5236
	[0.84]	[0.62]	[0.96]	[0.65]	[0.77]	[0.76]
ARCH 1-10	0.3649	0.5459	1.6507	0.4990	0.4466	0.4348
	[0.96]	[0.86]	[0.09]	[0.89]	[0.92]	[0.93]
Q(10)	8.9305	9.9931	7.7063	10.5118	9.6617	10.337
	[0.26]	[0.19]	[0.36]	[0.16]	[0.21]	[0.17]
Q(20)	24.5297	24.6745	24.1810	24.2939	25.2740	25.9489
	[0.11]	[0.10]	[0.11]	[0.11]	[0.09]	[0.08]
Q^2(10)	3.7353	5.5057	16.387	5.0213	4.4921	4.3740
	[0.05]	[0.70]	[0.04]*	[0.76]	[0.81]	[0.82]
Q^2(20)	13.6308	12.9050	31.9519	12.834	12.6373	12.5860
	[0.25]	[0.80]	[0.02]*	[0.80]	[0.81]	[0.82]

Notes: The numbers in the parentheses and brackets are t-statistics and *p*-values respectively. All values are computed using OxMetrics and G@RCH package. Q( ) and Q^2( ) is the Ljung–Box *Q*-statistics of order 5, 10, 20 on the raw and squared standardized residuals respectively. * Significant at 5%; ** Significant at 1%.

Table 3.5: In-sample Estimation Results for GBP/USD - 08.11.1993-29.12.2000

	ARCH	GARCH	EGARCH	IGARCH	FIGARCH	HYGARCH
C(M)	0.00001	0.00001	0.00002	0.00001	0.00001	-0.00005
	(0.16)	(0.10)	(0.21)	(0.09)	(0.09)	(-0.45)
C(V)	0.1649	0.0026	-62277.96	0.0008	0.0134	-0.0003
	(11.3)**	(2.37)*	(-154)**	(1.25)	(3.20)**	(-0.15)
AR(1)	0.0366	0.0342	0.0426	0.0338	0.0319	0.0307
	(1.52)	(1.42)	(1.02)	(1.40)	(1.33)	(1.28)
AR(2)	-0.0101	-0.0058	-0.0079	-0.0014	-0.0057	-0.0001
	(-0.42)	(-0.25)	(-0.33)	(-0.06)	(-0.24)	(-0.01)
AR(3)	-0.0814	-0.0800	-0.0851	-0.0801	-0.0790	-0.0797
	(-3.42)**	(-3.56)**	(-3.69)**	(-3.58)**	(-3.50)**	(-3.50)**
α(1)	0.0866	0.0355	-0.0204	0.0377	0.4534	0.5631
	(2.53)*	(4.44)**	(-0.12)	(2.51)*	(5.88)**	(4.38)**
α(5)	0.0561					
	(1.89)					
β(1)		0.9543	0.7969	0.9623	0.6797	0.7061
		(101)**	(18.0)**		(19.8)**	(5.36)**
θ(1)			0.0171			
			(0.60)			
θ(2)			0.2717			
			(5.26)**			
Log(α) HYGARCH						0.3987
						(1.12)
Student-DF	5.0892	5.2864	5.3773	5.0274	5.2410	
	(8.31)**	(8.05)**	(8.66)**	(8.47)**	(8.02)**	
Asymmetry						-0.0374
						(0.23)
Tail						5.1923
						(8.17)
d					0.3164	0.1595
					(4.68)**	(1.45)
Log-Lik	7217.46	7229.92	7200.61	7229.99	7228.7	7230.96
AIC	-7.9806	-7.9977	-7.9630	-7.9967	-7.9952	-7.9933
SBC	-7.9471	-7.9733	-7.9326	7.9693	-7.9678	-7.9537
HQC	-7.9682	-7.9887	-7.9518	-7.9866	-7.9851	-7.9787
Shibata	-7.9807	-7.9977	-7.9631	7.9967	-7.9953	-7.9934
ARCH 1-5	0.4077	0.8490	1.7859	0.7653	0.8785	0.9155
	[0.84]	[0.51]	[0.11]	[0.58]	[0.49]	[0.47]
ARCH 1-10	1.0185	0.7197	1.2234	0.6843	0.7226	0.7353
	[0.42]	[0.71]	[0.27]	[0.74]	[0.70]	[0.69]
Q(10)	10.7796	10.7627	10.0370	9.4314	10.2334	8.6872
	[0.15]	[0.15]	[0.19]	[0.09]	[0.18]	[0.12]
Q(20)	27.7914	25.0282	26.1712	22.6025	25.7785	23.4992
	[0.05]*	[0.09]	[0.07]	[0.09]	[0.08]	[0.07]*
Q^2(10)	9.9771	7.2174	12.4866	6.8446	7.8127	7.9862
	[0.08]	[0.51]	[0.13]	[0.55]	[0.45]	[0.43]
Q^2(20)	26.3881	16.7621	28.6082	15.7847	18.3302	17.9223
	[0.03]*	[0.54]	[0.05]	[0.61]	[0.43]	[0.46]

Notes: The numbers in the parentheses and brackets are t-statistics and *p*-values respectively. All values are computed using OxMetrics and G@RCH package. Q( ) and Q^2( ) is the Ljung–Box *Q*-statistics of order 5, 10, 20 on the raw and squared standardized residuals respectively. * Significant at 5%; ** Significant at 1%.

Table 3.6: In-sample Estimation Results for NOK/USD - 08.11.1993-29.12.2000

	ARCH	GARCH	EGARCH	IGARCH	FIGARCH	HYGARCH
C(M)	0.0002	0.0002	0.0003	0.0002	0.0002	0.0001
	(2.15)*	(1.81)	(2.26)*	(1.76)	(1.82)	(0.79)
C(V)	0.1890	0.0072	0.0000	0.0029	0.0153	0.0163
	(9.84)**	(1.45)	(0.00)	(1.72)	(1.41)	(0.82)
α(1)	0.1404	0.0829	0.1937	0.0878	0.3895	0.3863
	(3.45)**	(3.49)**	(0.81)	(3.45)**	(3.33)**	(2.89)**
α(5)	0.0888					
	(2.53)*					
β(1)		0.2775	0.8629	0.2950	0.6295	0.6308
		(2.95)**	(40.3)**		(4.20)**	(4.02)**
β(2)		0.6214		0.6172		
		(7.04)**		(7.13)**		
θ(1)			0.0491			
			(1.91)			
θ(2)			0.2958			
			(4.51)**			
Log(α) HYGARCH						-0.0085
						(-0.06)
Student-DF	6.0641	6.0724	6.6486	5.6498	6.1129	
	(7.46)**	(7.41)**	(7.38)**	(8.37)**	(7.50)**	
Asymmetry						-0.0838
						(-2.66)**
Tail						6.1337
						(7.41)**
d					0.3631	0.3689
					(3.60)**	(2.39)*
Log-Lik	6855.66	6868.19	6831.86	6867.05	6867.43	6870.83
AIC	-7.5832	-7.5993	-7.5580	-7.5992	-7.5985	-7.600
SBC	-7.5589	-7.5811	-7.5367	-7.5839	-7.5802	-7.5757
HQC	-7.5742	-7.5926	-7.5501	-7.5935	-7.5917	-7.5910
Shibata	-7.5833	-7.5993	-7.5580	-7.5992	-7.5985	-7.6001
ARCH 1-5	0.4952	2.4934	1.4758	2.1407	0.3106	0.3595
	[0.78]	[0.03]*	[0.23]	[0.06]*	[0.91]	[0.88]
ARCH 1-10	0.9295	1.7460	0.6880	1.5635	0.6751	0.6926
	[0.50]	[0.07]	[0.63]	[0.11]	[0.75]	[0.73]
Q(10)	11.6757	13.4593	13.7567	13.4407	12.6929	12.7339
	[0.31]	[0.20]	[0.18]	[0.20]	[0.24]	[0.24]
Q(20)	20.0668	21.8805	21.4356	21.8954	21.2334	21.3049
	[0.45]	[0.35]	[0.37]	[0.35]	[0.38]	[0.38]
Q^2(10)	9.61552	19.2047	7.72791	16.9697	7.12625	7.32433
	[0.09]	[0.01]*	[0.46]	[0.02]*	[0.52]	[0.50]
Q^2(20)	17.6884	26.9396	16.0324	24.9675	14.1934	14.3142
	[0.28]	[0.06]	[0.59]	[0.10]	[0.72]	[0.71]

Notes: The numbers in the parentheses and brackets are t-statistics and *p*-values respectively. All values are computed using OxMetrics and G@RCH package. Q( ) and Q^2( ) is the Ljung–Box *Q*-statistics of order 5, 10, 20 on the raw and squared standardized residuals respectively. * Significant at 5%; ** Significant at 1%.

According to the first column of Tables 3.3, 3.4, 3.5 and 3.6, the ARCH model is correctly specified for all return series. However, there is evidence of 20^{th} order serial correlation in the standardized and squared standardized residuals of GBP/USD at 5% level of significance. In addition, for all return series the log-likelihood values are less than those of the GARCH, IGARCH, FIGARCH and HYGARCH and all information criteria are not at a minimum for the ARCH. This implies that the ARCH is not the most appropriate model to capture the time varying volatility.

The more parsimonious GARCH model, according to the second column of Tables 3.3, 3.4, 3.5 and 3.6, seems to capture much better the time varying volatility as opposed to the ARCH model, as all the estimated parameters and specifically $\hat{\alpha}_i$ and $\hat{\beta}_j$ of equation (3.6) are significant at 5% level. Moreover, the residual tests of the GARCH model indicate no evidence of further ARCH effects and serial correlation at 5% level of significance apart from the NOK/USD series wherein is evidence of further ARCH effects up to 5 lags and serial correlation of 10th order on the squared standardized residuals. Even though the GARCH model is correctly specified for the rest of the three series, the sum of $\hat{\alpha}_i + \hat{\beta}_j$ is very close to one and a LR test, which under the null has a Chi-square distribution with one degree of freedom, could not reject the null hypothesis that the sum of $\hat{\alpha}_i + \hat{\beta}_j = 1$ for each of the four series. This implies that the dispersion of exchange rate shocks has almost infinite persistence and could be better approximated by either an IGARCH, or FIGARCH, or HYGARCH process, which account for long run dependencies.

Prior to analysing the models that account for long run dependencies in volatility the estimated parameters and the residual tests of the EGARCH model for all four return series are presented on column 3 of Tables 3.3, 3.4, 3.5 and 3.6. The results obtained from the EGARCH in all returns series are rather strange. The estimated parameter $\hat{\theta}_1$ of equation (3.9) which captures the asymmetric effects is insignificant at 5% apart from the JPY/USD. These means that negative shocks (bad news) generate greater volatility than positive shocks (good news) in the JPY/USD series. However, the estimated parameters $\hat{\alpha}_1$ and $\hat{\beta}_1$ are insignificant at 5% for all four series (apart from the $\hat{\beta}_1$ parameter of JPY/USD, GBP/USD and NOK/USD) and the residual tests indicate evidence of serial correlation for up to 20 lags in the squared standardized residuals in the CHF/USD and JPY/USD series at 5% significant level. Moreover, there is evidence of further ARCH effects for the CHF/USD return series up to 10. Hence, the EGARCH model is misspecified. Thus, the EGARCH model is not able to detect any asymmetric effects in the conditional variance dynamics for each four returns series. This phenomenon of no asymmetric effects in exchange returns series is empirically supported by Bollerslev, Chou and Kroner (1992), Kisinbay (2003) and Balaban (2004).

The analysis continues with the parameter estimates of the models able to capture long run dependencies in volatility. The fourth column of Tables 3.3, 3.4, 3.5 and 3.6 present the estimated parameters and the residual tests of the IGARCH. In all four exchange returns series the estimated parameters under concern are significant at the 5% level. In addition, the residual tests show no evidence of further ARCH effects and no serial correlation in the standardized and squared standardized residuals at the 5% level of significance apart from a minor case in the NOK/USD series where is evidence of 10th order serial correlation in squared standardized residuals. Apart from that case the IGARCH formulation fits the data well. This means that the dispersion of exchange rate shocks in industrialised countries seems to have infinite persistence.

However, the log-likelihood values for all four return series apart from the GBP/USD return series are smaller than those of the FIGARCH model. The parameter estimates of the FIGARCH models and their residuals tests are presented on the fifth column of Tables 3.3, 3.4, 3.5 and 3.6. The estimated long run parameter $\hat{d}$ is significantly positive in each of four return series at 1% level of significance and ranges between 0.23 and 0.36, which is similar with the ones documented by the empirical literature for exchange rate return series (see for instance Baillie, Cecen and Han, 2000). This means that the long run dependencies in volatility processes have been successfully captured by the FIGARCH. In addition, the residual tests report no evidence of further ARCH effects and no serial correlation in the standardized and squared standardized residuals, according to the ARCH-LM and Q and Q-squared statistics respectively. This means that the dispersion of exchange rate shocks to the conditional variance decays at a slow hyperbolic rate as implied by the FIGARCH model rather than an exponential rate of decay, or an infinite persistence of a shock as implied by the GARCH and IGARCH models respectively. Therefore the FIGARCH formulation captures extremely well the long run dependencies in volatility. This superiority of the FIGARCH model for daily exchange return series is also noted by Vilasuso (2002).

The final model under investigation able to capture long run dependencies in volatility persistence is the HYGARCH model. The estimated parameters and the residuals tests of the HYGARCH model are presented on the sixth column of Tables 3.3, 3.4, 3.5 and 3.6. Even though the log-likelihood values are greater than those of the alternative 5 models and the residual tests report no evidence of serial correlation and further ARCH effects, the estimated parameter $\log(\hat{\alpha})$ of equation (2.12) in all four cases is not found significantly negative at 5% as it was supposed.[31] Hence the HYGARCH model does not observe the usual covariance stationarity restrictions and thus, is not appropriate in modelling exchange rate volatility in our industrialised countries' sample.

In conclusion, among the six volatility models, the FIGARCH, IGARCH and the GARCH models seem to perform better than the ARCH, EGARCH and the HYGARCH models in terms of capturing the time varying volatility in industrialised countries' return series. Among the GARCH, IGARCH and the FIGARCH models, because the sum of the $\hat{\alpha}_i + \hat{\beta}_j$ is very close to one for the GARCH model, and a LR test (which under the null has a Chi-square distribution with one degree of freedom) for all four return series could not reject the null hypothesis that the sum of $\hat{\alpha}_1 + \hat{\beta}_1 = 1$, the IGARCH and FIGARCH models are preferred. Among the IGARCH and the FIGARCH models, the FIGARCH is preferred for the CHF/USD, JPY/USD and the NOK/USD return series and the IGARCH for the GBP/USD return series, as the log-likelihood values of the FIGARCH (IGARCH) are greater for the CHF/USD,

[31] The econometric package (G'@RCH 4.0) used for the estimation of the HYGARCH model reports log(α) rather than α in equation (2.12). This however does not affect the rest of the model's estimates parameters.

JPY/USD and the NOK/USD (GBP/USD) return series as opposed to those of the IGARCH (FIGARCH).[32] However, since the difference between the IGARCH and FIGARCH in the GBP/USD returns series is negligible, and as long as the estimated long run parameter $\hat{d}$ is significantly positive for all four return series at the 1% level of significance for the FIGARCH model, we do not reject it against the IGARCH model.

Hence, from the previous analysis of the six alternative exchange rate volatility models we find that the FIGARCH model consistently ranks first in terms of capturing the conditional volatility dynamics for all four industrialised countries' daily exchanges return series. This is in line with the estimation results of Baillie, Bolerslev and Mikkelsen (1996) and Vilasuso (2002).

3.3.2.2 Developing Countries

For the conditional mean specification of the CLP/USD, CYP/USD, BWP/USD and MUR/USD exchange returns, according to our preliminary approach, we found that an AR(1), AR(1), AR(6) and an AR(1), respectively, were sufficient to eliminate any serial correlation. This is also supported from the ACF in the upper-right panel of Figures 3.6, 3.7, 3.8 and 3.9, respectively (and also from the overfitting tests on the residuals[33]).

[32] This fact is partly due to the more parameters included in the FIGARCH specification.
[33] The tests are not presented but can be provided upon request.

Figure 3.6: DLCLP, ACF-DLCLP, sqresDLCLP, ACF-sqresDLCLP

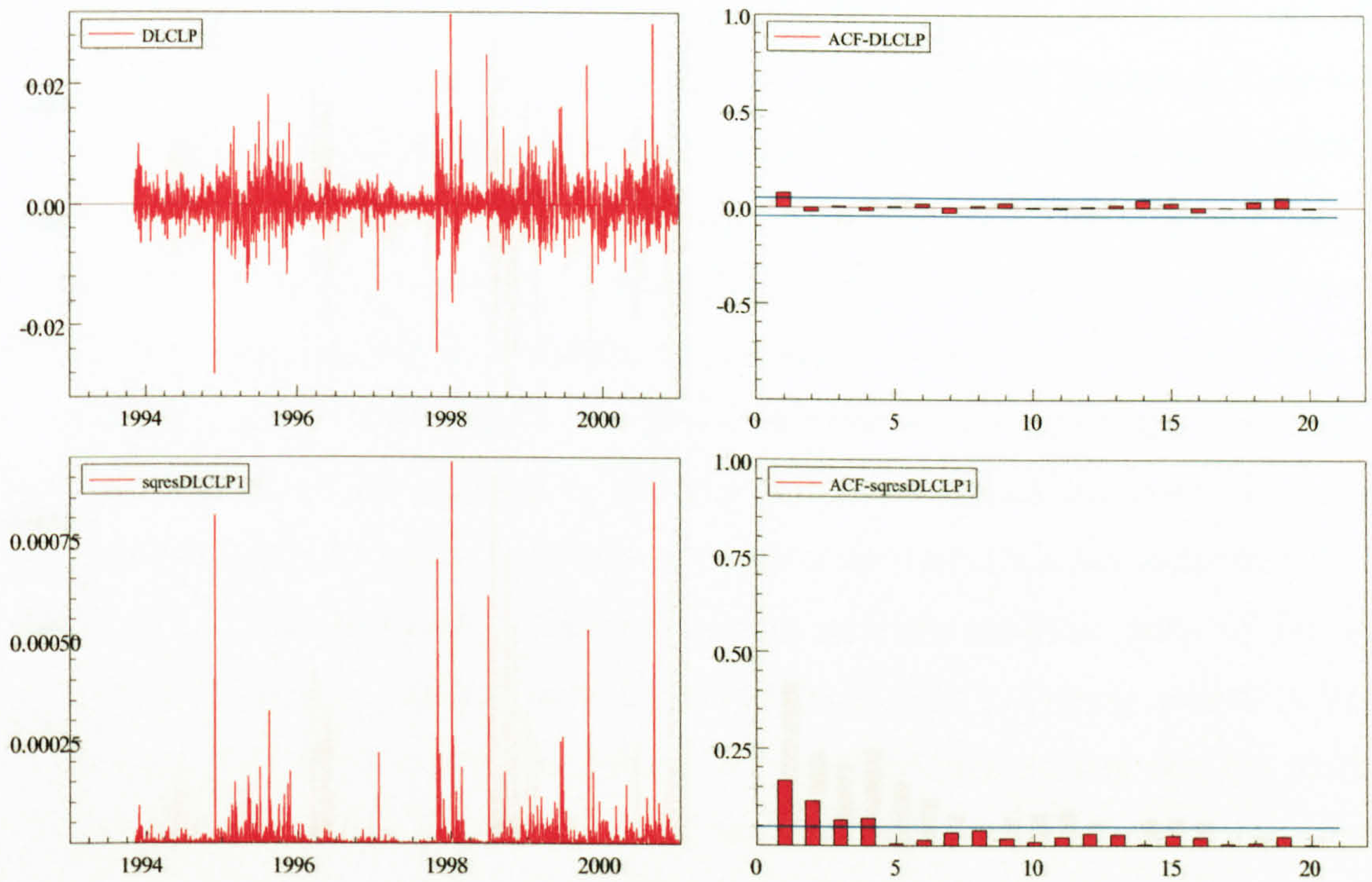


Figure 3.7: DLCYP, ACF-DLCYP, sqresDLCYP, ACF-sqresDLCYP

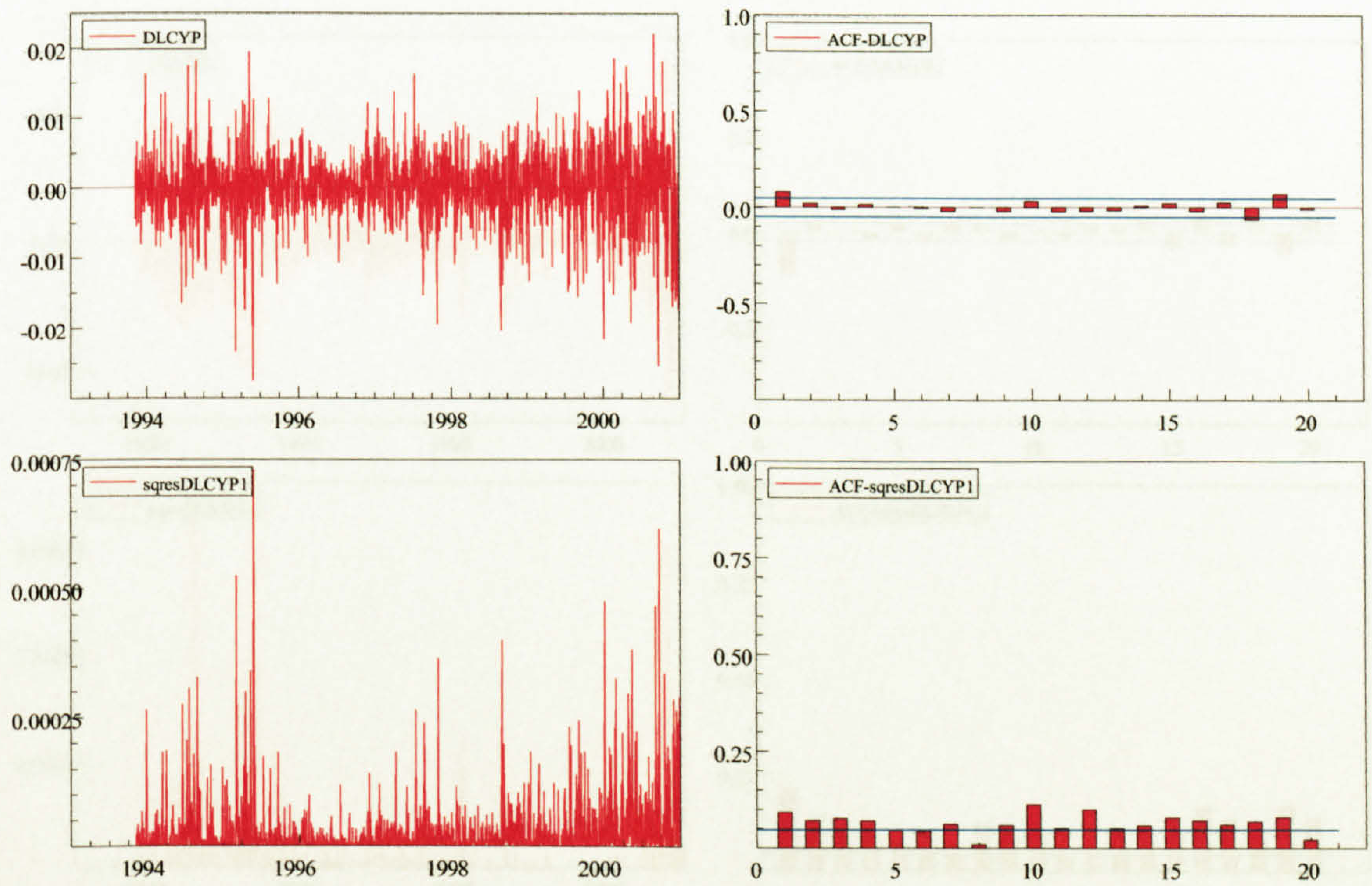


Figure 3.8: DLBWP, ACF-DLBWP, sqresDLBWP, ACF-sqresDLBWP

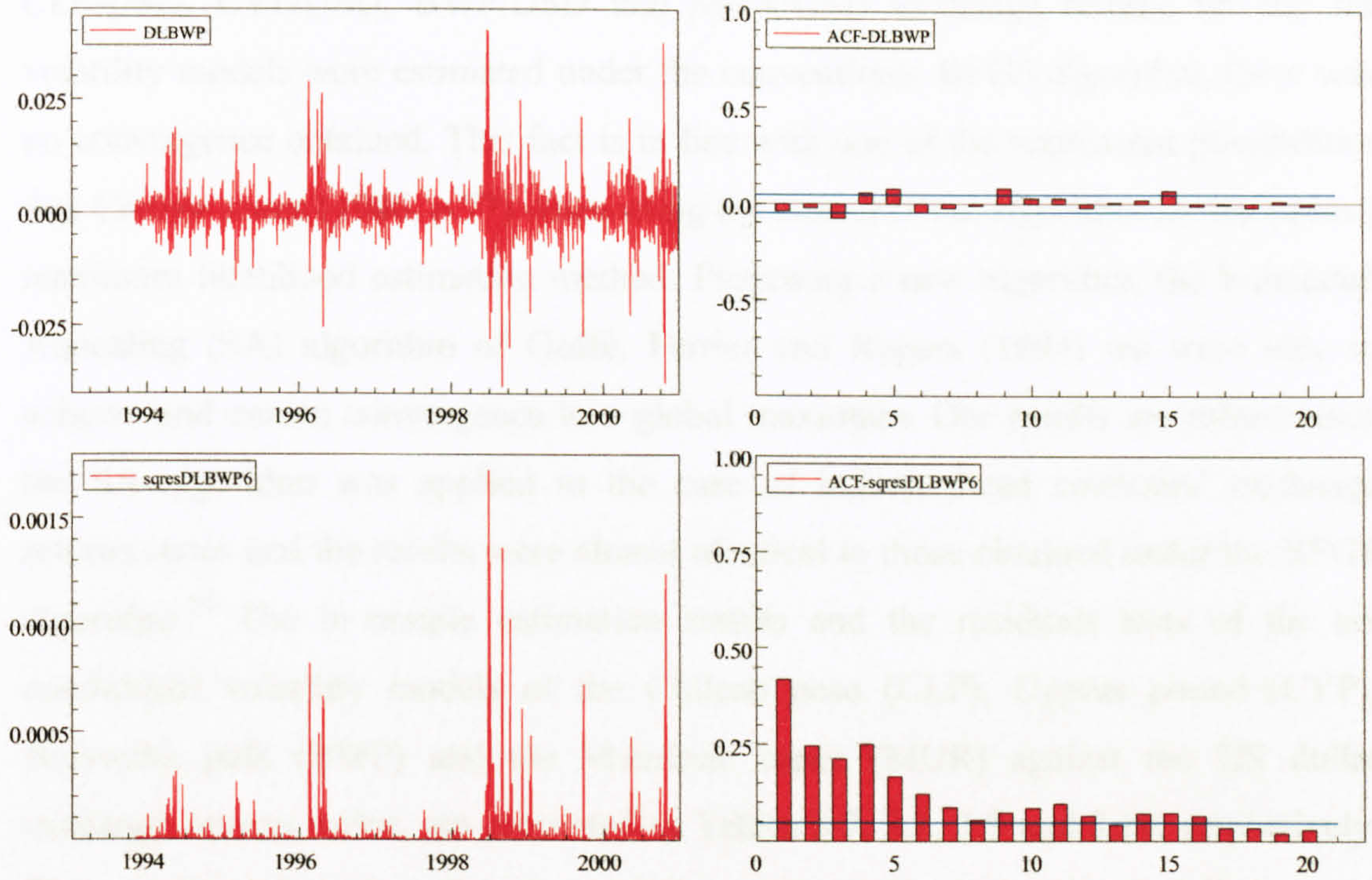
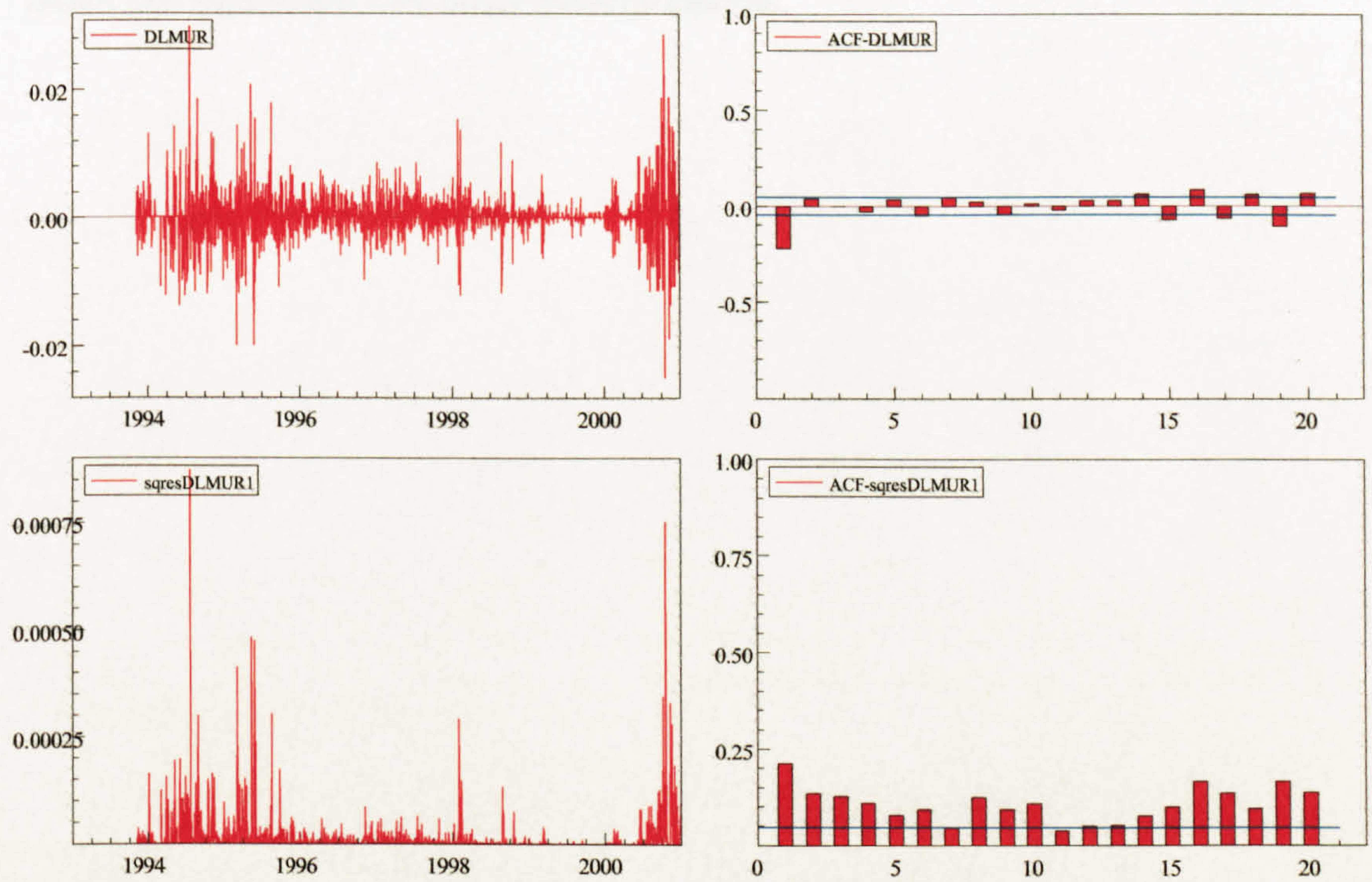


Figure 3.9: DLMUR, ACF-DLMUR, sqresDLMUR, ACF-sqresDLMUR



However, when both the conditional mean and variance specification of the CLP/USD, CYP/USD, BWP/USD and MUR/USD exchange returns for the six volatility models were estimated under the conventional BFGS algorithm, there was no convergence obtained. This fact is in line with one of the unpleasant possibilities that Cramer states (1986, p.77) when using the conventional algorithm for the (quasi) maximum likelihood estimation method. Proposing a new algorithm, the Simulated Annealing (SA) algorithm of Goffe, Ferrier and Rogers (1994) we were able to achieve and ensure convergence to a global maximum. Our results are robust since the SA algorithm was applied in the case of industrialized countries' exchange returns series and the results were almost identical to those obtained under the BFGS algorithm.[34] The in-sample estimation results and the residuals tests of the six conditional volatility models of the Chilean peso (CLP), Cyprus pound (CYP), Botswana pula (BWP) and the Mauritian rupee (MUR) against the US dollar exchange returns series, are presented in Tables 3.7, 3.8, 3.9 and 3.10, respectively. The conditional mean of each exchange rate return series is modelled as an autoregressive process of order 1 or AR(1)[35] that takes into account the economically minor but significant first order autocorrelation.

[34] The results of the industrialised countries' return series under the simulated annealing algorithm are not presented but can be provided upon request.
[35] Despite the fact that the preliminary approach suggested an AR(6) for the conditional mean of the BWP/USD, when both the conditional mean and variance were modelled, an AR(1) was sufficient.

Table 3.7: In-sample Estimation Results for CLP/USD - 08.11.1993-29.12.2000

	ARCH	GARCH	EGARCH	IGARCH	FIGARCH	HYGARCH
C(M)	0.00003	0.00002	0.00002	0.00003	0.00004	0.00015
	(0.59)	(0.32)	(0.27)	(0.59)	(0.64)	(2.04)*
C(V)	0.0904	0.0061	0.0997	0.0097	0.0342	-0.0178
	(59.1)**	(10.9)**	(6.13)**	(22.6)**	(22.3)**	(-14.7)**
AR(1)	0.1085	0.0979	-68358.5	0.1013	0.1085	0.1056
	(4.27)**	(5.52)**	(-4494)**	(4.17)**	(4.05)**	(4.80)**
α(1)	0.7376	0.3611	-0.0779	0.1160	0.3665	0.4735
	(11.8)**	(132)**	(-43.9)**	(37.6)**	(4.12)**	(397)**
α(4)	0.119475					
	(3.38)**					
β(1)		0.8986	0.9235	0.8840	0.5723	0.4042
		(600)**	(797)**		(56.0)**	(53.8)**
θ(1)			0.0197			
			(1.69)			
θ(2)			0.5508			
			(239)**			
Log(α) HYGARCH						1.9363
						(79.6)**
Student-DF	2.4900	2.2166	2.2620	2.5559	2.5980	
	(47.3)**	(166)**	(977)**	(56.2)**	(49.3)**	
Asymmetry						0.0644
						(2.51)*
Tail						2.2052
						(131)**
d					0.5368	0.1565
					(10.8)**	(5.75)**
Log-Lik	7962.41	7990.79	7954.66	7973.47	7974.51	7998.31
AIC	-8.8089	-8.8425	-8.8003	-8.8244	-8.8234	-8.8475
SBC	-8.7845	-8.8242	-8.7759	-8.8092	-8.8021	-8.8201
HQC	-8.7999	-8.8358	-8.7913	-8.8188	-8.8155	-8.8374
Shibata	-8.8089	-8.8425	-8.8003	-8.8245	-8.8234	-8.8476
ARCH 1-5	0.4005	0.1421	0.1557	0.4426	0.1520	0.1360
	[0.85]	[0.98]	[0.98]	[0.82]	[1.00]	[0.98]
ARCH 1-10	0.2379	0.1291	0.1156	0.2775	0.0918	0.0889
	[0.99]	[1.00]	[1.00]	[0.99]	[1.00]	[1.00]
Q(10)	11.9980	7.22721	8.44808	6.01075	8.71003	9.37348
	[0.21]	[0.61]	[0.49]	[0.74]	[0.46]	[0.40]
Q(20)	29.9133	16.0921	23.6531	18.8535	24.1113	22.0923
	[0.06]	[0.65]	[0.21]	[0.47]	[0.19]	[0.28]
$Q^2(10)$	2.3451	1.3107	1.0986	2.8882	0.8954	0.8550
	[0.89]	[1.00]	[1.00]	[0.94]	[1.00]	[1.00]
$Q^2(20)$	8.25650	2.25816	4.10659	4.00393	3.07996	1.50201
	[0.94]	[1.00]	[1.00]	[1.00]	[1.00]	[1.00]

Notes: The numbers in the parentheses and brackets are t-statistics and *p*-values respectively. All values are computed using OxMetrics and G@RCH package. Q( ) and Q^2( ) is the Ljung-Box *Q*-statistics of order 5, 10, 20 on the raw and squared standardized residuals respectively. * Significant at 5%; ** significant at 1%.

Table 3.8: In-sample Estimation Results for CYP/USD - 08.11.1993-29.12.2000

	ARCH	GARCH	EGARCH	IGARCH	FIGARCH	HYGARCH
C(M)	0.0002	0.0002	0.0002	0.0002	0.0002	0.0001
	(2.01)*	(1.87)	(1.55)	(1.88)	(1.90)	(1.00)
C(V)	0.1329	0.0007	-84471.7	0.0009	0.0011	-0.0022
	(7.77)**	(2.7)**	(-58.7)**	(3.73)**	(1.38)	(-2.12)*
AR(1)	0.0625	0.0639	0.0654	0.0641	0.0658	0.0662
	(2.79)**	(3.2)**	(3.01)**	(2.98)**	(3.02)**	(4.08)**
α(1)	0.0867	0.0248	0.4027	0.0346	0.0812	0.4593
	(2.04)**	(10.2)**	(1.24)	(21.1)**	(3.49)**	(94.9)**
α(10)	0.0732					
	(1.98)*					
β(1)		0.9665	0.7077	0.9654	0.9526	0.8225
		(363)**	(9.90)**		(47.7)**	(94.3)**
θ(1)			-0.0830			
			(-2.05)*			
θ(2)			0.2121			
			(3.69)**			
Log(α) HYGARCH						0.1208 (11.6)**
Student-DF	3.8612	4.2163	3.6272	4.2755	4.3565	
	(10.6)**	(11.3)**	(11.3)**	(11.7)**	(10.6)**	
Asymmetry						-0.0346
						(-1.26)
Tail						4.0460
						(10.2)**
d					0.9231	0.3968
					(26.1)**	(61.4)**
Log-Lik	7156.49	7177.28	7132.32	7177.24	7178.02	7175.94
AIC	-7.9097	-7.9416	-7.8896	-7.9427	-7.9413	-7.9368
SBC	-7.8671	-7.9234	-7.8653	-7.9275	7.9200	-7.9094
HQC	-7.8940	-7.9349	-7.8806	-7.9371	-7.9335	-7.9267
Shibata	-7.9099	-7.9416	-7.8897	-7.9427	-7.9414	-7.9369
ARCH 1-5	0.54782	1.0138	0.6207	1.0045	0.4430	0.2330
	[0.74]	[0.41]	[0.68]	[0.41]	[0.82]	[0.95]
ARCH 1-10	0.7518	0.6833	1.7733	0.6865	0.4160	0.4049
	[0.68]	[0.74]	[0.06]	[0.74]	[0.94]	[0.95]
Q(10)	7.3725	7.8917	6.7672	7.8243	7.1080	7.0618
	[0.60]	[0.55]	[0.66]	[0.55]	[0.63]	[0.63]
Q(20)	22.3171	18.6271	22.2899	18.7046	18.1972	17.8916
	[0.27]	[0.48]	[0.27]	[0.48]	[0.51]	[0.53]
$Q^2(10)$	7.4064	6.8040	17.9243	6.8322	4.1529	4.0889
	[1.00]	[0.56]	[0.02]*	[0.55]	[0.84]	[0.85]
$Q^2(20)$	20.0082	12.7740	48.1348	12.7742	10.8530	11.8861
	[0.03]*	[0.80]	[0.00]**	[0.80]	[0.90]	[0.85]

Notes: The numbers in the parentheses and brackets are t-statistics and *p*-values respectively. All values are computed using OxMetrics and G@RCH package. Q( ) and Q^2( ) is the Ljung-Box *Q*-statistics of order 5, 10, 20 on the raw and squared standardized residuals respectively. * Significant at 5%; ** significant at 1%.

Table 3.9: In-sample Estimation Results for BWP/USD - 08.11.1993-29.12.2000

	ARCH	GARCH	EGARCH	IGARCH	FIGARCH	HYGARCH
C(M)	0.0002	0.0002	0.0002	0.0002	0.0002	0.0003
	(3.46)**	(3.73)**	(4.68)**	(3.85)**	(3.78)**	(3.94)**
C(V)	0.0916	0.0234	-62956.87	0.0229	0.0194	0.0095
	(62.7)**	(30.3)**	(-462)**	(38.2)**	(24.9)**	(2.11)*
AR(1)	-0.0400	-0.0353	-0.0317	-0.0393	-0.0414	-0.0476
	(-1.68)	(-1.42)	(-11.6)**	(-1.94)	(-1.84)	(-2.35)*
α(1)	0.8733	0.2811	-0.0214	0.3013	0.4078	0.5681
	(6.86)**	(16.3)**	(-6.82)**	(87.3)**	(55.7)**	(56.6)**
α(4)	0.4262					
	(4.08)**					
β(1)		0.7023	0.8705	0.3864	0.6972	0.7060
		(193)**	(586)**		(460)**	(30.6)**
β(2)				0.3124		
				(6.03)**		
θ(1)			0.1844			
			(12.0)**			
θ(2)			0.7567			
			(190)**			
Log(α) HYGARCH						0.6014
						(65.1)**
Student-DF	2.4349	2.7956	2.4273	2.7439	2.7719	
	(52.2)**	(37.4)**	(696)**	(41.8)**	(40.4)**	
Asymmetry						0.0380
						(1.62)
Tail						2.4236
						(71.2)**
d					0.6557	0.5236
					(304)**	(23.8)**
Log-Lik	7659.89	7662.11	7648.69	7666.08	7671.73	7684.4
AIC	-8.4739	-8.4785	-8.4615	-8.4829	-8.4881	-8.4999
SBC	-8.4495	-8.4603	-8.4371	-8.4647	-8.4668	-8.4725
HQC	-8.4649	-8.4718	-8.4525	-8.4762	-8.4802	-8.4898
Shibata	-8.4739	-8.4785	-8.4615	-8.4829	-8.4881	-8.4999
ARCH 1-5	0.7642	1.4715	0.5694	1.3982	1.6457	0.4973
	[0.58]	[0.20]	[0.72]	[0.22]	[0.15]	[0.78]
ARCH 1-10	0.8913	0.8934	0.5297	0.8321	0.9307	0.4153
	[0.54]	[0.54]	[0.87]	[0.60]	[0.50]	[0.94]
Q(10)	18.881	18.413	17.705	17.130	18.605	17.949
	[0.03]*	[0.03]*	[0.04]*	[0.05]*	[0.03]*	[0.04]*
Q(20)	34.6487	30.5950	30.6479	28.9268	30.3922	31.7822
	[0.02]*	[0.04]*	[0.04]*	[0.07]	[0.05]*	[0.03]*
Q^2(10)	8.7647	9.2648	5.3619	8.6153	10.1616	4.3338
	[0.19]	[0.32]	[0.72]	[0.28]	[0.25]	[0.83]
Q^2(20)	27.1845	34.9985	24.9968	25.6746	23.8694	14.4573
	[0.04]*	[0.01]**	[0.12]	[0.08]	[0.15]	[0.70]

Notes: The numbers in the parentheses and brackets are t-statistics and p-values respectively. All values are computed using OxMetrics and G@RCH package. Q( ) and Q^2( ) is the Ljung–Box Q-statistics of order 5, 10, 20 on the raw and squared standardized residuals respectively. * Significant at 5%; ** significant at 1%.

Table 3.10: In-sample Estimation Results for MUR/USD - 08.11.1993-29.12.2000

	ARCH	GARCH	EGARCH	IGARCH	FIGARCH	HYGARCH
C(M)	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(4.57)**	(4.70)**	(2.98)**	(4.64)**	(4.67)**	(2.84)**
C(V)	0.0736	0.0271	-1585.257	0.0144	0.0378	-0.6202
	(40.7)**	(42.7)**	(-512)**	(57.3)**	(52.4)**	(-1542)**
AR(1)	-0.0881	-0.0865	-0.0664	-0.0742	-0.0843	-0.0980
	(-10.5)**	(-3.74)**	(-3.28)**	(-3.58)**	(-3.28)**	(-21.3)**
α(1)	1.0000	0.2534	0.5492	0.1525	0.2556	0.0195
	(11.9)**	(9.26)**	(1.47)**	(112)**	(2.58)**	(14.4)**
α(10)	1.0000					
	(2.12)*					
β(1)		0.7245	0.9800	0.4099	0.5943	0.4017
		(134)**	(227)**		(77.4)**	(299)**
β(2)				0.4375		
				(7.27)**		
θ(1)			0.1332			
			(0.75)			
θ(2)			1.2006			
			(4.54)**			
Log(α) HYGARCH						4.8484
						(4410)**
Student-DF	2.0751	2.2976	2.0110	2.2776	2.2856	
	(220)**	(77.2)**	(728)**	(93.9)**	(91.1)**	
Asymmetry						0.0138
						(1.05)
Tail						2.0037
						(8517)**
d					0.5928	0.3684
					(6.37)**	(620)**
Log-Lik	8316.77	8216.96	8338.1	8226.46	8226.49	8388.33
AIC	-9.1945	-9.0930	-9.2249	-9.1035	-9.1024	-9.2794
SBC	-9.1520	-9.0747	-9.2006	-9.0852	-9.0811	-9.2520
HQC	-9.1789	-9.0862	-9.2159	-9.0968	-9.0946	-9.2693
Shibata	-9.1948	-9.0930	-9.2249	-9.1035	-9.1025	-9.2795
ARCH 1-5	0.2532	0.4698	0.0898	1.7481	0.8378	0.4683
	[0.94]	[0.80]	[0.99]	[0.12]	[0.52]	[0.80]
ARCH 1-10	0.4104	1.4780	0.0968	1.7712	1.7319	0.6913
	[0.94]	[0.14]	[1.00]	[0.06]	[0.07]	[0.73]
Q(10)	10.2896	10.8527	12.3784	13.8910	11.6261	10.3002
	[0.33]	[0.29]	[0.19]	[0.13]	[0.23]	[0.33]
Q(20)	30.8773	36.9211	32.9484	35.3915	36.1821	27.0237
	[0.04]	[0.01]**	[0.02]*	[0.01]*	[0.01]*	[0.10]
Q^2(10)	4.4342	15.0195	0.9605	18.8994	18.0327	6.8431
	[1.00]	[0.06]	[1.00]	[0.01]**	[0.02]*	[0.55]
Q^2(20)	56.9675	77.1368	26.8848	53.4295	71.7564	23.8641
	[0.00]**	[0.00]**	[0.08]	[0.00]**	[0.00]**	[0.16]

Notes: The numbers in the parentheses and brackets are t-statistics and *p*-values respectively. All values are computed using OxMetrics and G@RCH package. Q( ) and Q^2( ) is the Ljung-Box *Q*-statistics of order 5, 10, 20 on the raw and squared standardized residuals respectively. * Significant at 5%; ** significant at 1%.

According to the ARCH estimate parameters and the residual tests reported in the first column of Tables 3.7, 3.8, 3.9 and 3.10 for each of the four exchange return series, the positivity constraint of the conditional variance is ensured but the stationarity constraint, apart from the CYP/USD return series, is not met as α(q)>1, denoting that the processes are non-stationary. However, even for the CYP/USD return series there is evidence of 20th order serial correlation in the squared standardized residuals at the 5% level of significance. In addition, for each return series the log-likelihood values is less than those of the GARCH, IGARCH, FIGARCH and HYGARCH and all information criteria are not minimum for the ARCH. This means that the ARCH model for each of the four series is not the most appropriate in capturing the time varying volatility.

The more parsimonious GARCH model, according to the second column of Tables 3.7, 3.8, 3.9 and 3.10, seems to capture better the time varying volatility for all four exchange returns series as opposed to the ARCH model. All the estimated parameters of interest for the GARCH(1,1) model for the CLP/USD, CYP/USD, BWP/USD and MUR/USD return series are significant at the 5% level of significance. In addition, the positivity and stationarity constraints are met as $\hat{\alpha}_1 + \hat{\beta}_1 \geq 0$ and $\hat{\alpha}_1 + \hat{\beta}_1 < 1$ respectively, apart from the CLP/USD where $\hat{\alpha}_1 + \hat{\beta}_1 > 1$. However, the sum of $\hat{\alpha}_1 + \hat{\beta}_1$ is very close to one and a LR test (which under the null hypothesis has a Chi-square distribution with one degree of freedom) for the CYP/USD, BWP/USD and MUR/USD return series could not reject the null hypothesis that the sum of $\hat{\alpha}_1 + \hat{\beta}_1 = 1$. This implies that the dispersion of exchange rate shocks in the CYP/USD, BWP/USD and MUR/USD squared exchange returns series almost has infinite persistence and could be better approximated by an IGARCH, FIGARCH or HYGARCH process, which accounts for long run dependencies.

Prior to analysing the processes that account for long run dependencies the parameter estimates and the residuals tests of the EGARCH model are presented on column three of Tables 3.7, 3.8, 3.9 and 3.10. The estimated parameter $\hat{\theta}_1$ of equation (2.10) which captures the asymmetric effects is insignificantly positive at the 5% level of significance for the CLP/USD and MUR/USD return series, significantly positive at 5% for the BWP/USD and significantly negative at 5% for the CYP/USD return series. This means that positive shock ('good news') generate more volatility than negative shocks ('bad news') for the case of BWP/USD return series, and less volatility than negative shocks for the case of CYP/USD return series. However, the estimated parameter $\hat{\alpha}_1$ is insignificantly positive at the 5% level for the CYP/USD return series and significantly negative for the BWP/USD return series (this means that in the case of BWP/USD return series, the positivity constraint is not ensured as $\hat{\alpha}_1 < 0$). In addition, the residual test of the EGARCH models of CYP/USD and BWP/USD series indicate evidence of serial correlation up to 20 and 10 lags in the squared standardized residuals of CYP/USD and in the standardized residuals of BWP/USD series, respectively, at 5% significant level. This means that the EGARCH formulation is not appropriate in capturing the time varying volatility for all four developing countries' exchange rate return series.[36] In other words, no asymmetric effects seem to be present for these four exchange return series. This phenomenon is empirically supported by Balaban (2004), Bollerslev, Chou and Kroner (1992) and Kisinbay (2003).

Our analysis continues with the parameter estimates of the IGARCH model, for each of the four exchange return series, which are presented on the fourth column of Tables 3.7, 3.8, 3.9 and 3.10, along with the their residuals tests. In all four exchange returns series the estimated parameters under concern are significant at 5%. In addition, there is no evidence of further ARCH effects and no serial correlation for the standardized and squared standardized residuals for the CLP/USD and CYP/USD return series. However, in the case of BWP/USD return series there is evidence of 10^{th} order serial correlation in the standardized residuals. In the case of MUR/USD return series there is evidence of 20^{th} order serial correlation in the standardized residuals and up to 20^{th} order serial correlation in the squared standardized residuals. This means that the IGARCH model fits well the CLP/USD and CYP/USD return data and not very well the BWP/USD and MUR/USD return data.

[36] Again the results for the EGARCH specification are rather strange. Other lag structures of the EGARCH have been estimated but results remained similar.

The next model under investigation which accounts for long run dependencies in volatility is the FIGARCH model. The parameter estimates and the residuals tests of the FIGARCH models are presented on the fifth column of Tables 3.7, 3.8, 3.9 and 3.10. The estimated long memory parameter $\hat{d}$ for all four return series is significant at 1% denoting that the long run dependencies in the volatility process have been captured. Moreover, the rest of the parameters of the FIGARCH model for each of the four return series are significant. In addition, the tests on the residuals for the CLP/USD and CYP/USD return series reported on the fifth column of Tables 3.7 and 3.8, respectively, indicate no evidence of further ARCH effects and no serial correlation in the standardized and squared standardized residuals. However, for the BWP/USD return series there is evidence of up to 20^{th} order serial correlation in the standardized residuals. In the case of the MUR/USD return series there is evidence of 20^{th} order serial correlation in the standardized residuals and up to 20^{th} order serial correlation in the squared standardized residuals. This means that the FIGARCH model does very well in terms of capturing the long run dependencies in volatility persistence for the CLP/USD and CYP/USD series and not very well for the BWP/USD and MUR/USD series.

The final model under investigation able in capturing the long run dependencies in volatility persistence is the HYGARCH model. The estimated parameters and the residual tests of the HYGARCH model are presented on the last column of Tables 3.7, 3.8, 3.9 and 3.10. Even though all the estimated parameters of the HYGARCH model for all four exchange return series are significant, the estimated parameter $\log(\hat{a})$ of equation (2.12) in all four cases is greater than zero.[37] This means that the HYGARCH process is not stationary as it does not satisfy the stationary condition: $\log(\hat{a}) < 0$. Thus, the HYGARCH model is not appropriate in capturing the conditional variance dynamics of these four exchange return series.

In conclusion, among these six volatility models, the GARCH the IGARCH and the FIGARCH models seem to perform better than the ARCH, EGARCH and the

[37] The econometric package (G'@RCH 4.0) used for the estimation of the HYGARCH model reports log(α) rather than α in equation (2.12). This however does not affect the rest of the model's estimates parameters.

HYGARCH models in terms of capturing the time varying volatility in developing countries' exchange return series. Among the GARCH, IGARCH and the FIGARCH models, although the FIGARCH model has the highest log-likelihood values, the information criteria (specifically the AIC, SBC, HQC and Shibata) are minimised for the IGARCH model in the case of the CYP/USD and MUR/USD return series. For the CLP/USD and BWP/USD series the information criteria are minimised for the GARCH and the FIGARCH model respectively. However, the GARCH model in the case of the CLP/USD return series and the FIGARCH model in the case of the BWP/USD return series, as previously mentioned, are not stationary as the sum of $\hat{\alpha}_1 + \hat{\beta}_1$ is greater than one. Hence, the IGARCH model consistently ranks first in terms of capturing time varying volatility. This means that the dispersion of exchange rate shocks have an infinite persistence in developing countries.

3.3.3 Out-of-Sample Forecast Evaluation

Nonetheless, the good in-sample model fitness does not unavoidably mean that the out-of-sample forecasts will be superior. In order to select a model with superior forecasting performance we need to consider the performance of out-of-sample forecast evaluation criteria. This section presents the empirical results for the out-of-sample forecast evaluation criteria in industrialised and developing countries.

We evaluate the 1-step out-of-sample volatility forecasts for the period between 02.01.2001 to 31.12.2001 (totalling 253 observations). The out-of sample volatility forecasts are calculated using the parameter estimates of the six conditional heteroskedasticity models examined in section 3. These volatility forecasts are then compared to the daily squared exchange rate returns, and the accuracy is judged based on the regression based test, MSE, and the SPA test.

3.3.3.1 Industrialised Countries

We begin our analysis with the out-of-sample volatility forecast results for the industrialised countries' exchange return series. Tables 3.11, 3.12, 3.13 and 3.14

present the results of the Mincer-Zarnowitz's regression based test. One would expect a model to be unbiased if α and β significantly equal to zero and one, respectively. All models are biased at 5% level of significance, apart from the EGARCH model, as the null hypothesis that the estimated parameters, $\hat{\alpha}$ and $\hat{\beta}$, equal to zero and to one, respectively, is jointly rejected. This is in line with the results obtained by Balaban (2004) which used daily ex-post returns as a proxy of true volatility. In addition, the R^2 for each return series and each model is extremely low. It ranges from 0.004% (for the HYGARCH in the CHF/USD series) to 4.26% (for the EGARCH in the GBP/USD series). The extremely low values of R^2 are in line with the empirical papers that used daily instead of intra-daily data as a proxy of realized volatility (see Andersen and Bollerslev, 1998a; Martens, 2001; Galbraith and Kisinbay, 2005).

Table 3.11: Mincer-Zarnowitz regression of y_t^2, for CHF/USD, on a constant and 1-step out-of-sample forecasts (K=253)

	α	β	R^2	Rank
ARCH	0,00004 (6.326)** [0,000007]	0,4823 (1.259) [0,3830]	0.0057	1
GARCH	0,00006 (2.445)* [0,00002]	-0,1782 (-0.2706) [0,6583]	0.0003	4
EGARCH	0,0003 (59.92)** [0,000003]	-0,0003 (-16.48)** [0,00002]	0.0040	3
IGARCH	0,00006 (1.826) [0,00003]	-0.1121 (-0.1995) [0,5619]	0.0002	5
FIGARCH	0,00005 (2.052)* [0,00002]	0,0383 (0,0716) [0,5351]	0.0040	2
HYGARCH	0,00005 (2.177)* [0,00002]	-0,0636 (-0.0912) [0,6966]	0,00004	6

Numbers in brackets and parenthesis are White (1980) Heteroskedastic Consistent S.E. and t-values respectively. * Significant at 5%; ** significant at 1%.

Table 3.12: Mincer-Zarnowitz regression of y_t^2, for JPY/USD, on a constant and 1-step out-of-sample forecasts (K=253)

	α	β	R^2	Rank
ARCH	0.00004 (5.211)** [0,000007]	0.04866 (0.1926) [0,2527]	0.0001	6
GARCH	0.00003 (2.898)** [0,00001]	0.1929 (0.5697) [0,3387]	0.0010	4
EGARCH	-0.000004 (-0.1492) [2.8142e-005]	0.0365 (1.402) [0.0261]	0.0050	1
IGARCH	0.00003 (2.786)** [0,00001]	0.1697 (0.5744) [0,2954]	0.0010	2
FIGARCH	0.00003 (2.414)* [0,00001]	0.1074 (0.2833) [0,3790]	0.0003	4
HYGARCH	0.00003 (2.496)* [0,00001]	0.0965 (0.2685) [0,3595]	0.00025	5

Numbers in brackets and parenthesis are White (1980) Heteroskedastic Consistent S.E. and t-values respectively. * Significant at 5%; ** significant at 1%.

Table 3.13: Mincer-Zarnowitz regression of y_t^2, for GBP/USD, on a constant and 1-step out-of-sample forecasts (K=253)

	α	β	R^2	Rank
ARCH	0.00002 (5.335)** [0,000004]	0.3931 (0.6796) [0,5784]	0.0032	6
GARCH	0.00001 (1.612) [0,00001]	0.5295 (1.183) [0,4478]	0.0063	2
EGARCH	0.0002 (7.231)** [2.1320e-005]	-0.0289 (-5.935)** [0.0049]	0.0426	1
IGARCH	0.00001 (1.547) [0,000009]	0.4157 (1.181) [0,3519]	0.0058	4
FIGARCH	0.00001 (1.147) [0,00001]	0.4833 (0.9838) [0,4961]	0.0061	3
HYGARCH	0.00001 (1.079) [0,00001]	0.3931 (0.8296) [0,4739]	0.0039	5

Numbers in brackets and parenthesis are White (1980) Heteroskedastic Consistent S.E. and t-values respectively. * Significant at 5%; ** significant at 1%.

Table 3.14: Mincer-Zarnowitz regression of y_t^2, for NOK/USD, on a constant and 1-step out-of-sample forecasts (k=253)

	α	β	R^2	Rank
ARCH	0.00004 (5.952)** [5.9425e-006]	0.1142 (0.4352) [0.2625]	0.0007	6
GARCH	0.00003 (1.981)* [1.3752e-005]	0.3220 (0.7860) [0.4097]	0.0030	2
EGARCH	0.0001 (4.492)** [2.4396e-005]	-0.0068 (-2.943)** [0.0023]	0.0074	1
IGARCH	0.00003 (1.802) [1.4789e-005]	0.2790 (0.7681) [0.3632]	0.0029	3
FIGARCH	0.00003 (2.436)* [1.2288e-005]	0.214553 (0.6498) [0.3302]	0.0017	5
HYGARCH	0.00003 (2.409)* [1.2294e-005]	0.2261 (0.6751) [0.3349]	0.0018	4

Numbers in brackets and parenthesis are White (1980) Heteroskedastic Consistent S.E. and t-values respectively. * Significant at 5%; ** significant at 1%.

We continue with the out-of-sample forecasts judged by the MSE. The results of the MSE are presented on Table 3.15. The MSE is minimized for the FIGARCH model in the JPY/USD and GBP/USD and for the IGARCH in the CHF/USD and NOK/USD return series. This means that the FIGARCH model is preferred for the JPY/USD and GBP/USD and the IGARCH for the CHF/USD and NOK/USD return series. However, in the all returns series their difference is negligible. Another feature of Table 3.15 is that the IGARCH, FIGARCH and HYGARCH models that account for long memory dependencies in volatility persistence outperform the short memory models apart from the NOK/USD series where the GARCH is ranked second and above the FIGARCH and HYGARCH. The ARCH and the EGARCH models are consistently found to rank in 5th and 6th place, implying their weak performance in forecasting and confirming our bad in-sample results (in the previous section) for these two models. In Vilasuso's (2002) study the FIGARCH was found to be superior. In our analysis the FIGARCH, evaluated by the MSE, performs better in the JPY/USD and GBP/USD series and since its difference with the IGARCH in the CHF/USD and NOK/USD series is negligible, we use the FIGARCH model as the benchmark model in the Superior Predictive Ability (SPA) forecast evaluation test.

Table 3.15: 1-step Out-of-Sample Forecast Evaluation Industrialised Countries (k=253)

	MSE							
	CHF/USD	**Rank**	**JPY/USD**	**Rank**	**GBP/USD**	**Rank**	**NOK/USD**	**Rank**
ARCH	0,000008831	5	0,000003206	5	0,00000202	5	0,000003390	5
GARCH	0,000007958	4	0,000003011	4	0,00000168	4	0,000002940	2
EGARCH	705,5	6	0,001187000	6	0,01963000	6	0,11400	6
IGARCH	**0,000007635**	1	0,000002999	3	0,00000167	2	**0,000002930**	1
FIGARCH	0,000007656	2	**0,000002988**	1	**0,00000166**	1	0,000002945	4
HYGARCH	0,000007929	3	0,000002994	2	0,00000168	3	0,000002944	3

All criteria must be multiplied by 10^{-3}.

Table 3.16: SPA test results evaluated by MSE – Industrialised Countries

CHF/USD				
	Models	Sample Loss	t-statistics	p-value
Benchmark	FIGARCH	8.4306e-009	-	-
Most Significant	IGARCH	8.4266e-009	0.0365	0.4620
Best model	IGARCH	8.4266e-009	0.0365	0.4620
Model 25%	HYGARCH	8.6829e-009	-2.0343	0.9730
Median model 50%	GARCH	8.7021e-009	-2.0940	0.9800
Model 75%	ARCH	9.7611e-009	-3.9648	0.9980
Worst	EGARCH	0.19182	-268.67	1.0000
SPA	Lower	Consistent		Upper
p-values	0.4810	0.4810		0.9600

JPY/USD				
	Models	Sample Loss	t-statistics	p-value
Benchmark	FIGARCH	2.8549e-009	-	-
Most Significant	HYGARCH	2.8582e-009	-0.4423	0.6450
Best model	HYGARCH	2.8582e-009	-0.4423	0.6450
Model 25%	IGARCH	2.8960e-009	-1.8810	0.9750
Median model 50%	GARCH	2.9062e-009	-1.6728	0.9500
Model 75%	ARCH	3.0118e-009	-1.9377	0.9740
Worst	EGARCH	1.1867e-006	-58.4883	1.0000
SPA	Lower	Consistent		Upper
p-values	0.6150	0.9860		0.9970

GBP/USD				
	Models	Sample Loss	t-statistics	p-value
Benchmark	FIGARCH	1.5575e-009	-	-
Most Significant	HYGARCH	1.5653e-009	-0.2527	0.6030
Best model	HYGARCH	1.5653e-009	-0.2527	0.6030
Model 25%	IGARCH	1.5711e-009	-0.4057	0.6550
Median model 50%	GARCH	1.5775e-009	-1.1465	0.8840
Model 75%	ARCH	1.9004e-009	-3.597	0.9980
Worst	EGARCH	1.9628e-005	-175.64	1.0000
SPA	Lower	Consistent		Upper
p-values	0.6500	0.9180		1.0000

NOK/USD				
	Models	Sample Loss	t-statistics	p-value
Benchmark	FIGARCH	2.8675e-009	-	-
Most Significant	GARCH	2.8226e-009	1.6024	0.0630
Best model	GARCH	2.8226e-009	1.6024	0.0630
Model 25%	IGARCH	2.8267e-009	1.0761	0.1500
Median model 50%	HYGARCH	2.8661e-009	0.4294	0.3460
Model 75%	ARCH	3.2758e-009	-3.2396	0.9990
Worst	EGARCH	0.00011406	-194.34	1.0000
SPA	Lower	Consistent		Upper
p-values	0.4710	0.5710		0.7990

Table 3.16 presents the SPA test results in the industrialised countries. In the first column of this table one can see the model's ranking selected by the SPA test. Moreover, according to the p-values in the last column of this table, the null hypothesis that the FIGARCH (benchmark model in the SPA test)[38] model is not inferior to each of the alternatives models is not rejected for each return series at the 5% level of significance. The superiority of the FIGARCH in terms of out-of-sample forecasting is also supported by Vilasuso's study (2002) for industrialised countries' daily returns data. Nevertheless, the superiority of the FIGARCH model in the case of industrialised countries, in Vilasuso's study, was based on the out-of-sample forecast performance among two alternative models. A contribution of this chapter is that the superiority of the FIGARCH model is confirmed among five alternative models. Another contribution of this paper is that the superiority of the FIGARCH model in Vilasuso's study was based on the Diebold and Mariano (DM) test that evaluates whether the forecasting accuracy between only two models is the same, whereas in this study a SPA test is employed that is able to evaluate the superiority among all the alternative models simultaneously.

Concluding the out-of-sample forecast analysis in industrialised countries we provide a summary of the rank selected by the SPA test in Table 3.17. One important finding of this summary table is that volatility models which take into account both long memory dependency and persistence in the volatility process perform superior out-of-sample forecasts as opposed to the short memory models. That is, the FIGARCH, IGARCH and the HYGARCH models always rank above the GARCH, ARCH and the EGARCH models apart from the NOK/USD series, wherein, the GARCH model ranks above the IGARCH and the HYGARCH but below the FIGARCH. The FIGARCH model is consistently superior in generating out-of-sample forecasts for each exchange return series and the ARCH and the EGARCH consistently capture the 5th and the 6th place denoting that these two models are incapable of generating accurate out-of-sample forecast in industrialised countries' exchange rate volatility. Another feature of Table 3.17 is that the rank of volatility models selected by SPA is

[38] The SPA test has been evaluated by having the IGARCH as the benchmark model and testing whether is inferior to any of the alternative specifications. The results are not reported but can be provided upon request.

identical for the JPY/USD and GBP/USD series. This means that the volatility processes of the Japanese yen and the GB pound share similar properties.

Table 3.17: Models ranked by SPA test – Industrialised countries

Rank	CHF/USD	JPY/USD	GBP/USD	NOK/USD
1	FIGARCH	FIGARCH	FIGARCH	FIGARCH
2	IGARCH	HYGARCH	HYGARCH	GARCH
3	HYGARCH	IGARCH	IGARCH	IGARCH
4	GARCH	GARCH	GARCH	HYGARCH
5	ARCH	ARCH	ARCH	ARCH
6	EGARCH	EGARCH	EGARCH	EGARCH

3.3.3.2 Developing countries

Having empirically evaluated the superior forecasting performance of the FIGARCH model, regarding daily exchange rate volatility in industrialised countries, and compared the results with the empirical literature, the analysis continues with the following question: does the FIGARCH model perform equally well in developing countries' daily exchange rate volatility forecasting among the alternative models?

Tables 3.18, 3.19, 3.20 and 3.21 present the results of the Mincer-Zarnowitz's regression test for the CLP/USD, CYP/USD, BWP/USD and the MUR/USD returns series, respectively. In the case of the CLP/USD and CYP/USD series, all models are biased at 5% level of significance, apart from the EGARCH model, as the null hypothesis that the estimated parameters $\hat{\alpha}$ and $\hat{\beta}$ equal to zero and to one is jointly rejected. For the BWP/USD series all six models are unbiased and for the MUR/USD series the IGARCH, FIGARCH and the HYGARCH are unbiased at 5%. We can observe that almost all the models in developing countries are found unbiased than in industrialised countries. In addition, the measure of predictability (R^2), even though is still low, has slightly increased compared to that in industrialised countries and ranges now between 0,021% (for the ARCH in BWP/USD series) to 5.49% (for the HYGARCH in the MUR/USD). This slight increase in the R^2 might be depicted by the fact that, since in developing countries the markets are not as liquid as that in industrialised countries, using daily ex-post return as a proxy of realised volatility is sufficient to account for the unobservable intraday effects. Nonetheless, it would be of interest to see how the R^2 could be affected by using higher frequency (such as 30-min intraday data) as a proxy of true volatility. However, such practice is impossible at the moment because of the lack of higher frequency data in developing countries.

Table 3.18: Mincer-Zarnowitz regression of y_t^2, for CLP/USD, on a constant and 1-step out-of-sample forecasts (k=253)

	α	β	R^2	Rank
ARCH	0.0001 (3.495)** [1.5782e-005]	0.1552 (1.141) [0.1360]	0.0246	2
GARCH	0.00005 (3.776)** [1.2580e-005]	0.1003 (1.401) [0.0716]	0.0115	6
EGARCH	-0.0002 (-1.427) [0.00010417]	0.0645 (1.754) [0.0367]	0.0273	1
IGARCH	0.00005 (3.774)** [1.2580e-005]	0.3474 (1.354) [0.257]	0.0122	5
FIGARCH	0.00005 (2.914)** [1.8274e-005]	0.2820 (1.181) [0.2387]	0.0148	4
HYGARCH	0.00005 (2.697)** [1.8699e-005]	0.0866 (1.194) [0.0725]	0.0161	3

Numbers in brackets and parenthesis are White (1980) Heteroskedastic Consistent S.E. and t-values respectively. * Significant at 5%; ** significant at 1%.

Table 3.19: Mincer-Zarnowitz regression of y_t^2, for CYP/USD, on a constant and 1-step out-of-sample forecasts (k=253)

	α	β	R^2	Rank
ARCH	0.0001 (3.005)** [2.1973e-005]	-0.2027 (-0.7455) [0.2719]	0.0016	5
GARCH	0.0001 (1.124) [7.7770e-005]	-0.4654 (-0.4327) [1.0754]	0.0028	3
EGARCH	0.00001 (0.1243) [5.9498e-005]	0.0008 (1.043) [0.0008]	0.00025	6
IGARCH	0.0001 (1.142) [7.6183e-005]	-0.4752 (-0.4370) [1.0875]	0.0028	2
FIGARCH	0.0001 (1.164) [7.3808e-005]	-0.4605 (-0.4360) [1.0564]	0.0027	4
HYGARCH	0.0001 (1.350) [6.4472e-005]	-0.3957 (-0.5338) [0.7414]	0.0031	1

Numbers in brackets and parenthesis are White (1980) Heteroskedastic Consistent S.E. and t-values respectively. * Significant at 5%; ** significant at 1%.

Table 3.20: Mincer-Zarnowitz regression of y_t^2, for BWP/USD, on a constant and 1-step out-of-sample forecasts (k=253)

	α	β	R^2	Rank
ARCH	0.00004 (1.888) [2.2252e-005]	-0.0132 (-0.9897) [0.0133]	0.00021	6
GARCH	0.00004 (1.875) [2.2828e-005]	-0.0465 (-1.095) [0.0425]	0.00033	3
EGARCH	0.0001 (1.179) [6.5229e-005]	-0.0222 (-0.8012) [0.0277]	0.0022	1
IGARCH	0.00004 (1.869) [2.3142e-005]	-0.0552 (-1.099) [0.0502]	0.0004	2
FIGARCH	0.00004 (1.873) [2.2795e-005]	-0.0433 (-0.9833) [0.0441]	0.00029	5
HYGARCH	0.00004 (1.869) [2.2828e-005]	-0.0197 (-0.9484) [0.0207]	0.00031	4

Numbers in brackets and parenthesis are White (1980) Heteroskedastic Consistent S.E. and t-values respectively. * Significant at 5%; ** significant at 1%.

Table 3.21: Mincer-Zarnowitz regression of y_t^2, for MUR/USD, on a constant and 1-step out-of-sample forecasts (k=253)

	α	β	R^2	Rank
ARCH	0.00001 (3.751)** [2.1998e-006]	0.0456 (2.634)** [0.0173]	0.0260	6
GARCH	0.00001 (1.974)** [3.1460e-006]	0.4853 (2.187)* [0.222]	0.0349	5
EGARCH	0.000005 (2.358)* [2.2784e-006]	0.0113 (3.350)** [0.0034]	0.0503	2
IGARCH	0.000004 (1.538) [2.7572e-006]	0.5431 (3.248)** [0.1672]	0.0420	4
FIGARCH	0.000005 (1.659) [2.8549e-006]	0.5392 (2.849)** [0.1893]	0.0470	3
HYGARCH	0.000005 (1.873) [2.6985e-006]	0.0028 (2.868)** [0.0010]	0.0549	1

Numbers in brackets and parenthesis are White (1980) Heteroskedastic Consistent S.E. and t-values respectively. * Significant at 5%; ** significant at 1%.

In Table 3.22 we present the out-of-sample forecasts judged by the MSE criterion. The MSE is minimized for the IGARCH model in each but the MUR/USD return series. For the latter series the MSE is minimized under the FIGARCH model. This means that the IGARCH model performs better in out-of-sample forecasts for the CLP/USD, CYP/USD and the BWP/USD and the FIGARCH for the MUR/USD return series. However, even in the MUR/USD series their difference is negligible. The GARCH model captures the second, third, third and fourth place for the BWP/USD, CYP/USD, MUR/USD and CLP/USD series, respectively. The ARCH model ranks third for the CLP/USD but does not perform well for the other returns series and the EGARCH ranks in the worst place for each series apart from the

MUR/USD where ranks 5th. In conclusion, under the MSE evaluation the IGARCH performs better than the FIGARCH, and as the latter's difference with the IGARCH in the MUR/USD series is negligible, we use the IGARCH model as the benchmark model in the Superior Predictive Ability (SPA) forecast evaluation test.[39]

Table 3.22: 1-step Out-of-Sample Forecast Evaluation Developing Countries (k=253)

	MSE							
	CLP/USD	**Rank**	**CYP/USD**	**Rank**	**BWP/USD**	**Rank**	**MUR/USD**	**Rank**
ARCH	0,00025	3	0,00004516	5	0,0002553	5	0,000018810	4
GARCH	0,00031	4	0,00004340	3	0,0001317	2	0,000000802	3
EGARCH	0,01221	6	4,031	6	3,138	6	0,000765600	5
IGARCH	**0,00015**	1	**0,00004337**	1	**0,0001307**	1	0,000000798	2
FIGARCH	0,00016	2	0,00004339	2	0,0001323	3	**0,000000793**	1
HYGARCH	0,00043	5	0,00004400	4	0,0002082	4	0,014090000	6

All criteria must be multiplied by 10^{-3}.

Table 3.23 presents the results obtained from the SPA test. One can clearly see that the null hypothesis that the IGARCH model (the benchmark) is not inferior to each of the alternatives models is not rejected, according to the p-values of the last column of Table 3.23. In addition, two out of the three models (the IGARCH and the FIGARCH) that account for long memory dependencies in volatility persistence outperform the short memory models.

[39] The SPA test has been evaluated by having the FIGARCH as the benchmark model and testing whether is inferior to any of the alternative specifications. The results are not reported but can be provided upon request.

Table 3.23: SPA test results evaluated by MSE – Developing Countries

	Models	Sample Loss	t-statistics	p-value
		CLP/USD		
	Models	Sample Loss	t-statistics	p-value
Benchmark	IGARCH	1.6204e-007	-	-
Most Significant	FIGARCH	1.7509e-007	-1.0249	0.8340
Best model	FIGARCH	1.7509e-007	-1.0249	0.8340
Model 25%	ARCH	2.9822e-007	-1.5164	0.9110
Median model 50%	GARCH	3.4013e-007	-2.8132	0.9960
Model 75%	HYGARCH	4.8903e-007	-1.6343	0.9250
Worst	EGARCH	0. 1.2303e-005	-14.296	1.0000
SPA	Lower	Consistent	Upper	
p-values	0.5600	0.8750	0.9450	
		CYP/USD		
	Models	Sample Loss	t-statistics	p-value
Benchmark	IGARCH	4.2788e-008	-	-
Most Significant	FIGARCH	4.2804e-008	-0.1998	0.5780
Best model	FIGARCH	4.2804e-008	-0.1998	0.5780
Model 25%	GARCH	4.2831e-008	-1.1704	0.9090
Median model 50%	HYGARCH	4.3520e-008	-2.0523	0.9810
Model 75%	ARCH	4.4355e-008	-2.0752	0.9770
Worst	EGARCH	0.0040315	-208.1589	1.0000
SPA	Lower	Consistent	Upper	
p-values	0.6040	0.8350	0.9880	
		BWP/USD		
	Models	Sample Loss	t-statistics	p-value
Benchmark	IGARCH	1.3450e-007	-	-
Most Significant	FIGARCH	1.3620e-007	-0.3481	0.6750
Best model	GARCH	1.3558e-007	-0.4241	0.7080
Model 25%	FIGARCH	1.3620e-007	-0.3481	0.6750
Median model 50%	HYGARCH	2.1265e-007	-1.1271	0.9000
Model 75%	ARCH	2.6014e-007	-1.3152	0.8930
Worst	EGARCH	3.1470e-006	-6.4579	1.0000
SPA	Lower	Consistent	Upper	
p-values	0.7650	0.9150	0.9170	
Table 23 continues		MUR/USD		
	Models	Sample Loss	t-statistics	p-value
Benchmark	IGARCH	7.2190e-010	-	-
Most Significant	FIGARCH	7.2858e-010	-0.3701	0.6480
Best model	FIGARCH	7.2858e-010	-0.3701	0.6480
Model 25%	GARCH	7.3397e-010	-0.5517	0.7120
Median model 50%	ARCH	1.8506e-008	-5.9612	1.0000
Model 75%	EGARCH	7.6534e-007	-6.3775	1.0000
Worst	HYGARCH	1.4084e-005	-6.1866	1.0000
SPA	Lower	Consistent	Upper	
p-values	0.5560	0.7400	0.8950	

In addition, we provide in Table 3.24 a summary of the models' ranks selected by the SPA test. A contributory finding of this summary table is that the IGARCH and the FIGARCH models that take into account both long memory dependency and persistence in the volatility process perform superior out-of-sample forecasts as opposed to the short memory models (that is the ARCH, GARCH and the EGARCH). Although the third model that accounts for long memory dependency, specifically the HYGARCH, seems inappropriate in out-of-sample forecasts as it ranks fourth for the CYP/USD and BWP/USD, fifth for the CLP/USD and sixth for the MUR/USD series. The short memory models capture the rest places with the EGARCH having the worst performance. These results in the case of out-of-sample daily exchange rate volatility forecasting are contributory since there does not exist any other paper, to my best knowledge, focusing on the forecasting performance in developing countries' exchange rate volatility with daily data. The fact that the IGARCH was found to be superior (even though its difference in terms of performance with the FIGARCH is small) in out-of-sample forecast performance in developing countries, has serious implications for policy makers and various groups of agents. Since the IGARCH denotes an infinite persistence of a shock in developing countries, proponents of fixed exchange rate regimes would argue that these countries should peg their currencies against the US dollar in order to avoid extreme episodes such as currency crises that harmed many developing countries in the 20th century.

Table 3.24: Models ranked by SPA test – Developing Countries

Rank	CLP/USD	CYP/USD	BWP/USD	MUR/USD
1	IGARCH	IGARCH	IGARCH	FIGARCH
2	FIGARCH	FIGARCH	FIGARCH	IGARCH
3	ARCH	GARCH	GARCH	GARCH
4	GARCH	HYGARCH	HYGARCH	ARCH
5	HYGARCH	ARCH	ARCH	EGARCH
6	EGARCH	EGARCH	EGARCH	HYGARCH

3.4 Robustness Analysis

Having found that the FIGARCH and the IGARCH models are preferred in industrialised and developing countries, respectively, both in in-sample and out-of-sample performance and since the models' difference is rather negligible in both groups of countries a final robustness check is performed. That is, we carry an additional forecasting test, namely the forecast encompassing test to check whether the IGARCH (FIGARCH) model carries additional information over the base FIGARCH (IGARCH) model in industrialised (developing) countries. This forecast encompassing test originally considered by Chong and Hendry (1996) is defined in Eq. (2.26). The results of the forecast encompassing test are presented in Table 3.25.

Table 3.25: Forecast encompassing test: FIGARCH and IGARCH

	Industrialised countries			Developing countries	
	FIGARCH	IGARCH		IGARCH	FIGARCH
CHF/USD	-0.30 (-0.34)	1.29 (2.06)*	CLP/USD	0.64 (2.01)*	0.31 (0.98)
JPY/USD	1.12 (3.12)**	0.09 (0.54)	CYP/USD	0.57 (1.99)*	0.41 (1.45)
GBP/USD	0.88 (2.26)*	0.10 (0.65)	BWP/USD	0.89 (3.34)**	0.08 (0.73)
NOK/USD	0.67 (1.99)*	0.25 (1.43)	MUR/USD	0.16 (0.32)	0.84 (2.49)*

Numbers in parenthesis are t-values. * Significant at 5%; ** Significant at 1%.

The results of the forecast encompassing test in industrialised countries suggest that the (base) FIGARCH model encompasses the IGARCH model in all exchange return series apart from the CHF/USD series. Thus, there is no additional information contained in the IGARCH model over the FIGARCH model apart from the CHF/USD series which to a great extend confirms our previous results in Table 3.15. Turning to the results of the forecast encompassing test in developing countries one can see that the (base) IGARCH model encompasses the FIGARCH in all series except MUR/USD series. That is, apart from the MUR/USD series the FIGARCH does not contain any additional information over the IGARCH which again generally confirms our previous results in Table 3.22. In conclusion, the results of the forecast encompassing tests in developing and industrialised countries strengthens our previous finding that the FIGARCH and the IGARCH models are preferred in industrialised and developing countries, respectively.

3.5 Assessing the VaR performance of the models

This section provides a final analysis to ascertain if the selected FIGARCH and the IGARCH models in industrialised and developing countries, respectively, improve on the one-day ahead Value-at-Risk (VaR) forecasts compared to the alternative models previously assessed. The VaR approach is widely used by large financial institutions and refers to a portfolio's worst outcome that is likely to occur at a given level, α (e.g. 5 or 2.5 per cent) over a given period of time. With the use of the VaR approach one can calculate the loss associated to a portfolio, during one day, one week or a year, with a pre-specified probability. For instance, if a portfolio, which consists of long positions in foreign currencies, has a one-day 5% VaR of 2 millions, then there is a 5% probability that the portfolio will fall by more than 2 millions in value over a one-day period.

Specifically, in our case, we use the estimated coefficients obtained from the previous six models, reported in Tables 3.3 - 3.6 and Tables 3.7 – 3.11 for the case of industrialised and developing countries, respectively, to evaluate the one-day ahead volatility forecasting accuracy. For instance, for the Student GARCH model, the VaR for long and short positions is given by $\mu_t + st_{\alpha,\upsilon}\sigma_t$ and $\mu_t + st_{1-\alpha,\upsilon}\sigma_t$,[40] with $st_{\alpha,\upsilon}$ being the left quantile at α% for the Student distribution with estimated number of degrees of freedom υ and $st_{1-\alpha,\upsilon}$ is the right quantile at α% for the same distribution. We evaluate all models with a VaR level α ranging from 5% to 0.25% (that is for quantiles equal to 0.95, 0.975, 0.99, 0.995, 0.9975) and gauge their performance by computing the failure rate for each of the exchange returns. The failure rate refers to the number of times returns exceed (in absolute value) the forecasted VaR. In a correctly specified VaR model, the failure rate should be equal

[40] Note that when computing the VaR, μ_t (conditional mean) and σ_t (conditional standard deviation) are evaluated by replacing the unknown parameters by theur quasi-maximum likelihood estimates.

to the predetermined VaR level, α. We define the failure rate for short (long) trading positions as f_s (f_l), which is equal to the percentage of positive (negative) returns larger (smaller) than the one-day ahead VaR for short (long) positions. Having calculated the empirical failure rates, we can explicitly test whether these empirical failure rates equal the predetermined VaR level α using the Kupiec (1995) LR test. The Kupiec LR statistic which tests the null hypothesis $H_0 : f = \alpha$ against the alternative $H_a : f \neq \alpha$ is defined as:

$$LR = -2\ln(\alpha^{T-N}(1-\alpha)^N) + 2\ln((1-(N/T))^{T-N}(N/T)^N) \qquad (3.3)$$

where T is the total number of observations, N is the number of VaR violations and f is the true failure rate. Under the null hypothesis, the LR test is asymptotically distributed as a chi-square distribution with one degree of freedom.

Tables 3.26 and 3.27 present the *P-values* for the Kupiec LR test in industrialised and developing countries, respectively, for the one-day ahead Value-at-Risk (VaR) forecasts.

The results reported in both tables strengthen our previous findings. Specifically, in the case of industrialised countries, in Table 3.26, the FIGARCH model yields significant improvement in the one-day ahead VaR forecasts, as the *P-values* for the null hypothesis that the failure rate is equal to the predetermined level, α, indicate that the null is not rejected (apart from a minor case in GBP/USD case at $\alpha = 0.25\%$). The rest of the models our found to perform not so well, as the P-values indicate rejection of the null hypothesis at level α equal or below to 2.5%.

Table 3.26: Failure rate results for exchange returns in industrialised countries

	VaR for short positions					VaR for long position				
α	5%	2.5%	1%	0.5%	0.25%	5%	2.5%	1%	0.5%	0.25%
CHF/USD										
ARCH	0.054	**0.037**	**0.018**	**0.019**	**0.045**	0.139	0.181	**0.033**	**0.036**	**0.002**
GARCH	0.070	0.057	0.059	**0.042**	**0.041**	0.069	0.063	0.181	**0.042**	**0.046**
EGARCH	0.072	**0.049**	**0.011**	**0.042**	**0.045**	0.262	**0.023**	**0.008**	**0.049**	**0.026**
IGARCH	0.141	0.115	0.131	**0.144**	**0.009**	0.157	0.086	0.652	0.214	**0.005**
FIGARCH	0.170	0.179	0.181	0.199	0.065	0.186	0.133	0.181	0.169	0.059
HYGARCH	0.563	0.782	0.072	**0.042**	**0.003**	0.256	0.982	0.498	**0.014**	**0.029**
JPY/USD										
ARCH	0.103	0.065	**0.007**	**0.039**	**0.045**	0.155	**0.025**	**0.021**	**0.025**	**0.019**
GARCH	0.563	0.079	**0.001**	**0.004**	**0.013**	0.256	0.114	**0.036**	**0.046**	**0.026**
EGARCH	0.060	**0.043**	**0.003**	**0.019**	**0.013**	0.099	**0.046**	**0.038**	**0.025**	**0.019**
IGARCH	0.307	0.215	0.051	**0.028**	**0.011**	0.412	0.313	0.652	**0.025**	**0.043**
FIGARCH	0.257	0.343	0.321	0.344	0.183	0.215	0.249	0.278	0.214	0.126
HYGARCH	0.291	0.231	0.183	**0.018**	**0.004**	0.772	0.387	0.368	**0.046**	**0.043**
GBP/USD										
ARCH	0.343	0.631	**0.038**	**0.001**	**0.001**	0.615	0.387	**0.031**	**0.025**	**0.026**
GARCH	0.542	0.343	0.057	**0.042**	**0.047**	0.542	0.567	**0.044**	**0.046**	**0.022**
EGARCH	0.110	**0.038**	**0.019**	**0.001**	**0.000**	0.212	**0.023**	**0.024**	**0.028**	**0.019**
IGARCH	0.632	0.268	0.317	**0.031**	**0.047**	0.615	0.671	0.628	**0.025**	**0.025**
FIGARCH	0.724	0.631	0.317	0.181	0.057	0.542	0.567	0.266	0.146	**0.048**
HYGARCH	0.515	0.982	0.619	**0.041**	**0.037**	0.940	0.982	0.654	**0.042**	**0.022**
NOK/USD										
ARCH	0.176	0.057	**0.009**	**0.042**	**0.003**	0.078	0.225	**0.020**	**0.013**	**0.037**
GARCH	0.214	0.112	0.106	**0.042**	**0.035**	0.213	0.248	0.224	**0.043**	**0.039**
EGARCH	0.076	**0.031**	**0.042**	**0.019**	**0.008**	**0.030**	**0.045**	**0.020**	**0.024**	**0.021**
IGARCH	0.090	0.154	0.072	**0.043**	**0.025**	0.178	0.985	0.802	**0.024**	**0.028**
FIGARCH	0.414	0.370	0.357	0.282	0.096	0.554	0.364	0.350	0.145	0.088
HYGARCH	0.387	0.098	**0.041**	**0.027**	**0.005**	0.892	**0.034**	**0.041**	**0.024**	**0.021**

Notes: Numbers represent *P-values* for the null hypothesis $H_0 : f = \alpha$ (e.g. the failure rate for short positions is equal to α). Bold numbers denote that $H_0 : f = \alpha$ is rejected at 5% level of significance or lower (e.g. 1%) against the alternative $H_0 : f \neq \alpha$ (e.g. the failure rate for short positions are not equal to α).

In the case of developing countries, in Table 3.27, the one-day ahead VaR forecasts obtained from the IGARCH model outperform those obtained from the various alternatives. This is due to the fact that the null hypothesis is always not rejected for the IGARCH model for each of the exchange rate series and at each level, α.

Table 3.27: Failure rate results for exchange returns in developing countries

	VaR for short positions					VaR for long position				
α	5%	2.5%	1%	0.5%	0.25%	5%	2.5%	1%	0.5%	0.25%
CLP/USD										
ARCH	0.474	0.358	0.217	**0.031**	**0.024**	0.370	0.190	**0.027**	**0.014**	**0.045**
GARCH	0.141	0.065	**0.037**	**0.041**	**0.034**	0.152	0.082	**0.042**	**0.003**	**0.037**
EGARCH	**0.017**	**0.001**	**0.072**	**0.011**	**0.004**	**0.023**	**0.022**	**0.011**	**0.004**	**0.043**
IGARCH	0.720	0.537	0.456	0.481	0.822	0.617	0.522	0.411	0.434	0.545
FIGARCH	0.640	0.453	0.319	0.162	**0.044**	0.523	0.305	0.333	0.119	**0.047**
HYGARCH	0.231	**0.041**	**0.032**	**0.039**	**0.017**	0.222	**0.024**	**0.021**	**0.034**	**0.046**
CYP/USD										
ARCH	0.074	**0.011**	**0.018**	**0.031**	**0.045**	0.063	**0.033**	**0.021**	**0.042**	**0.034**
GARCH	0.320	0.415	0.208	**0.049**	**0.033**	0.363	0.446	0.325	**0.032**	**0.027**
EGARCH	**0.024**	**0.029**	**0.005**	**0.006**	**0.017**	0.121	**0.003**	**0.005**	**0.069**	**0.029**
IGARCH	0.888	0.624	0.317	0.281	0.183	0.663	0.546	0.525	0.692	0.822
FIGARCH	0.542	0.211	0.119	0.081	**0.047**	0.679	0.325	0.098	**0.040**	**0.022**
HYGARCH	0.327	0.137	**0.047**	**0.041**	**0.003**	0.256	0.151	**0.036**	**0.031**	**0.004**
BWP/USD										
ARCH	0.111	**0.002**	**0.019**	**0.031**	**0.005**	0.291	**0.055**	**0.007**	**0.019**	**0.017**
GARCH	0.215	0.231	0.117	**0.041**	**0.037**	0.141	0.105	**0.008**	**0.024**	**0.025**
EGARCH	**0.040**	**0.042**	**0.025**	**0.028**	**0.004**	**0.048**	**0.003**	**0.037**	**0.059**	**0.019**
IGARCH	0.179	0.387	0.368	0.992	0.804	0.491	0.205	0.172	0.104	0.150
FIGARCH	0.256	0.387	0.368	0.525	**0.042**	0.363	0.111	0.137	0.054	**0.023**
HYGARCH	0.220	**0.043**	**0.017**	**0.021**	**0.045**	0.147	**0.005**	**0.003**	**0.004**	**0.000**
MUR/USD										
ARCH	0.270	0.115	**0.025**	**0.032**	**0.004**	0.113	0.153	**0.046**	**0.040**	**0.347**
GARCH	0.321	0.222	0.119	**0.031**	**0.023**	0.291	0.223	0.132	**0.019**	**0.039**
EGARCH	**0.002**	**0.045**	**0.006**	**0.022**	**0.007**	**0.048**	**0.031**	**0.007**	**0.012**	**0.033**
IGARCH	0.140	0.147	0.281	0.192	0.083	0.163	0.234	0.317	0.278	0.117
FIGARCH	0.230	0.133	0.298	0.125	**0.046**	0.150	0.251	0.456	0.281	**0.045**
HYGARCH	**0.013**	**0.033**	**0.019**	**0.026**	**0.045**	**0.043**	**0.009**	**0.018**	**0.042**	**0.027**

Notes: Numbers represent *P-values* for the null hypothesis $H_0 : f = \alpha$ (e.g. the failure rate for short positions is equal to α). Bold numbers denote that $H_0 : f = \alpha$ is rejected at 5% level of significance or lower (e.g. 1%) against the alternative $H_0 : f \neq \alpha$ (e.g. the failure rate for short positions are not equal to α).

In conclusion, even under a one-day ahead VaR forecasting assessment, supporting evidence of the superiority of the FIGARCH and IGARCH models in industrialised and developing countries, respectively, is also provided. These findings have serious implications for various groups of agents. For instance, such models could be used effectively to manage and measure currency risk exposure in these two sets of countries in an attempt to reduce central banks' and other group of agents' vulnerabilities to major exchange rate movements, especially after the currency crisis episodes over recent decades that gave rise to greater uncertainty.

3.6 Conclusion

The main purpose of this research was to examine the forecasting performance of exchange rate volatility in industrialised and developing countries. The key question was whether the traditional univariate volatility models used widely and successfully in previous studies of industrialised countries could perform equally well when applied to data for developing countries. The exchange rate series investigated in this study were the CHF/USD, JPY/USD and GBP/USD and the NOK/USD in the case of industrialised countries and the CLP/USD, CYP/USD, BWP/USD and MUR/USD in the case of developing countries. An extensive examination of the ARCH, GARCH, EGARCH, IGARCH, FIGARCH and the HYGARCH models was performed and revealed that, although some of the models perform extremely well in industrialised countries' exchange rate returns series under the conventional BFGS algorithm in the estimation process, these models could not be applied successfully in the case of developing countries' daily exchange rate return series when employing the same algorithm. This might be one of the reasons why the empirical literature on exchange rate volatility forecasting is rather silent in this area. However, on application of the Simulated Annealing algorithm of Goffe, Ferrier and Rogers (1994), which has better properties, we were able to provide results for exchange rate volatility forecasting in developing countries.[41]

In the case of industrialised countries' daily exchange rate returns series, the results support previous empirical findings. Both in-sample estimation and out-of-sample forecast evaluation show that the FIGARCH model not only fits the data better than the HYGARCH, IGARCH, GARCH, ARCH and EGARCH models but, in most of the cases it is also superior in out-of-sample forecasting performance. The FIGARCH model captures the long memory dependencies and persistence in the volatility process very well. In other words, modelling the long memory and volatility clustering properties simultaneously results in substantial gains in the out-of-sample forecast performance. This result is also supported by a study of Vilasuso

[41] Our results are robust since the simulated annealing algorithm was applied in the case of industrialized countries' exchange returns series and the results were almost identical to those obtained when employing the BFGS algorithm.

(2002), where the FIGARCH model is found to be superior to alternative models for all daily exchange returns series at every forecasting horizon examined. Nevertheless, the superiority of the FIGARCH model in Vilasuso's study, in the case of industrialised countries, was based on the out-of-sample forecast performance of only two alternative models (specifically the GARCH and the IGARCH) whereas, in this paper, the superiority of the FIGARCH model is confirmed among all five of alternative models previously mentioned. Hence we strengthen the existing empirical literature on the superiority of the FIGARCH model for modelling daily exchange returns.

In the case of developing countries' exchange rate returns, by proposing the Simulated Annealing algorithm of Goffe, Ferrier and Rogers (1994) it was found that, both in-sample estimation and out-of-sample forecast evaluation, the IGARCH model not only fits the data better than the FIGARCH, GARCH, HYGARCH, ARCH and EGARCH models for the in-sample estimation, but, in most of the cases, it is also superior in out-of-sample forecasting performance. The IGARCH model that indicates an infinite persistence in the dispersion of exchange rate shocks captures the volatility process in the case of developing countries extremely well. In addition, the FIGARCH model was found to rank second in order in terms of both in-sample estimation and out-of-sample forecasting performance. In other words, modelling both the long memory and volatility clustering properties results in substantial gains in the out-of-sample forecast performance in developing countries.

Even under a one-day ahead VaR forecasting assessment, supporting evidence of the superiority of the FIGARCH and IGARCH models in industrialised and developing countries, respectively, was also provided. These findings have important implications for various groups of agents. For instance, such models could be used effectively to manage and measure currency risk exposure in these two sets of countries in an attempt to reduce central banks' vulnerabilities to major exchange rate movements, especially after the currency crisis episodes of recent decades.

In the case of developing countries these results contribute to a sparse area of forecasting exchange rate volatility using daily data. There is no literature, to my best knowledge, that focuses on the forecasting performance in developing countries' exchange rate volatility with daily data. Further work along these lines may be called for, to check that results are not specific to the particular data set and/or the specification in the volatility process. For instance, it would be of great interest to check whether our results for four developing countries can be generalised for the rest of the developing countries. In addition, our results are based on a single regime model, so do not consider any possible structural changes in the volatility process over time. Diebold and Inoue (2001) argue that the apparent finding of long-memory in volatility persistence, such that captured by the FIGARCH or the IGARCH models, could be due to the existence of regime switching in the volatility process. Hence, our finding of the superiority of the IGARCH model in developing countries, and the FIGARCH model confirmation of other studies in industrialised countries' return series, might be explained by the presence of structural breaks rather than long memory (slow mean reversion) in the conditional variance dynamics of exchange rate returns series. Therefore, it would be of interest to see whether the key findings stand up to consideration of a regime switching model in the estimation process.

Chapter 4

Exchange Rate Volatility Co-movements and Spillovers before and after the Introduction of Euro: A Multivariate GARCH Approach

4.1 Introduction

The purpose of this chapter is to examine and compare exchange rate volatility co-movements and spillovers among major financial markets before and after the introduction of the euro.

Our motivation derives from the fact that studies have analysed exchange rate volatility comovements and spillovers in the post-euro period (see, for instance, Inagaki, 2007; Nikkinen et al., 2006 and Pérez-Rodríguez, 2006) up to 2004. Little is known about the current evolution of exchange rate volatility co-movements and spillovers among major currencies. Such studies have not compared that evolution with the pre-euro period. Such an investigation might reveal valuable insights.

As this chapter examines volatility co-movements and spillovers in the pre- and post-euro period it deals, in a way, with regime change, which was not considered in the previous chapter. This is a further motivation of this chapter.

Undoubtedly, one of the most important events for the international financial markets has been the implementation of the Economic Monetary Union on the 1st of January 1999, when the exchange rates for the countries involved were locked to the euro.

The euro came into circulation on January 1st 2002 and since then it has subsequently become a serious competitor to the dollar in international usage. According to the Bank for International Settlements (BIS) (2007), the euro rapidly became the second most traded currency behind the US dollar in the international exchange markets. The BIS's Triennial Central Bank Survey on Foreign Exchange and Derivative Market Activity in 2007 showed that, from April 2004 to April 2007, the average daily turnover of the euro accounted for 37% of all transactions (such as spot and forward transactions and FX swaps), while the US dollar accounts for 86.3%. The Japanese yen, the British Pound and the Swiss franc follow the euro with average daily turnovers of 16.5%, 15% and 6.8%, respectively.[42]

As the Euro area is enlarged with new members that will subsequently adopt the euro, there exists the possibility that the new currency might in the near future rival or surpass the US dollar as the world's leading international reserve currency (Chinn and Frankel, 2007). One of the many factors that may influence such a development is the stability of the euro/US dollar exchange rate in terms of volatility. Besides, the purpose of euro participation was for countries to cushion shocks arriving from this area as well as to shocks arriving from outside (the later is known as the 'spillover' effect). Given the status of the Euro as the anchor currency in the EMU, it is of great importance to examine its volatility and its impact on other currencies.

The contribution of this chapter to the literature on exchange rate volatility co-movements and spillovers since the introduction of the euro is twofold. First, this study has the advantage of a longer sample period than most comparable papers. This allows a more extended study of the volatility dynamics of euro and the main traded currencies. Second, it compares the post-euro with the pre-euro period.

The key results of this chapter are that the dominance of the Deutsche mark in volatility transmission is succeeded by the dominance of the Euro following its launch, in that both exert unidirectional and persistent spillovers on sterling, the Swiss franc and the Japanese yen. Further, there is evidence of greater stability in

[42] The reason % shares exceed 100% is because two currencies are involved in each transaction hence, the sum of the % shares of individual currencies used in the BIS report totals 200%.

financial markets after the launch of the Euro in that conditional variances, covariances and correlations in exchange rate returns declined significantly.

This chapter is organised as follows. Section 4.2 presents the literature review. The data and methodology employed in this chapter are described in section 4.3. Section 4.4 presents the empirical results and section 4.5 concludes.

4.2 Literature Review

The most recent studies that have investigated the volatility of the Euro since its introduction were based on univariate framework and have produced mixed results. Cotter (2005) and Coppel et al. (2000) reported no significant increase in the exchange rate volatility after the introduction of the Euro. Hau et al. (2002) found a slight decrease in the Euro/USD volatility compared to the DM/USD volatility. Malik (2005) and Wan and Kao (2008) found significant evidence that the euro is much more volatile than the British pound but the persistence of volatility has decreased for the euro while increasing for the British pound after the launch of the euro. The fact that these studies have not reached clear conclusions might be attributed to the estimation techniques and/or data samples. For instance, in Wan and Kao (2008) the pre-euro period is very short to provide a good assessment and comparison of the evolution of volatility with that in the post-euro period. Even though exchange rate volatility has been the focal point of recent research, little is known about volatility linkages between exchange rates, or about the transmission of volatility between currencies since the introduction of the euro.

Studies that analysed the exchange rate volatility transmission mechanism were initiated by Engle et al., (1990) where they have formulated two possible hypotheses named the 'heat waves' and the 'meteor shower'. The former refers to exchange rate volatility in one particular market having only country specific effects while, the later refers to volatility being transmitted to other countries. The authors found supporting evidence of the 'meteor shower' hypothesis. On this basis, studies were extended by Bollerslev (1990), Kearney and Patton (2000), Speight and McMillan (2001), Melvin and Melvin (2003), Black and McMillan (2004) and by Calvet, Fisher and Thompson (2006) among others. The main feature of these studies is the application of GARCH modelling to assess volatility dependencies across currencies. The main conclusions from these studies concern volatility comovements and spillovers between exchange rates. Some of the reasons for volatility dependencies across currencies might be news announcements about central bank interventions and fundamentals, or speculative bubbles.

Even so, few studies have so far investigated volatility co-movements and spillovers among exchange rates and especially since the introduction of the euro. One can divide these few studies into the following frameworks. Those based on Granger-causality tests and vector auto-regressions (VAR) and those based on multivariate GARCH methodologies.

Inagaki (2007) uses a residual cross-correlation function (CCF) approach originally proposed by Cheung and Ng (1996). The objective was to construct a Granger (1969) causality test to investigate volatility spillover between the British pound/US dollar and the euro/US dollar spot exchange rates (by employing daily data for the period spanning 5 January 1999 to 30 December 2004). The author uses the sample cross-correlation function between the two squared standardized residuals obtained from univariate GARCH models to apply the Granger causality test. The author finds unidirectional volatility spillover from the euro to the British pound. Specifically, he finds that the euro Granger-causes the British pound but the British pound does not Granger-cause the euro.

On similar grounds, Nikkinen et al. (2006) provided additional support for Inagaki's result. They investigated daily implied volatility spillovers within a VAR framework between the British pound, the Euro and the Swiss franc from January 2001 to September 2003. The authors found that the highest correlation exist between the euro and the franc. In addition, the euro is the dominant currency in volatility transmission as the euro was found to Granger-cause the pound and the franc but not vice-versa.

Perez-Rodriguez (2006) examined volatility spillovers in the post-euro period using a DCC approach. Using daily spot exchange rates for the Euro, the British pound and the Japanese yen against the US dollar, for the period of January 1, 1999 to May 1, 2004, they found significant volatility spillovers among these currencies, with the Euro and the pound capturing the highest correlation coefficients. In addition, under a volatility impulse response analysis he found that volatility diminishes rapidly, thus indicating a short-run dynamic effect after news announcements.

Two more studies that examined exchange rate volatility spillovers, however, not in the post-euro period, are from Bollerslev (1990) and Kearney and Patton (2000). Bollerslev (1990) employed a multivariate GARCH framework to investigate European exchange rate volatility spillovers in the pre- and post- European Monetary System (EMS) periods. He applied the Constant Conditional Correlation (CCC) MGARCH to a set of five weekly European spot exchange rates against the US dollar, namely the Deutsche Mark, the French franc, the Italian lira, the Swiss franc and the British pound for the period of July 1973 to August 1985. The author found significant comovements in volatility of these five exchange rates, which were significantly greater in the post-EMS period. Even though, it is argued that the CCC-MGARCH model explicitly restricts conditional correlations to be constant overtime, and as discussed earlier, it is a rather unrealistic assumption in many empirical finance applications (see e.g. Longin and Solnik, 1995 and Sheady, 1997).

Kearney and Patton (2000) offered an application of the so called BEKK[43] MGARCH model, proposed by Engle & Kroner (1995), to examine exchange rate volatility spillovers in the EMS period. This approach does not impose the restrictive assumption of constant conditional correlations through time and offers a very attractive formulation of volatility spillovers. In addition, it can distinguish between "direct" volatility spillovers (which are manifest in conditional variances) or/and of "indirect" spillovers (which are manifest in the conditional covariances). The currencies investigated by Kearney and Patton (2000) included the most important

[43] The acronym comes from the conjoint work of Baba, Engle, Kraft and Kroner.

currencies within the EMS, that is the Deutsche mark, the French Franc, the Italian lira, the British pound as well as the European Currency Unit, all against the US dollar. Their analysis covered data from April 1979 through to March 1997. The authors found evidence of both direct and indirect volatility transmission within the EMS (through the conditional variances and covariances, respectively) in both daily and weekly data for the European Currency Unit (ECU), German mark, French franc, Italian lira and the British pound. In addition, they provided evidence that the German mark held a dominant position in terms of volatility transmission. The mark was found to be relatively insulated from outside shocks while transmitting more volatility than the other currencies. Their results obtained using weekly data were less significant than those on daily data. This decrease in significance, derived from the temporal aggregation of the data from daily to weekly, is in line with the conjecture that markets are more likely to transmit volatility in active phases rather than in calm ones (e.g. see Ghose and Kroner, 1996).

In conclusion, the main feature of the previous studies that examined volatility spillovers in the post-euro period is that the sample period ends in 2003-04. Little is known about the current evolution of volatility spillovers. In addition, even less is known about the evolution of volatility spillovers in the pre-euro period. A more natural context of assessment of volatility spillovers in the post-euro period would be a comparison with the pre-euro period. Such an investigation would more carefully assess the evolution of volatility spillovers in the euro period since its launch. This is the ultimate feature this chapter tries to address.

The next section describes the data and the methodology used in this analysis.

4.3 Data and Methodology

The data consist of daily spot exchange rates of the Euro, British pound, Japanese yen and the Swiss franc against the US dollar over the period of January 5, 1990 to

December 31, 2007.[44] The series were obtained from the Bank of England online database.[45] The four currencies chosen are among the most traded currencies as defined by the daily trading volume and the size of the economy in the BIS report (2007). The data were split into two sub-periods; the periods i) prior to and ii) after the introduction of euro. Specifically, the date of separation is January 1, 1999, the date on which exchange rates were irrevocably fixed against the euro. The reason the sample period starts on January 1990 and ends on December 2007 giving equal numbers of observations in the pre- and the post- euro period (specifically 2274 and 2272 daily observations, respectively). For the pre-euro period analysis, the DM/US dollar spot rate replaces the EUR/US dollar rate. The choice of separation date and the same approach of replacing the euro/dollar with the DM/dollar rate was also used by Cotter (2005)[46] and Calvet, Fisher and Thompson (2006).[47] All exchange rates were converted to returns according to equation (2.1) to obtain stationarity.[48]

The main Multivariate GARCH models employed in this chapter are the Dynamic Conditional Correlation (DCC) model proposed by Engle (2002) and the Full-BEKK[49] model proposed by Engle and Kroner (1995) which are described in detail in chapter 2.[50] The DCC model is estimated using the 2-step procedure (see chapter 2).

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[44] The reason why the analysis in this chapter ends in 2007 is because the period of writing this chapter was at the beginning of 2008.

[45] The website is: http://www.bankofengland.co.uk/statistics/index.htm and was accessed on January 2008.

[46] Even though Cotter (2005) has the same pre-euro sample (1 January 1990 - 31 December 1998), the post-euro sample is rather small (1 January 1999 – 31 December 2001) to account for the effects of the introduction of the euro.

[47] Moreover, having artificial data for the EUR/USD (obtained from the Bank of England online database) over the first sub-period, it is found that the unconditional correlation between the euro and the Deutsche mark is 0.98763. In addition, to take into account of the bias expected because of the lower inter-euro volatility in the pre-euro period, and especially in 1997-1999, we have re-estimated the pre-euro period using artificial data from the Bank of England's database and the results remained similar to those using the DM/USD in the pre-euro period. The results can be provided from the author upon request. These two facts also highly support the idea of replacing the Euro with the Deutsche mark for the first sub-period.

[48] The results of the unit root test showing that all returns are stationary are available from the author upon request.

[49] The acronym comes from the conjoint work of Baba, Engle, Kraft and Kroner.

[50] In addition, the CCC model of Bollerslev (1990) is employed to check whether correlation are indeed time varying.

As previously discussed, even though, the DCC model is very flexible and it produces estimates of the time-varying correlation coefficients between variables, it does not quantify which variable (Granger-) causes the other. That is, the DCC model does not distinguish the direction of spillovers. For instance, having found a significant estimated correlation coefficient between the DM(EUR) and the GBP volatility, one cannot distinguish whether the DM(EUR) volatility Granger-causes the GBP volatility or the opposite. That is why the Full-BEKK model proposed by Engle and Kroner (1995) is also applied. This model can capture the exact direction of spillovers between volatility in exchange rates. That is, this not only allows the investigation of the impact of innovations and volatility persistence of a market in that particular market but also allows the examination of cross-innovations and cross-volatility persistence (spillovers). Being more specific, the coefficients of A and B matrices in (2.16) are of interest since they indicate the innovations in markets and the persistence (or the rate of the decay) of news in markets, respectively. Specifically, the diagonal coefficients of A and B matrices capture the own innovation and own volatility persistence effects of each market, respectively, whereas, the off-diagonal coefficients capture the cross-innovation and cross-volatility persistence (or spillovers) between exchange markets, respectively. The coefficients of the lower triangular $C'C$ matrix (of constants) are of no interest and their matrix decomposition is used only to ensure positive definiteness of H_t.

The DCC and the Full-BEKK multivariate GARCH models employed in this paper are estimated using the Quasi-Maximum Likelihood (QML) estimator under a multivariate Student distribution (see Harvey, Ruiz, and Sentana, 1992; Fiorentini, Sentana and Calzolari, 2003, Laurent, 2007). The multivariate Student distribution is applied as it is well known that the normality assumption of the innovations is rejected in most empirical applications dealing with daily exchange returns data. This adds an extra parameter to the estimation of each model, namely the degrees of freedom parameter, denoted by υ. When υ tends to infinity, the Student distribution tends to the normal density. When it tends to zero, the tails of the density become thicker and thicker. The parameter value indicates the order of existence of the moments, e.g. if $\upsilon = 2$, the second moments do not exist, but the first moments exist.

For this reason it is convenient to assume that $\upsilon > 2$, so that the conditional variance-covariance matrix H_t is always interpretable as a conditional covariance matrix. Under this assumption, the Student density can be defined as:

$$g\langle z_t|\theta,\upsilon\rangle = \frac{\Gamma\left(\frac{\upsilon+n}{2}\right)}{\Gamma\left(\frac{n}{2}\right)\left[\pi(\upsilon-2)\right]^{\frac{n}{2}}}\left[1+\frac{z_t{}'z_t}{\upsilon-2}\right]^{-\frac{n+\upsilon}{2}} \qquad (4.1)$$

Where $\Gamma(.)$ is the Gamma function. The density function of y_t (exchange returns) is easily obtained by applying:

$$f\langle y_t|\theta,\Omega_{t-1}\rangle = |H_t|^{-1/2}\, g\langle H_t^{-1/2}(y_t-\mu_t|\upsilon\rangle \qquad (4.2)$$

Where $|H_t|^{-1/2}$ is the Jacobian that arises in the transformation from the innovations to the observables. All the other parameters are defined as above.

There exist various multivariate GARCH extensions but are out of scope of this thesis.[51]

4.4 Empirical results

4.4.1 Descriptive statistics

Table 4.1 presents descriptive statistics of the mark(euro), the pound, the yen and the franc returns series for the pre- and the post-euro period. The returns are calculated by taking the first logarithmic differences in exchange rates as denoted in equation (2.1).

The means in all returns series are negative but small. This means that on average each of the exchange rate have slightly appreciated in both periods against the US dollar (the nominal exchange rate is defined as the number of domestic currency needed to buy one US dollar). The daily unconditional standard deviations and variances of the spot exchange rates show an interesting feature. For each of the

[51] For a survey on multivariate GARCH models see Bauwens, Laurent and Rombouts (2006).

sample periods, the pound's return daily unconditional standard deviation (variance) is the smallest. The euro, the yen and the franc rank in the second, third and fourth place, respectively. In addition, the unconditional standard deviations (and subsequently the unconditional variances) for all the returns have declined since the introduction of the euro. Specifically, the euro-mark, pound, yen and the franc standard deviations (variances) have declined from 0.665 (0.442), 0.607 (0.369), 0.736 (0.541) and 0.735 (0.541) in the pre-euro period to 0.595 (0.354), 0.503 (0.253), 0.616 (0.389) and 0.637 (0.406) in the post-euro period.[52] This indicates that the launch of the euro itself have coincided with greater stability in these four currencies. The excess kurtosis coefficient is highly significantly greater than zero for each of the four currencies at each sample period indicating non-normality of returns.[53] However, the excess kurtosis has significantly declined since the introduction of the euro. This fact also provides evidence that the launch of the euro coincided with greater stability, as extreme events (such as currency crises) are seem to have declined in frequency compared to the pre-euro period. In addition, the Jarque-Bera statistic confirms that exchange returns are, as expected, not normally distributed since the null hypothesis of normally distributed returns is persuasively rejected and the data are clearly skewed.

[52] An F-test on the null hypothesis that the standard deviation in the pre-euro period is greater than the standard deviation in the post-euro period was not rejected for each return series. The results can be provided from the author upon request.

[53] The excess kurtosis is defined as: $K = \frac{E\left[(y-\mu)^4\right]}{\sigma^4} - 3$. A distribution with positive excess kurtosis is said to have heavy tails, implying that the distribution puts more mass on the tails of its support than a normal distribution does. If returns are normally distributed, then the excess kurtosis coefficient should be zero.

Table 4.1: Descriptive Statistics of Returns, Pre- & Post- Period

	Pre-Euro period: 05.01.1990 - 31.12.1998				Post-Euro period: 05.01.1999 – 31.12.2007			
	DM (EUR)	GBP	JPY	CHF	EUR	GBP	JPY	CHF
Mean	-6E-06	-10E-06	-0.0001	-5E-05	-9E-05	-8E-05	-4E-06	-8E-05
Standard Deviation	0.665	0.607	0.736	0.735	0.595	0.503	0.616	0.637
Variance	0.442	0.369	0.541	0.541	0.354	0.253	0.380	0.406
Skewness	0.061 [0.24]	0.238 [0.00]**	-0.789 [0.00]**	-0.155 [0.00]**	-0.187 [0.00]**	-0.023 [0.65]	-0.282 [0.00]**	-0.194 [0.00]**
Excess Kurtosis	2.253 [0.00]**	3.337 [0.00]**	6.157 [0.00]**	1.894 [0.00]**	1.225 [0.00]**	0.847 [0.00]**	1.577 [0.00]**	1.046 [0.00]**
Normality Test (JB)	482 [0.00]**	1077 [0.00]**	3828 [0.00]**	349 [0.00]**	155 [0.00]**	68.2 [0.00]**	265 [0.00]**	118 [0.00]**
Q(10)	17.69 [0.06]	37.13 [0.00]**	18.05 [0.05]	16.87 [0.08]	2.931 [0.98]	10.69 [0.38]	5.000 [0.89]	8.225 [0.61]
$Q^2(10)$	200 [0.00]**	286 [0.00]**	252 [0.00]**	141 [0.00]**	50.29 [0.00]**	64.92 [0.00]**	40.33 [0.0000] **	23.31 [0.0097] **
ARCH(5)	17.05 [0.00]**	25.92 [0.00]**	24.13 [0.00]**	13.64 [0.00]**	4.243 [0.00]**	4.190 [0.00]**	4.088 [0.00]**	2.172 [0.05]

Notes: [] denote p-values. Q(10) and $Q^2(10)$ is the Ljung-Box statistic for serial correlation in raw series and squared series, respectively. * 5% significant; ** 1% significant.

The Ljung-Box Q statistic tests the null hypothesis of no serial correlation and is calculated using up to 10 lags for both daily returns and squared returns series. A significant Q statistic rejects the null hypothesis of no serial correlation in returns, while a significant Q statistic for the squared returns series is rejecting the null hypothesis of homoskedastic returns. Table 4.1 reports the Q statistics to be insignificant at 10 lags across each returns series, apart from the pound returns in the pre-euro period. This indicates that all returns but the pound can be characterized as random walk processes. However, the Q statistic in the squared returns is significant for each return series indicating strong non-linear dependencies. This is also supported by Engle's ARCH-LM statistic. The last column of Table 4.1 clearly shows the presence of ARCH effects in returns up to 5 lags. The null hypothesis of no ARCH effects is rejected for each series at the 5% level of significance.[54]

Figures 4.1 and 4.2, which plot returns in the left hand side and their autocorrelation functions on the right hand side, support the phenomenon of no autocorrelation in returns (apart from the British pound return for the 1 lag) and volatility clustering. The latter means that large (small) changes tend to be followed by large (small) changes of either sign.

[54] For the Swiss franc the null hypothesis of no ARCH effects is rejected at 10% level of significance.

Figure 4.1: Returns & ACF of Returns – Pre-Euro Period

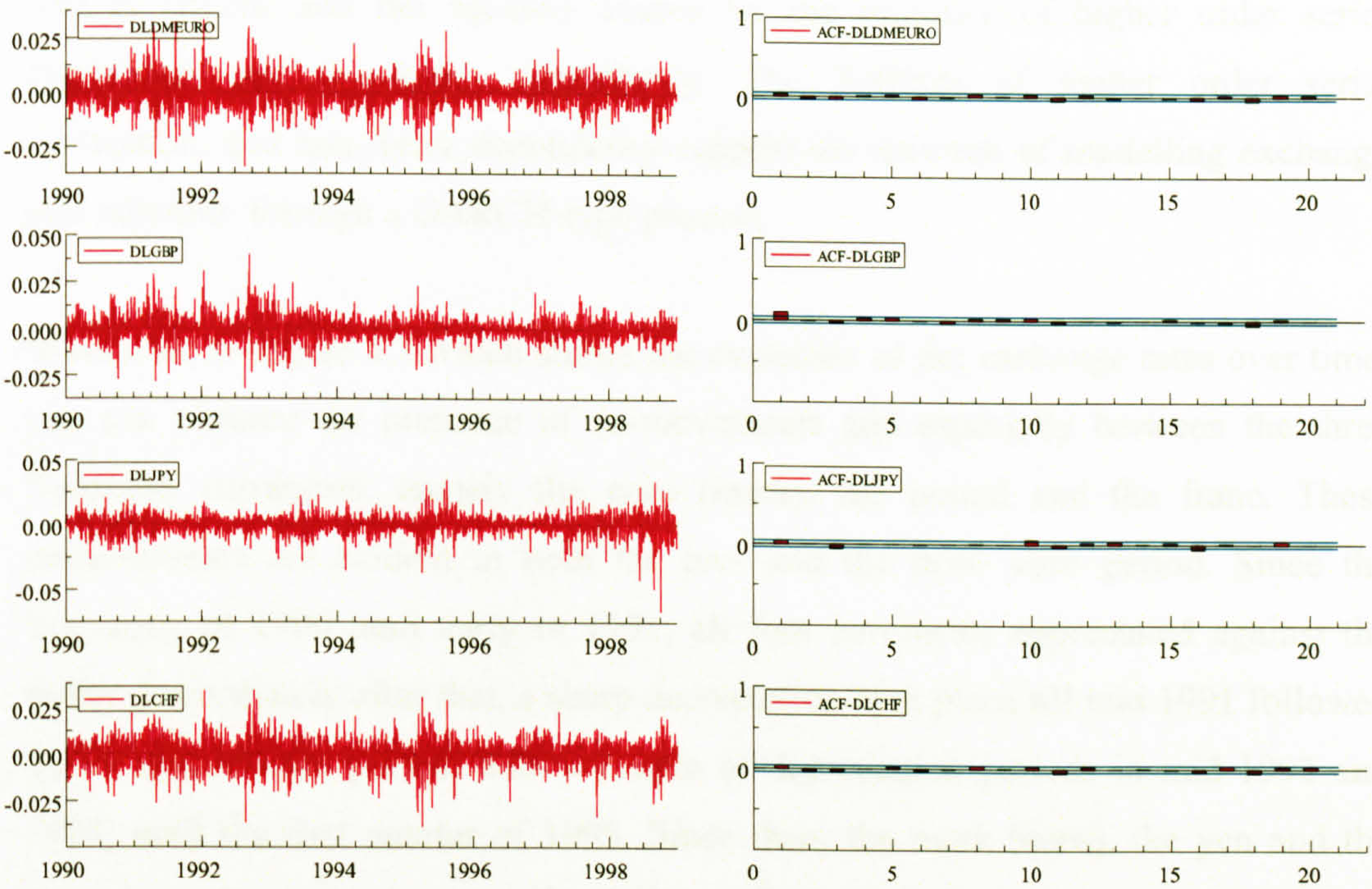
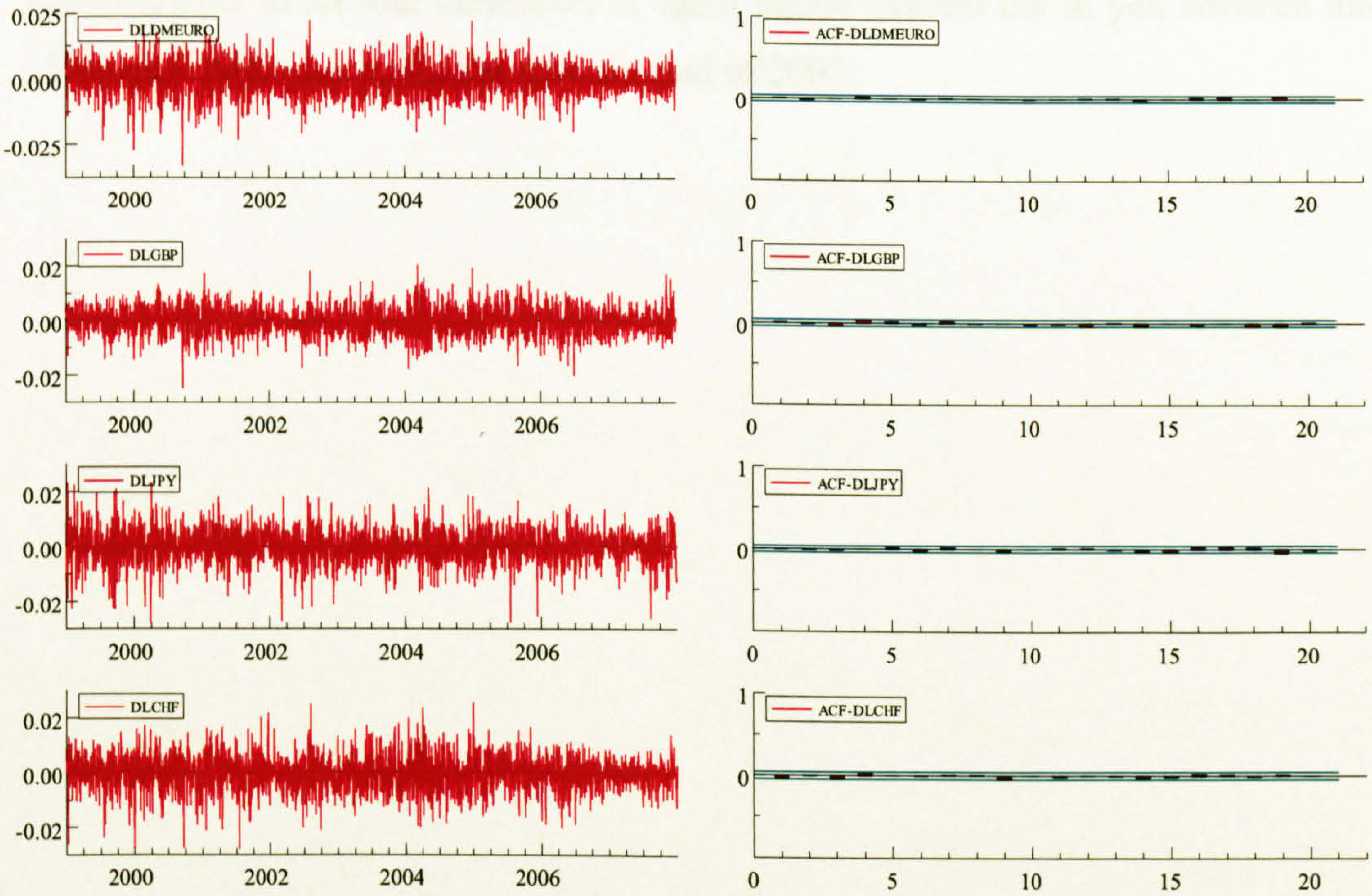


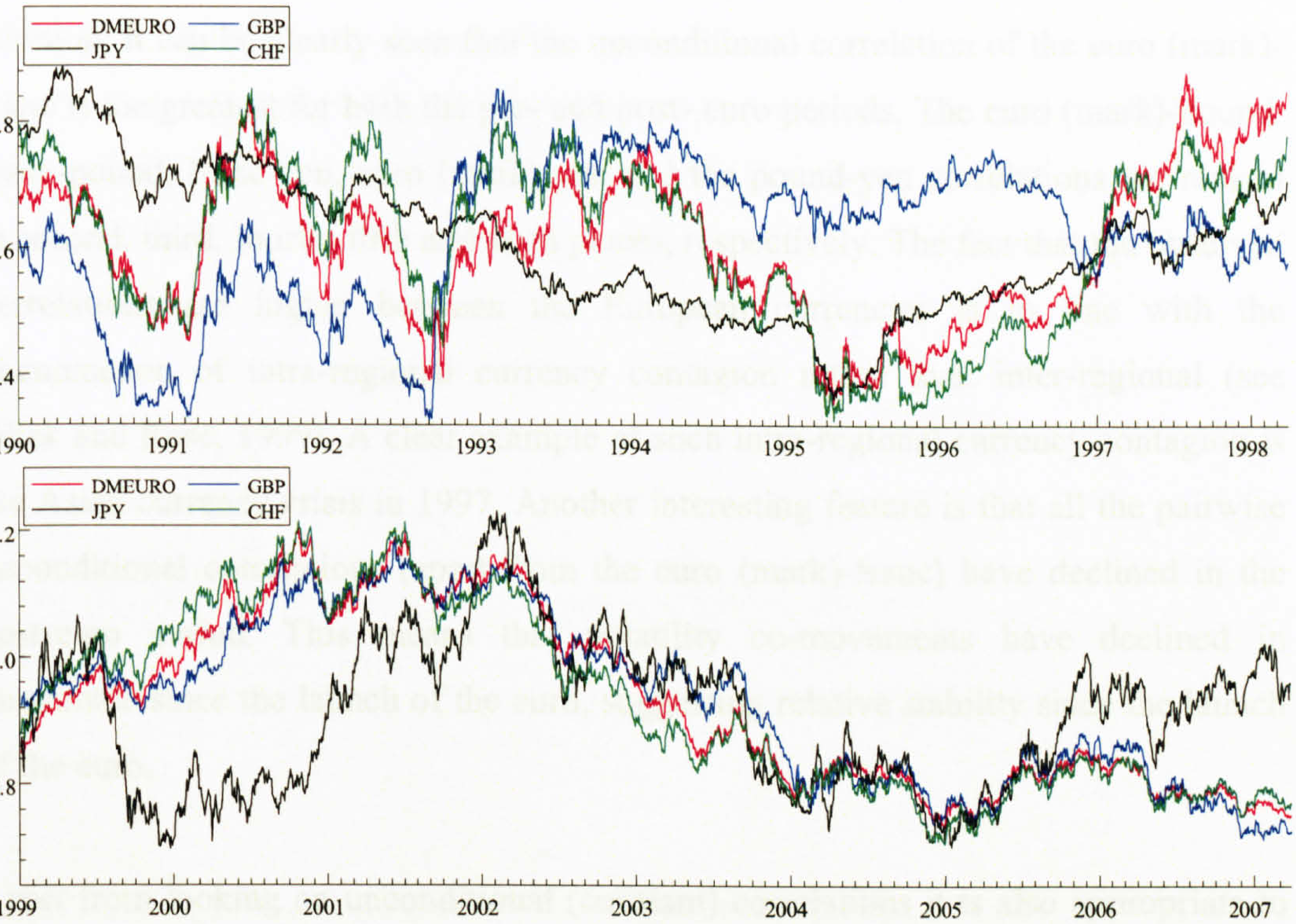
Figure 4.2: Returns & ACF of Returns – Post-Euro Period



Thus, the returns series are characterised by non-randomness and the presence of ARCH effects, and the squared returns by the presence of higher order serial correlation and non-linear dependency. The findings of higher order serial correlation, and non-linear dependency support the decision of modelling exchange rate volatility through a GARCH-type process.

Moreover, in Figure 4.3 which shows the evolution of the exchange rates over time, one can observe the presence of co-movements and especially between the three European currencies, namely the euro (mark), the pound and the franc. These comovements are evident in both the pre- and the post- euro period. Since the beginning of 1990 until early in 1991, all four currencies appreciated against the dollar. Immediately after that, a sharp depreciation took place till mid 1991 followed by an appreciation period, with a couple of depreciation periods in mid 1992 and 1993, until the first quarter of 1995. Since then, the mark (euro), the yen and the franc have depreciated against the dollar until the introduction of the euro, and the pound remained relatively stable. Since the launch of the euro, the presence of comovements in all four currencies is again highly evident but in yen between mid 1999 until 2002 and mid 2005 until the end of 2007.

Figure 4.3: Pre- & Post- Euro Exchange Rates



Notes: exchange rates are scaled by their means

4.4.2 Volatility comovements and spillovers

Before proceeding with the multivariate GARCH modelling, Table 4.2 presents the unconditional sample correlations between these currencies.

Table 4.2: Unconditional Correlations, Pre- & Post- Euro Period

Pre-Euro period: 05.01.1990 – 31.12.1998 (Observations: 2274)				
	DLEUR(DM)	**DLGBP**	**DLJPY**	**DLCHF**
DLEUR(DM)	1.0000			
DLGBP	0.7188	1.0000		
DLJPY	0.4992	0.3514	1.0000	
DLCHF	0.9209	0.6825	0.5012	1.0000
Post-Euro period: 05.01.1999 – 31.12.2007 (Observations: 2272)				
	DLEUR	**DLGBP**	**DLJPY**	**DLCHF**
DLEUR	1.0000			
DLGBP	0.6960	1.0000		
DLJPY	0.3440	0.3143	1.0000	
DLCHF	0.9400	0.6804	0.3934	1.0000

These correlations indicate that the market expectations of future exchange rate volatilities are contemporaneously and positively correlated across these four major currencies. They range from 0.3143 for the yen-pound to 0.94 for the euro-franc. In addition, it can be clearly seen that the unconditional correlation of the euro (mark)-franc is the greatest for both the pre- and post- euro periods. The euro (mark)-pound, franc-pound, franc-yen, euro (mark)-yen and the pound-yen correlations are ranked in second, third, fourth, fifth and sixth places, respectively. The fact that the observed correlations are higher between the European currencies is in line with the phenomenon of intra-regional currency contagion rather than inter-regional (see Glick and Rose, 1999). A clear example of such intra-regional currency contagion is the Asian currency crisis in 1997. Another interesting feature is that all the pairwise unconditional correlations (apart from the euro (mark)-franc) have declined in the post-euro period. This means that volatility co-movements have declined in magnitude since the launch of the euro, suggesting relative stability since the launch of the euro.

Apart from looking on unconditional (constant) correlations it is also appropriate to examine time-varying conditional correlations. In order to check whether correlations are time-varying, we employ both the CCC and DCC multivariate GARCH models and compare their performance.[55] The estimation results of the CCC and the DCC models, with a AR(2) filter for the conditional mean specification, for the full sample, are shown on Table 4.3.

Even though both models are well specified, on the basis that the univariate and multivariate tests on the standardized and squared standardized residuals do not find evidence of significant serial correlation (apart from the univariate Q statistic on the pound's squared standardized residuals of the DCC model), the two test statistics for constant conditional correlations of Tse (2000) and Engle and Sheppard (2001) reject the null hypothesis of constant conditional correlations at the 1% and 5% levels of significance, respectively. That is, we find supporting evidence that the conditional correlations are time-varying under the DCC specification. All the information criteria along with the log likelihood value support the DCC specification of time-varying conditional correlation. This model is also supported in Figure 4.4, where the

[55] The reason both the CCC and DCC models are employed in this point is to provide statistical evidence whether correlations are time-varying or not.

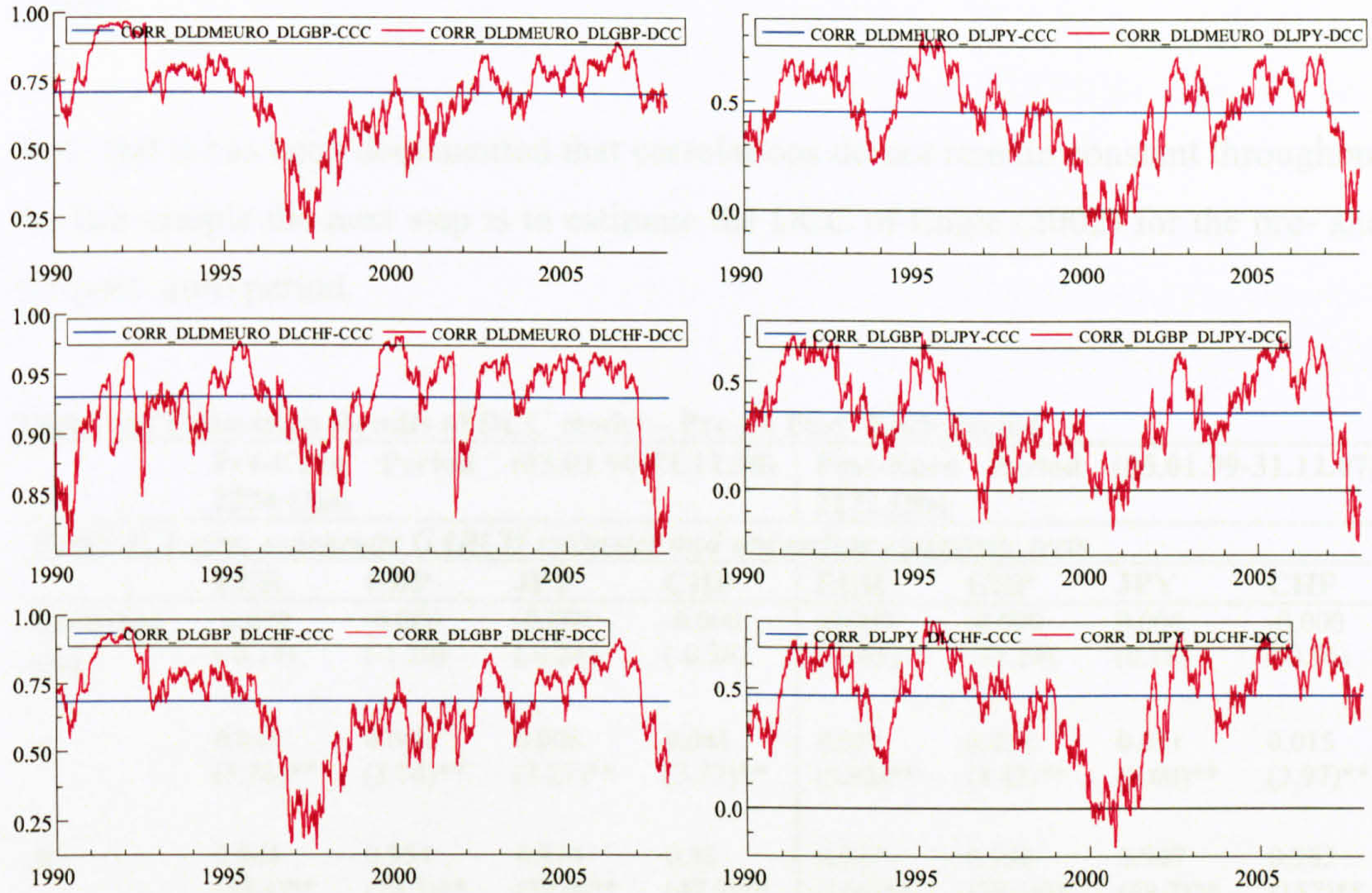
blue (horizontal) and the red lines denote correlations of the CCC and DCC models, respectively.

Table 4.3: Estimation Results of CCC and DCC models – Full sample (05.01.90-31.12.07)

	CCC-MGARCH(1,1)				DCC-MGARCH(1,1)			
Panel A: 1-step, univariate GARCH estimates and univariate diagnostic tests								
	EUR	**GBP**	**JPY**	**CHF**	**EUR**	**GBP**	**JPY**	**CHF**
Constant	-0.0001	-0.0001	-0.00001	-0.0001	-0.0001	-0.0001	-0.00001	-0.0001
(m)	(-0.78)	(-1.64)	(-0.05)	(-1.00)	(-0.78)	(-1.64)	(-0.05)	(-1.00)
α	0.076	0.038	0.045	0.027	0.075	0.038	0.045	0.027
	(7.30)**	(6.41)**	(4.92)**	(5.22]**	(7.30]**	(6.41)**	(4.92)**	(5.22)**
β	0.854	0.953	0.937	0.962	0.854	0.953	0.937	0.962
	(25.2)**	(143)**	(68.7)**	(114)**	(25.2)**	(143)**	(68.7)**	(114)**
Q(30)	42.86	39.31	25.27	18.10	40.32	40.27	27.04	19.85
	[0.06]	[0.12]	[0.71]	[0.96}	[0.10]	[0.10]	[0.62]	[0.92]
$Q^2(30)$	0.059	5.396	32.97	0.234	0.0731	74.6051	29.7339	0.3809
	[1.00]	[0.99]	[0.32]	[1.00}	[1.00]	[0.00]**	[0.48]	[1.00]
Panel B: 2-step, correlation estimates and multivariate diagnostic tests								
Constant	0.029	0.003	0.008	0.005	0.029	0.003	0.008	0.005
(v)	(2.40)*	(3.15)**	(2.63)**	(2.17)*	(2.40)*	(3.15)**	(2.63)**	(2.17)*
ρGBPEUR	0.599 (50.9)**				0.535 (13.5)**			
ρJPYEUR	0.312 (16.0)**				0.090 (1.34)			
ρCHFEUR	0.820 (204)**				0.733 (25.6)**			
ρJPYGBP	0.296 (21.3)**				0.083 (1.24)			
ρCHFGBP	0.655 (76.2)**				0.611 (17.1)**			
ρCHFJPY	0.397 (28.2)**				0.124 (1.79)			
α					0.029 (12.6)**			
β					0.965 (334)**			
df	4.218 (37.38)**				4.369 (35.0)**			
Log-Lik	70684.8				71035.9			
AIC	-31.077				-31.231			
SBC	31.033				-31.184			
HQC	-31.062				-31.214			
Shibata	-31.077				-31.231			
LMC(6)	3874.9 [0.000]**							
E-S Test(5)	12.705 [0.048]*							
H(30)	477.8 [0.49]				500.7 [0.23]			
$H^2(30)$	496.7 [0.27]				420.6 [0.97]			
LiMcL(30)	477.9 [0.49]				500.8 [0.23]			
$LiMcL^2(30)$	496.8 [0.27]				421.1 [0.97]			

Notes: LMC and E-S stands for the statistic for constant correlations of Tse (2000) and Engle and Sheppard (2001), respectively. Q( ) and Q^2( ) are the Ljung-Box portmanteau tests statistic for serial correlation in the univariate standardized and squared standardized residuals, respectively. H( ), H^2( ) and LiMcL( ), $LiMcL^2$( ) are the multivariate versions of Ljung-Box statistic of Hosking (1980) and Li and McLeod (1981), respectively. ( ) and [ ] denote t-values and p-values, respectively. '* 5% significant; ** 1% significant.

Figure 4.4: Conditional Correlations of CCC Vs DCC model – Full Sample (05.01.90-31.12.07)



From this figure it can be clearly seen that each six conditional correlations are not constant throughout the full sample. In addition, under the DCC model not all dynamic conditional correlations are significant as opposed to the CCC model, in which all constant conditional correlations are significant (see Table 4.3). According to the preferred DCC model only correlations between European currencies are significantly positive. Correlations between the euro-yen, pound-yen and franc-yen are insignificantly positive. This means that news arriving from one of the euro, pound or the franc markets positively affects the other two but it does not affect the yen market and the other way around. This is in line with the literature that currency contagions/spillovers are of intra-regional rather than inter-regional nature (see Glick and Rose, 1999). Another interesting feature of Figure 4.4 is that correlations between the European currencies have reached a peak during 1991-1992 when the British pound came under major pressure from currency speculators and was forced to exit the European Exchange Rate Mechanism (ERM). Whereas, correlations among European currencies have reached a minimum during 1997-1998. That is, during the Asian crises pair-wise correlations have slightly increased only between the Japanese yen and the European currencies but not between European currencies, when the latter hit bottom. This is additional evidence to results of Glick and Rose (1999).

Now that it has been documented that correlations do not remain constant throughout the full sample the next step is to estimate the DCC of Engle (2002) for the pre- and the post- euro period.

Table 4.4: Estimation Results of DCC model – Pre- & Post- Euro Period

	Pre-Euro Period (05.01.90-31.12.98) 2274 Obs.				**Post-Euro Period (05.01.99-31.12.07) 2272 Obs.**			
Panel A: 1-step, univariate GARCH estimates and univariate diagnostic tests								
	EUR	**GBP**	**JPY**	**CHF**	**EUR**	**GBP**	**JPY**	**CHF**
Constant (m)	-0.000 (-0.14)	-0.000 (-1.10)	-0.000 (-0.24)	-0.000 (-0.36)	-0.000 (-1.65)	-0.000 (-1.24)	0.000 (0.18)	-0.000 (-0.96)
α	0.043 (3.78)**	0.040 (3.74)**	0.068 (3.27)**	0.041 (3.77)**	0.021 (3.92)**	0.034 (4.42)**	0.031 (3.60)**	0.015 (2.97)**
β	0.943 (53.4)**	0.954 (76.5)**	0.914 (32.0)**	0.93 (47.5)**	0.977 (166)**	0.950 (78.3)**	0.947 (69.7)**	0.983 (157)**
Q(30)	33.80 [0.29]	27.47 [0.60]	38.04 [0.15]	30.80 [0.43]	60.10 [0.00]**	38.72 [0.13]	17.76 [0.96]	26.95 [0.63]
Q^2(30)	55.80 [0.00]**	17.04 [0.97]	28.80 [0.53]	25.47 [0.70]	21.64 [0.87]	25.33 [0.71]	18.80 [0.94]	84.82 [0.00]**
Panel B: 2-step, correlation estimates and multivariate diagnostic tests								
Constant (v)	0.006 (1.71)	0.002 (2.03)*	0.011 (1.77)	0.014 (2.12)*	0.001 (1.18)	0.004 (2.15)*	0.009 (2.45)*	0.001 (0.97)
ρGBPEUR	0.805 (13.97)**				0.666 (16.36)**			
ρJPYEUR	0.319 (2.781)**				0.422 (6.294)**			
ρCHFEUR	0.852 (21.90)**				0.950 (130.7)**			
ρJPYGBP	0.303 (2.413)*				0.334 (4.679)**			
ρCHFGBP	0.749 (12.22)**				0.663 (15.95)**			
ρCHFJPY	0.286 (2.429)*				0.452 (6.827)**			
α	0.022 (9.605)**				0.019 (7.007)**			
β	0.976 (357.8)**				0.976 (234.6)**			
df	6.875 (16.38)**				7.891 (14.81)**			
Log-Lik	36944.3				37973.1			
AIC	-32.460				-33.405			
SBC	-32.367				-33.342			
HQC	-32.426				-33.382			
Shibata	-32.461				-33.405			
H(30)	506.3 {0.17}				520.0 {0.10}			
H^2(30)	501.9 {0.22}				522.1 {0.08}			
LiMcL(30)	506.1 {0.17}				520.0 {0.10}			
$LiMcL^2$(30)	502.7 {0.21}				522.4 {0.08}			

Notes: Q() and Q^2() are the Ljung-Box portmanteau tests statistic for serial correlation in the univariate standardized and squared standardized residuals, respectively. H(), H^2() and LiMcL(), $LiMcL^2$() are the multivariate versions of Ljung-Box statistic of Hosking (1980) and Li and McLeod (1981), respectively. () and [] denote t-values and p-values, respectively. * 5% significant; ** 1% significant.

Table 4.4 presents the empirical results of the DCC model for the pre- and the post-euro period.[56] An AR(3)-DCC-MGARCH(1,1) and DCC-MGARCH(1,1) model were chosen in order to remove any serial correlation in returns for the pre and the post-euro, respectively.[57] For both periods, the DCC model seems to be well specified, as the diagnostic tests for serial correlation including the multivariate ones, which are of more interest, report no evidence of serial correlation. Hosking's (1980) and Li and McLeod (1981) multivariate versions of the Ljung-Box test statistics do not reject the null hypothesis of no serial correlation up to 30 lags.

The estimated correlation coefficients in Table 4.4 report strong evidence of significant dynamic conditional correlations for the both the pre- and the post-euro period. In addition, their significance has become greater in the post-euro period, indicating that volatility spillovers are more significant since the launch of the euro.

As expected, the largest volatility co-movements are between currencies belonging to countries geographically closer to each other, namely the euro, the pound and the franc. The strongest in magnitude volatility spillovers occur between the euro-franc, the euro-pound and the franc-pound currencies for both periods. Specifically, the estimated correlation coefficients between the franc-euro(mark), pound-euro(mark) and the franc-pound are 0.852, 0.805 and 0.749, respectively, in the pre-euro period and 0.950, 0.666 and 0.663, respectively in the post-euro period. The lowest are between the yen and the other three currencies. Specifically, the estimated correlation coefficients between the yen-euro(mark), yen-pound and the yen-franc are 0.319, 0.303 and 0.286, respectively, in the pre-euro period and 0.422, 0.334 and 0.452, respectively in the post-euro period. This result is again in line with the literature that

[56] A CCC model was also applied for the pre- and the post- euro period but was rejected against the DCC, as both tests for constant correlations rejected the null of no constant correlations at 1% level of significance. For the pre-euro period the test statistics of Tse (2000) and Engle and Sheppard (2001) were 74.16 and 66.11 with p-values of [0.00] and [0.00], respectively. For the post-euro period were 71.59 and 327.9 with [0.00] and [0.00] p-values, respectively. For the shake of brevity, the results of the CCC model for the pre- and post- euro period are not presented but can be provided from the author upon request.

[57] The Akaike Information Criterion (AIC), the Schwarz Bayesian Criterion (SBC) and overfitting approaches were used to determine the optimal lag structure of exchange returns in the conditional mean equation.

currency contagions/spillovers are of intra-regional rather than inter-regional nature (see Glick and Rose, 1999). As previously discussed, a disadvantage of the DCC approach is that it does not quantify explicitly the direction of spillovers. This drawback is surpassed by the application of the BEKK model which explicitly quantifies the direction of spillovers (see below).

Another interesting feature of Table 4.4 is that on average volatility spillovers have increased since the launch of euro. Out of the six dynamic conditional correlation coefficients, four have increased (namely the euro-yen, euro-franc, pound-yen and the franc-yen) and two have declined (the euro-pound and the franc-pound) since the introduction of the euro. In order to check whether those increases or decreases are significant, a standard Z-test statistic suggested by Morrison (1983) is applied for statistic inference.[58] This test is applied in two cases. One time, to test the null hypothesis of no increase in correlations, for each of the four previously mentioned correlations that have increased, and another time, to test the null hypothesis of no decrease in correlations[59] for each the two previously mentioned correlations that have declined. The results of this test are presented on Table 4.5. The null hypothesis of no increase in correlations since the launch of the euro is rejected for the euro-yen, euro-franc and the franc-yen correlations but not for the pound-yen at the 1% level of significance. In the other case the null hypothesis of no decrease in correlations since the launch of the euro is rejected for both the euro-pound and the franc-pound at the 1% level of significance. The fact that pair-wise correlations between European and

[58] The Z-test statistic suggested by Morrison (1983) for the null hypothesis of no increase in correlation is defined as: $T = \dfrac{Z_0 - Z_1}{\sqrt{\dfrac{1}{N_0 - 3} + \dfrac{1}{N_1 - 3}}}$, where $Z_0 = \dfrac{1}{2}\ln\left(\dfrac{1+\rho_0}{1-\rho_0}\right)$, $Z_1 = \dfrac{1}{2}\ln\left(\dfrac{1+\rho_1}{1-\rho_1}\right)$, ρ_0 and ρ_1 refer to pre-euro and post-euro correlations, respectively, $N_0 = 2274$ and $N_1 = 2272$. This test statistic is approximately normally distributed and is fairly robust to the non-normality of correlation coefficients.

[59] In the case of the null of no decrease in correlation, the null is defined as: $T = \dfrac{Z_1 - Z_0}{\sqrt{\dfrac{1}{N_0 - 3} + \dfrac{1}{N_1 - 3}}}$

Japanese markets have increased since the launch of the euro might be attributed to the globalization effect were business cycle co-movements among countries have increased (Kose, Prasad and Terrones, 2003).

Table 4.5: Test of significant increases or decreases in correlations

	Pre-Euro correlations	Post-Euro correlations	Ho: no increase in correlations	Ho: no decrease in correlations
ρGBPEUR	0.805	0.666		-10.47**
ρJPYEUR	0.319	0.422	-4.045**	
ρCHFEUR	0.852	0.950	-19.07**	
ρJPYGBP	0.303	0.334	-1.170	
ρCHFGBP	0.749	0.663		-5.800**
ρCHFJPY	0.286	0.452	-6.525**	

Notes: Correlations are obtained from the DCC models of Table 4. The 1% and 5% critical values for a one-sided test of the null are −2.32 and −1.64, respectively. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

An interesting finding is that, a shock arriving in the euro market in the pre-euro period is being transmitted to the pound market (or the other way around) by 80.5% while, a shock of the same magnitude in the post-euro period is being transmitted by 66.6%. This means that the volatilities of the euro and the pound became less closely tight in the post-euro period. In other words the volatilities of these currencies became more independent in the post-euro period. The lower the volatility spillovers of the euro to the pound (or the other way around) in the post-euro period has obviously important implications for the highly debated issue of the UK adopting the euro, but also for risk management and portfolio diversification. This particular finding definitely requires more research along this dimension before economists converge to any specific conclusions on this highly debated issue.

Figures 4.5 and 4.6 show the evolution of conditional correlations obtained from the DCC model between these four returns for both sub-samples.

Figure 4.5: Conditional Correlations of DCC model – Pre-Euro (05.01.90-31.12.98)

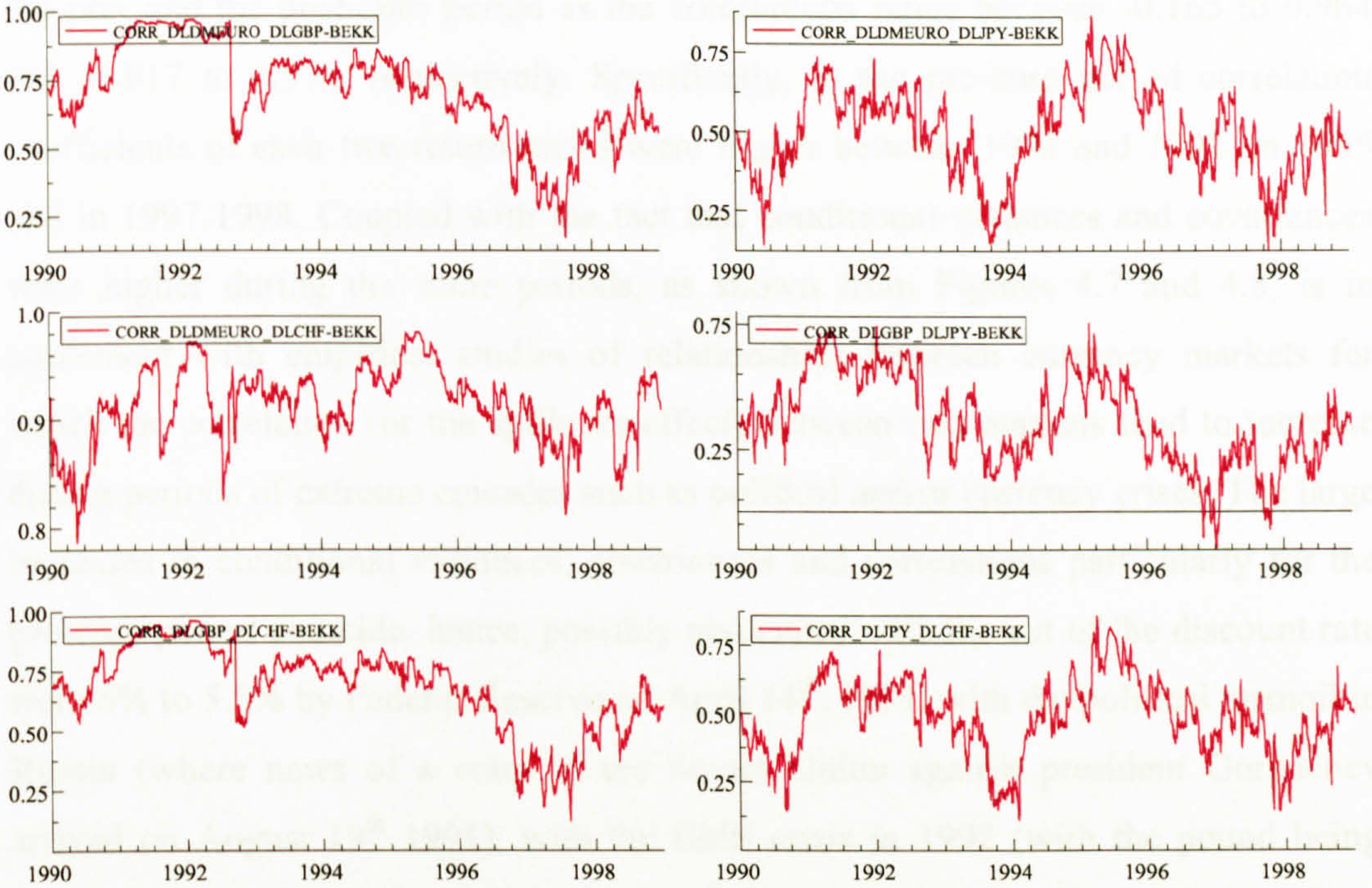
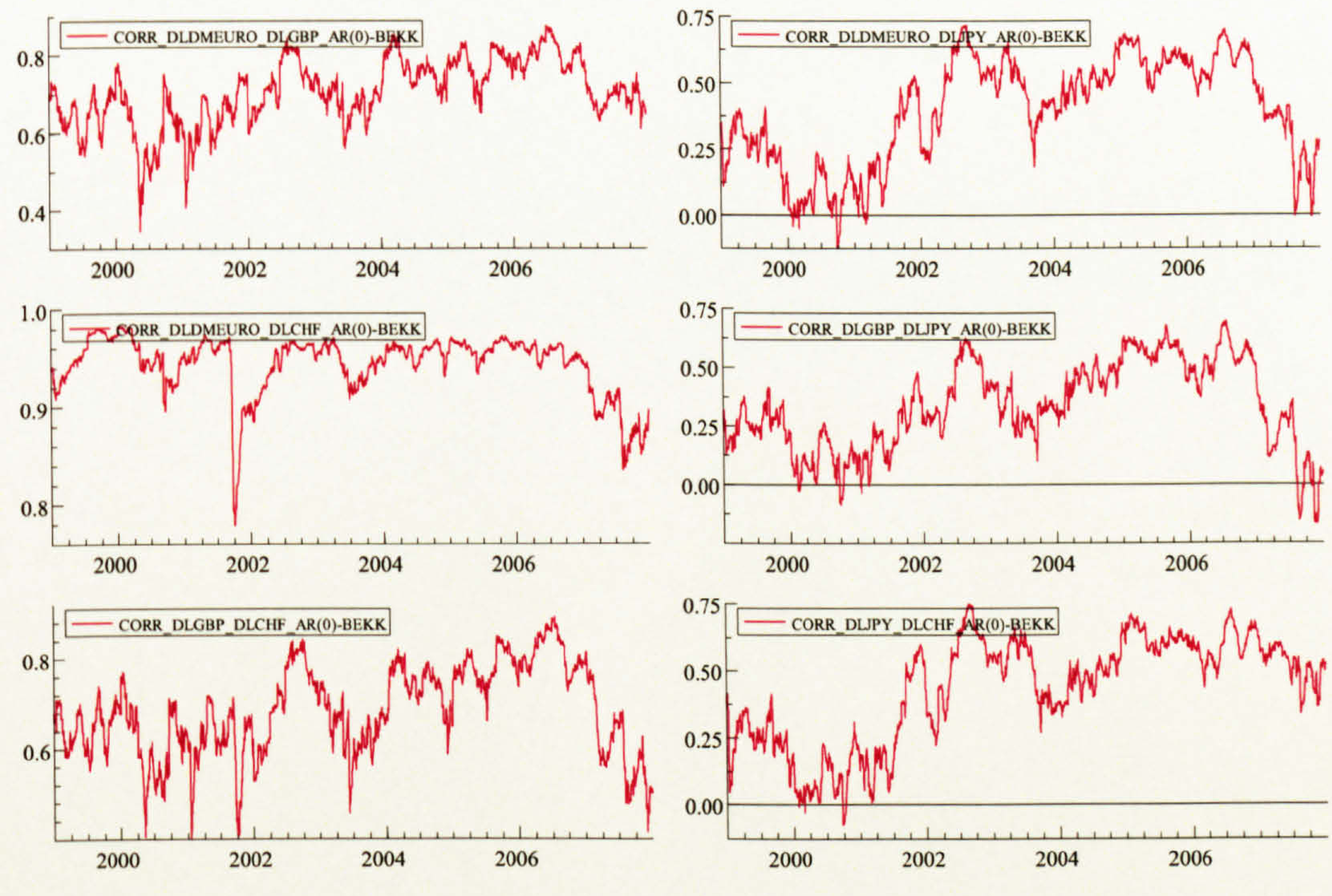


Figure 4.6: Conditional Correlations of DCC model – Post-Euro (05.01.99-31.12.07)



One can clearly observe that correlations do not remain constant over time in both the pre- and the post-euro period as the correlations range between -0.165 to 0.964 and -0.017 to 0.979, respectively. Specifically, in the pre-euro period correlation coefficients of each two return series were higher between 1991 and 1992, in 1995 and in 1997-1998. Coupled with the fact that conditional variances and covariances were higher during the same periods, as shown from Figures 4.7 and 4.8, is in agreement with empirical studies of relationships between currency markets for which the correlation (or the spillover effect) between two markets tend to increase during periods of extreme episodes such as political and/or currency crises. The large increases in conditional variances, covariances and correlations particularly for the pre-euro period coincide, hence, possibly associated with the cut of the discount rate from 6% to 5.5% by Federal Reserve on April 14th, 1991, with the political turmoil in Russia (where news of a coup in the Soviet Union against president Gorbachev arrived on August 19th 1991), with the EMS crisis in 1992 (with the pound being suspended from the ERM on September 16th 1992), the Mexican-Peso crisis in 1994-1995 and the Asian crisis in 1997-1998 (see Lobo, 2002).

Figure 4.7: Conditional Variances of DCC model – Pre-Euro (05.01.90-31.12.98)

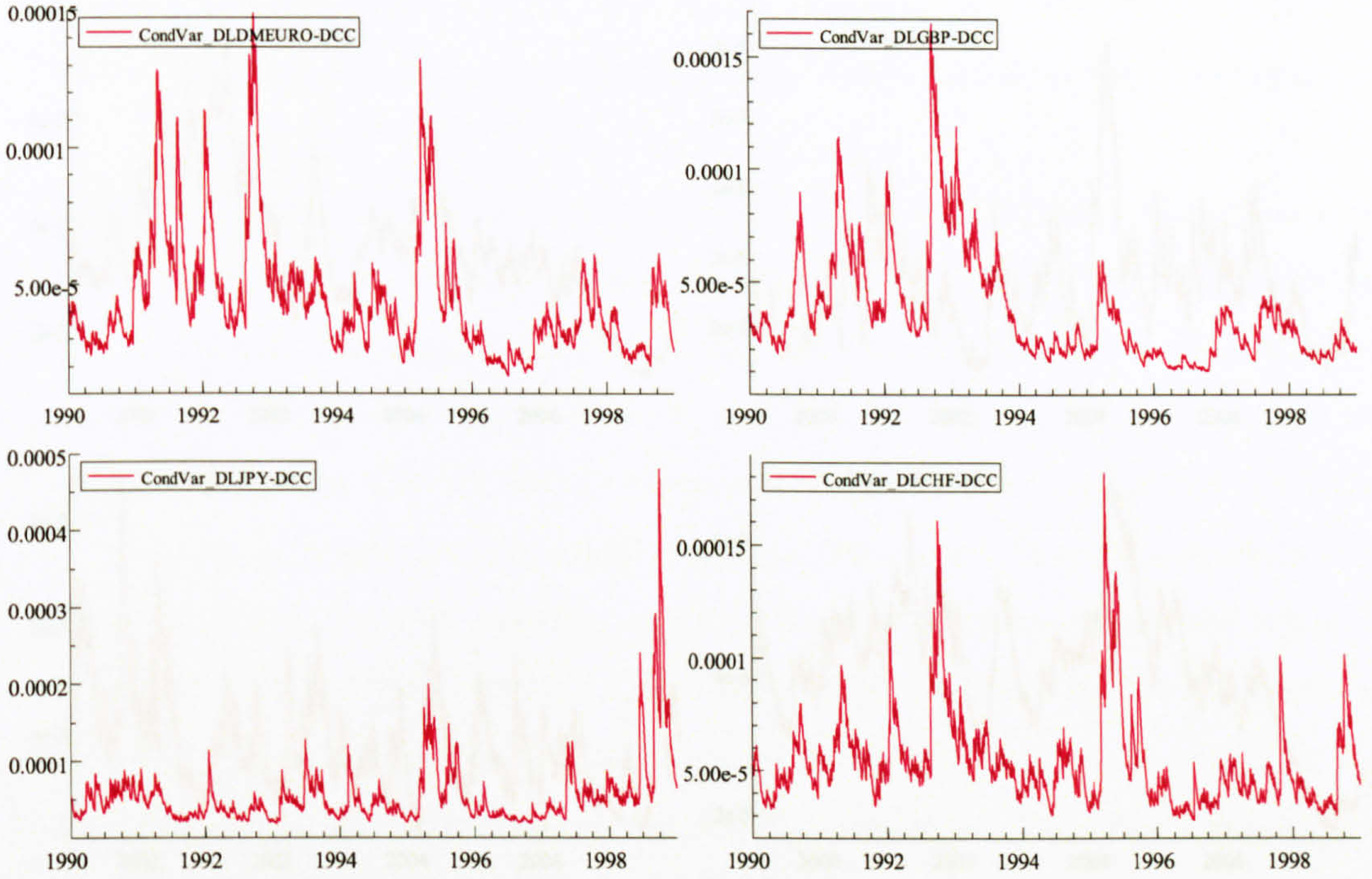


Figure 4.8: Conditional Covariances of DCC model – Pre-Euro Period (05.01.90-31.12.98)

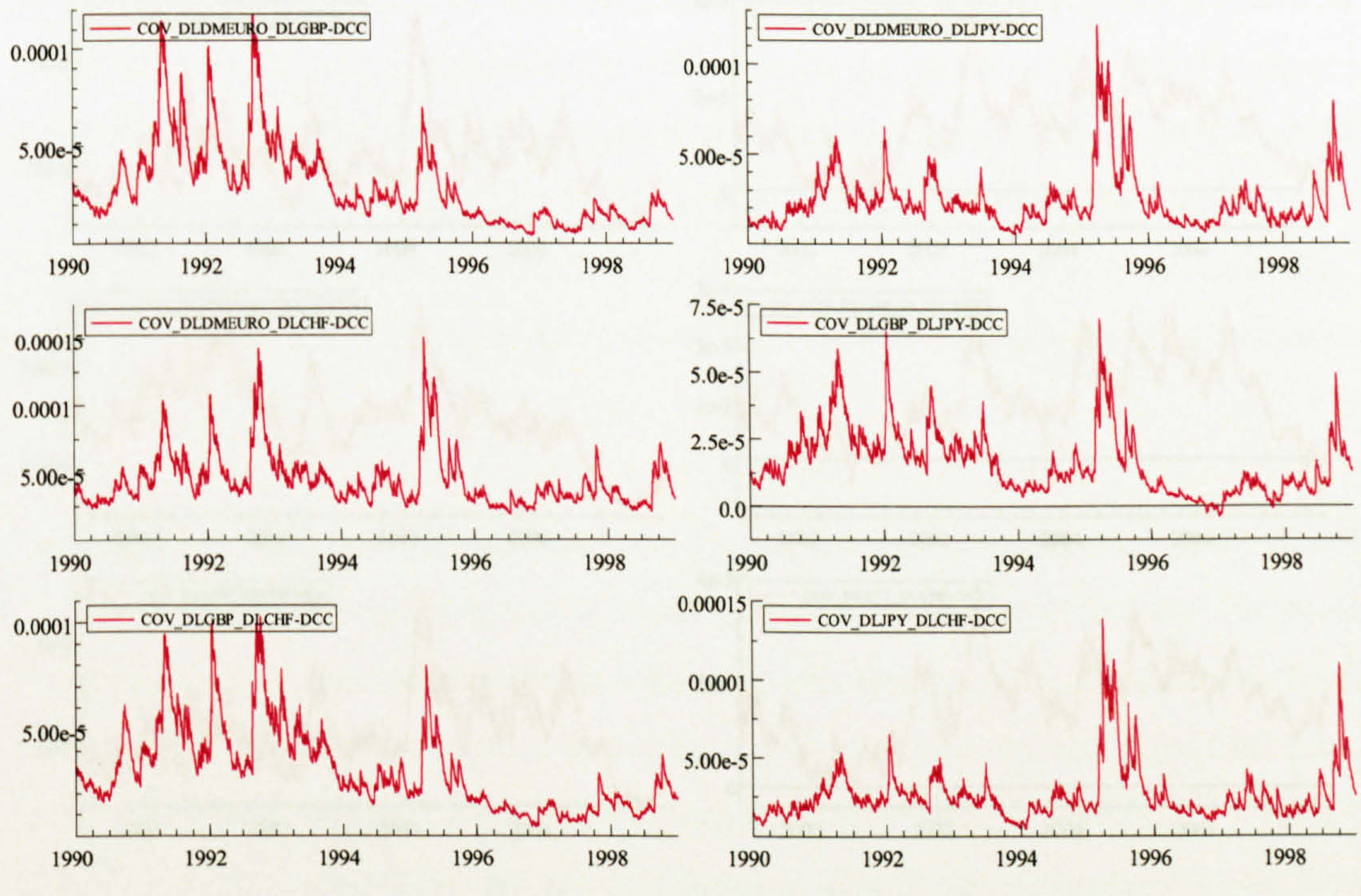


Figure 4.9: Conditional Variances of DCC model – Post-Euro Period (05.01.99-31.12.07)

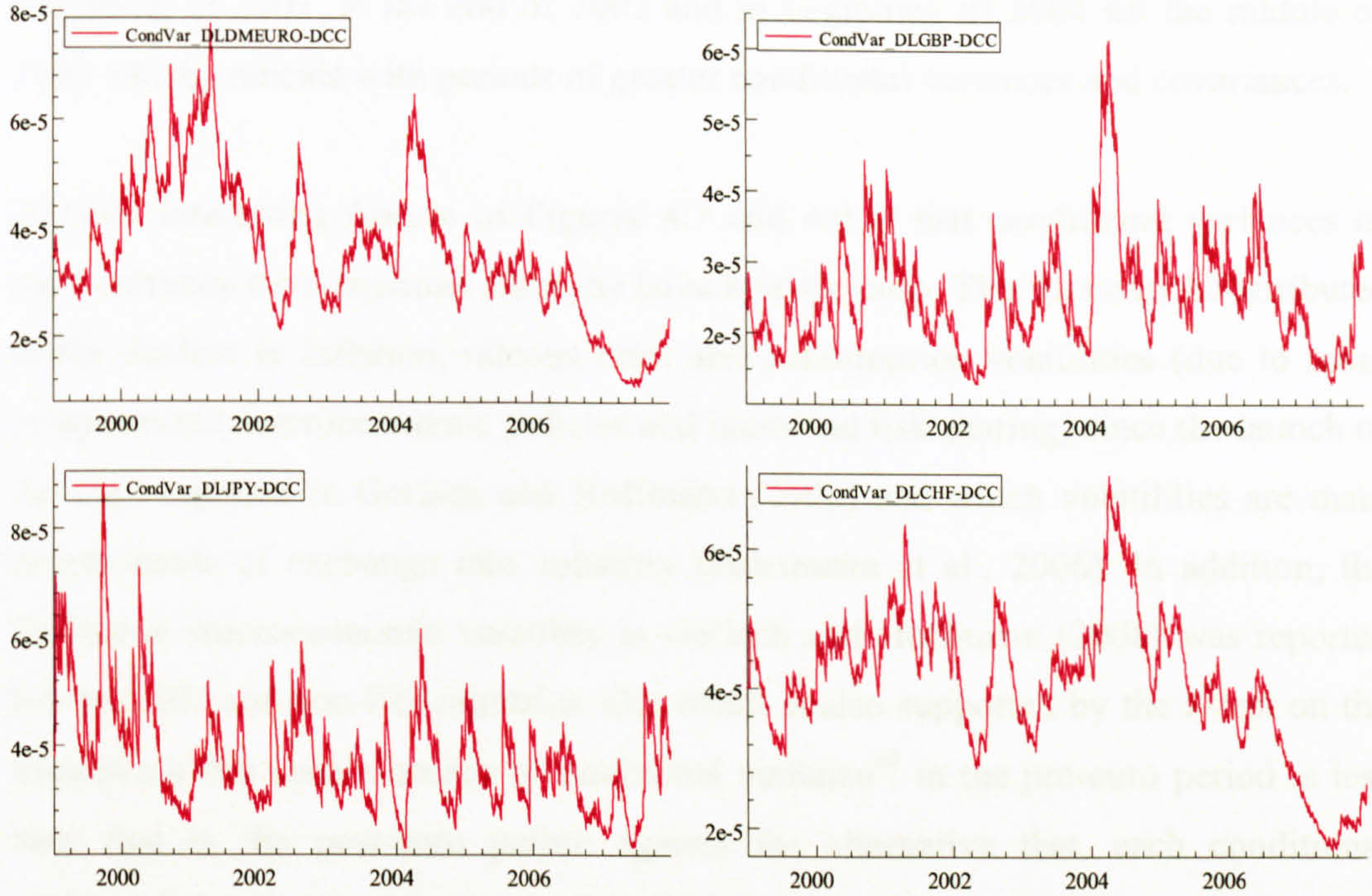
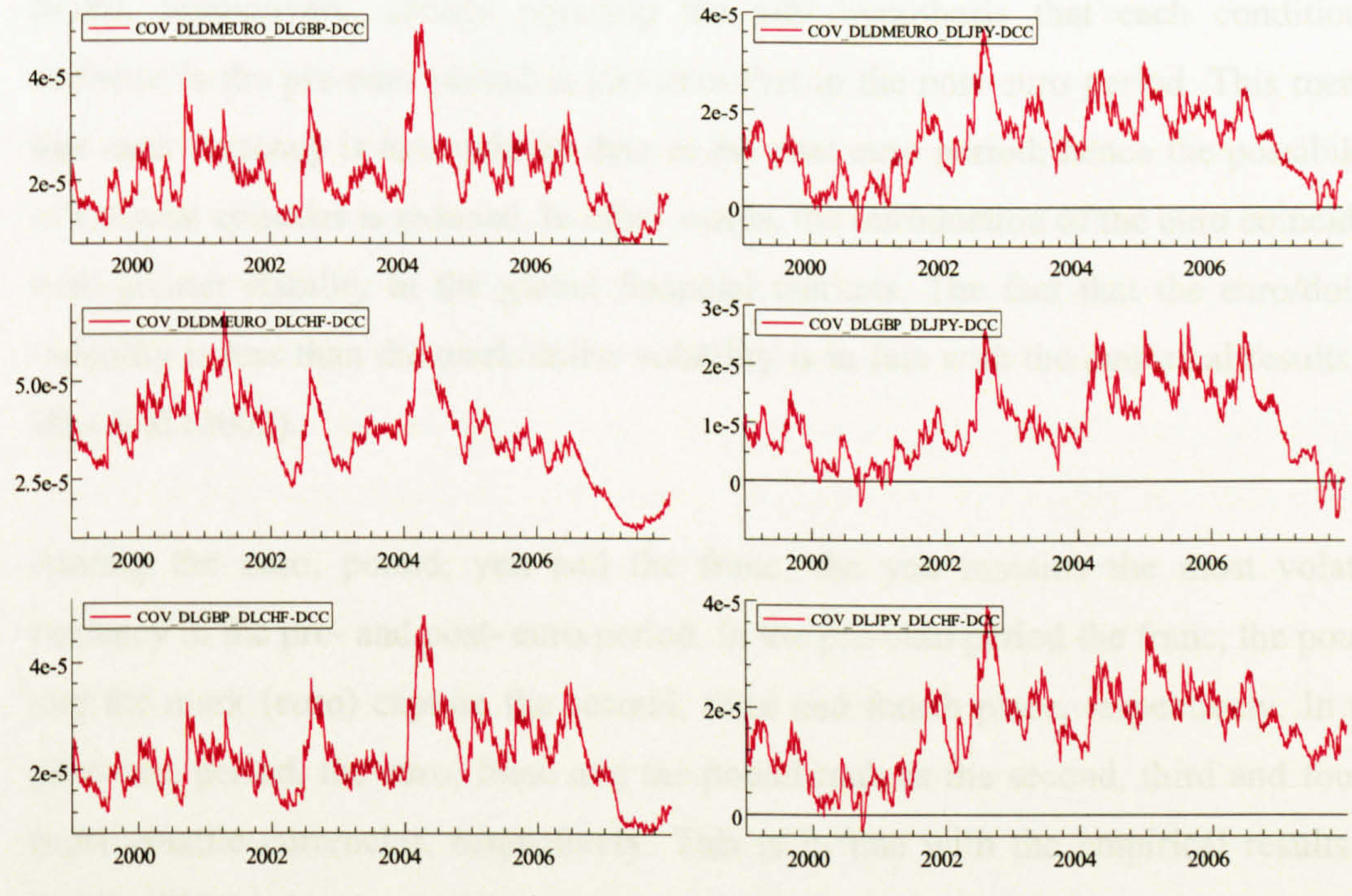


Figure 4.10: Conditional Covariances of DCC model – Post-Euro Period (05.01.99-31.12.07)



The same applies to the post-euro period. Correlations are greater during 2000 till the beginning of 2001, at the end of 2002 and in beginning of 2004 till the middle of 2006 which coincide with periods of greater conditional variances and covariances.

Another interesting feature of Figures 4.7 and 4.9 is that conditional variances of each currency have declined since the launch of the euro. This fact may be attributed to the decline in inflation, interest rates and consumption volatilities (due to more synchronized macroeconomic policies and increased risk sharing) since the launch of the euro reported in Gerlach and Hoffmann (2008) and which volatilities are main determinants of exchange rate volatility (Hausmann et al., 2006). In addition, the decline in macroeconomic volatility in Gerlach and Hoffmann (2008) was reported for both EU and non-EU countries. Our result is also supported by the F-test on the hypothesis that each currency's conditional variance[60] in the pre-euro period is less than that in the post-euro period against the alternative that, each conditional variance is less in the post-euro period. The F-test for the euro(mark), pound, yen and franc is 2.817, 10.01, 18.83 and 4.009 with a p-value of [0.00], [0.00], [0.00] and [0.00], respectively, clearly rejecting the null hypothesis that each conditional variance in the pre-euro period is less than that in the post-euro period. This means that each currency is less volatile than in the post-euro period; hence the possibility of extreme episodes is reduced. In other words, the introduction of the euro coincided with greater stability in the global financial markets. The fact that the euro/dollar volatility is less than the mark/dollar volatility is in line with the empirical results of Hau et al (2002).

Among the euro, pound, yen and the franc, the yen remains the most volatile currency in the pre- and post- euro period. In the pre-euro period the franc, the pound and the mark (euro) capture the second, third and fourth place, respectively. In the post-euro period, the euro, franc and the pound rank as the second, third and fourth most volatile currencies, respectively. This is in line with the empirical results of Malik (2005) who showed that the euro is more volatile than the pound in the post-euro period. This means that the pound became less volatile than the euro, since the

[60] The conditional variances of the AR(3)-DCC-MGARCH(1,1) and DCC-MGARCH(1,1) for the pre- and the post-euro period, respectively, where used to perform the F-test.

latter's introduction, as compared to the pre-euro period. This partly contradicts with the results of Wan and Kao (2008). The authors find that the euro is more volatile than the pound but the volatility of the former has declined and that of the latter has increased since the launch of the euro. There are possible explanations for their findings that the volatility of the pound has increased since the launch of the euro. One is that their estimation sample is up to March 31, 2006 and does not include 2007 a period characterised by lower volatility in the global financial markets as shown in Figure 4.9. Another reason is the choice of the pre- and the post-euro periods of their sample, which might affect estimation results. The date of separation of their data is the January 2002 (the date euro notes and coins began circulating) and not January 1999 when the currencies were fixed to the euro. In addition, their pre-euro period ranges from January 1999 till the end of 2001, a rather small sample to account for the dynamics of exchange rates. Last but not least, their analysis is based on a univariate framework.

Looking at the evolution of the conditional covariances from Figures 4.8 and 4.10 one can observe another interesting feature. Each of the six conditional covariances has also declined since the launch of the euro (according to the vertical axis of these tables), indicating that co-movents and spillovers among these currencies have declined in magnitude in the post-euro period. The greatest range in co-movements between currency markets exists between the euro(mark)-franc for both sub-periods. Before the introduction of the euro the second, third, fourth, fifth and last in magnitude comovements are between the yen-franc, euro(mark)-yen, euro(mark)-pound, franc-pound and euro(mark)-franc, respectively. The equivalent ones for the post-euro period are between the euro-pound, pound-franc, franc-yen, euro-yen and pound-yen, respectively. Since the euro(mark) capture the first places in the magnitude of comovements in volatility it clearly plays a dominant role in this volatility transmission and especially after the introduction of the euro. It transmits (receives) volatility among each of the four currencies and especially to (from) those geographically closer. The dominance of the mark in volatility spillovers was also reported in an empirical study of Kearney and Patton (2000) within the EMS period. In this study we provide evidence that the mark and the euro, the currency the former being replaced by, still holds a dominant position in terms of volatility transmission even after the introduction of the euro.

The second multivariate GARCH specification that is able to account for volatility co-movements and spillovers, and especially quantify the direction of the spillovers explicitly, is the full-BEKK model. The estimation results of the full-BEKK model for the pre- and the post- euro period are reported on Table 4.6. Again an AR(3) and a BEKK-MGARCH(1,1) for the pre- and the post-euro periods, respectively, were sufficient to filter any remaining serial correlation in the conditional mean specification.

The conditional variance-covariance matrix of the BEKK model sufficiently captures volatility and cross-volatility spillovers among these four exchange markets. Specifically, Table 4.6 presents only the estimated coefficients of the variance covariance matrix, which quantify the effect of the own and cross-innovations and own and cross-volatility persistence/spillovers on the own and cross-volatility of these four exchange markets.[61] The estimated coefficients are generally significant for own and cross-innovations, and for own and cross-volatility spillovers in all four exchange rates, and especially in the post-euro period. 15 out of 32 (47%) and 19 out of 32 (59%) of the estimated ARCH and GARCH coefficients are significant at 0.05 level in the pre- and post-euro period, respectively.

[61] For instance, the estimated coefficients $a_{DM(EUR),\ DM(EUR)}$ and $a_{DM(EUR),GBP}$ in the first panel row ($A_{DM(EUR)}$) of Table 4.6, quantify the own-innovations effect in the DM(EUR) market and the cross-innovation effect of the GBP to the DM(EUR) market, respectively.

Table 4.6: Estimation Results of BEKK model – Pre- & Post- Euro Period

		Pre-Euro (05.01.90-31.12.98)	Post-Euro (05.01.99-31.12.07)
$A_{DM(EUR)}$	$a_{DM(EUR), DM(EUR)}$	0.1829 (5.33)**	0.1730 (6.42)**
	$a_{DM(EUR), GBP}$	0.0264 (0.74)	0.0876 (1.54)
	$a_{DM(EUR), JPY}$	0.0166 (0.41)	0.1495 (1.36)
	$a_{DM(EUR), CHF}$	0.0278 (0.60)	0.0203 (0.58)
A_{GBP}	$a_{GBP, DM(EUR)}$	0.0371 (2.15)*	0.0107 (2.56)*
	$a_{GBP, GBP}$	0.1628 (9.08)**	0.1377 (5.63)**
	$a_{GBP, JPY}$	0.0396 (2.06)*	0.0262 (1.15)
	$a_{GBP, CHF}$	0.0104 (0.44)	0.0134 (0.65)
A_{JPY}	$a_{JPY, DM(EUR)}$	0.0028 (0.22)	0.0274 (2.13)*
	$a_{JPY, GBP}$	0.0030 (0.27)	0.0183 (1.49)
	$a_{JPY, JPY}$	0.2094 (9.09)**	0.1440 (10.8)**
	$a_{JPY, CHF}$	0.0130 (0.83)	0.0342 (2.52)*
A_{CHF}	$a_{CHF, DM(EUR)}$	0.0025 (0.09)	0.0721 (2.92)**
	$a_{CHF, GBP}$	0.0105 (0.36)	0.0569 (2.17)*
	$a_{CHF, JPY}$	0.0124 (0.31)	0.0757 (2.04)*
	$a_{CHF, CHF}$	0.1872 (4.88)**	0.1304 (3.83)**
$B_{DM(EUR)}$	$b_{DM(EUR), DM(EUR)}$	0.9922 (104)**	0.9824 (244)**
	$b_{DM(EUR), GBP}$	0.0252 (2.43)*	0.0130 (1.40)
	$b_{DM(EUR), JPY}$	0.0001 (0.01)	0.0248 (1.46)
	$b_{DM(EUR), CHF}$	0.0307 (2.17)*	0.0101 (1.34)
B_{GBP}	$b_{GBP, DM(EUR)}$	0.0071 (2.01)*	0.0051 (2.52)*
	$b_{GBP, GBP}$	0.9858 (293)**	0.9789 (178)**
	$b_{GBP, JPY}$	0.0082 (1.98)*	0.0029 (0.52)
	$b_{GBP, CHF}$	0.0033 (0.72)	0.0033 (0.65)
B_{JPY}	$b_{JPY, DM(EUR)}$	0.0030 (1.05)	0.0037 (2.32)*
	$b_{JPY, GBP}$	0.0030 (1.20)	0.0065 (2.41)*
	$b_{JPY, JPY}$	0.9742 (161)**	0.9858 (385)**
	$b_{JPY, CHF}$	0.0009 (0.24)	0.0053 (1.82)
B_{CHF}	$b_{CHF, DM(EUR)}$	0.0122 (1.45)	0.0137 (2.94)**
	$b_{CHF, GBP}$	0.0244 (2.57)*	0.0142 (2.42)*
	$b_{CHF, JPY}$	0.0002 (0.01)	0.0167 (1.75)
	$b_{CHF, CHF}$	0.9546 (75.1)**	0.9830 (119)**
	df	6.7267 (28.8)**	7.8140 (15.5)**
	Log-Lik	36981	38022
	H(30)	479.9 [0.48]	529.6 [0.07]
	H^2(30)	556.2 [0.10]	507.3 [0.16]

Notes: H( ), H^2( ) are the multivariate versions of Ljung-Box statistic of Hosking (1980). ( ) and [ ] denote t-values and p-values, respectively. * 5% significant; ** 1% significant. For the sake of brevity, the estimates for the lower triangular matrix C'C of equation (2.16) are not presented here, but can be provided upon request.

The own-innovation effects in all exchange markets are large and significant for both the pre- and the post-euro period. However, they have declined since the launch of the euro. These results indicate the presence of strong ARCH effects and are in line with the empirical results of the DCC model. Prior to the introduction of the euro the own-innovation effects range from 0.1628 in GBP to 0.2094 in JPY whereas, in the post-launch euro period they range from 0.1304 in CHF to 0.1730 in DM(EUR) market. In terms of cross-innovation spillover effects, only in the case of GBP market do cross innovations in the DM(EUR) and the JPY markets have a significant influence in that market in the pre-euro period. The other three markets' cross-innovation spillover effects are not significant in the pre-euro period. However, since the launch of the euro, the GBP market is affected only by cross innovations in the DM(EUR) market. In addition, in the JPY market, cross innovations of both the DM(EUR) and the CHF markets significantly affect that market. Last but not least, in the case of CHF market, all other markets' cross innovations have an influence on that market. Thus, we provide evidence that the DM(EUR) market is not influenced by cross innovations in any of the other markets in both the pre- and the post-euro period. Whereas, innovations in the DM(EUR) market exert an influence in all other markets in the post-euro period (and only on the GBP market in the pre-euro period). Hence, there is evidence of an unidirectional cross innovation spillover from the DM(EUR) to the GBP, JPY and CHF markets, especially in the post-euro period.

In terms of estimated coefficients for the own and cross-volatility persistence effects in these four exchange markets, the results are as follows. The own-volatility persistence effects are large and significant in both the pre- and the post-euro period for all markets at the 1% level. These results again indicate the presence of GARCH effects and are in line with the empirical results of the DCC model. They range from 0.9546 in CHF to 0.9922 in DM in the pre-euro period and from 0.9789 in GBP to 0.9858 in JPY. Another interesting feature is that the own-volatility persistence effects in the GBP and the EUR have declined and in the JPY and CHF have increased. On these grounds alone, this means that the pound and the euro have become the least volatile currencies among these four since the launch of the euro. This has several implications for its future development. For instance, on these grounds alone, proponents of the UK adopting the euro as its currency might need to revisit their opinion in the near future.

Turning to the cross-volatility persistence/spillovers effects, one can clearly see that the DM(EUR) has the lead in volatility perstistence/spillover effects on all other markets' volatility in the pre- and especially in the post- launch euro period (apart from the insignificant volatility spillover effect on JPY and CHF in the pre-euro period). Even though in the DM(EUR) market there exists significant cross-volatility spillovers from the GBP and CHF markets in the pre-euro period, they disappeared since euro's launch. In the case of the GBP market, cross-volatility spillovers from the DM(EUR) and the JPY markets significantly affect that market in the pre-euro period, and cross-volatility spillovers from the DM(EUR) market affect that market in the post-euro period. In the JPY, significant cross-volatility spillovers from the DM(EUR) and the GBP markets exist only since euro's introduction. Finally, significant cross-volatility spillovers from the GBP to the CHF market exist in both period and from the DM(EUR) to CHF market in the post-euro period.

The interesting finding of Table 4.6 is the presence of unidirectional spillover from the EUR to the GBP, the JPY and CHF since the former's launch. The fact that only innovation and volatility persistence in the DM-EUR market exert an influence on the GBP, the JPY and the CHF markets, and not the other way around, is in line with the empirical literature (see for instance, Nikkinen et al. 2006). However, in this research, not only additional evidence of the dominant position of the euro volatility transmission to the yen is provided, but it is also supported by a more extended sample.

Finally, the BEKK model is well specified according to the Hoskins (1980) test statistics as the null hypothesis of no serial correlation on both standardized and squared standardized residuals is not rejected up to 20 lags. Figures A.1 - A.6 in the Appendix, which plot the conditional variances, covariances and correlations of the BEKK model for the pre- and post- euro period, are almost identical with those obtained from the DCC model.[62]

A final robustness analysis is to check how rapidly a shock in one market is being transmitted to other markets in both the pre- and post- euro period. In order to do that, we calculate and present in Figures 4.5 and 4.6 the conditional volatility

[62] Hence, the analysis of these figures for the BEKK specification has the same qualitative nature as in the DCC specification and thus, not repeated for the sake of brevity.

impulse response functions (VIRF) in the pre- and post euro period, respectively. Specifically, the figures show the response of a shock in the ith market (where $i = 1, 2, 3, 4$) to all markets for n days after the shock, According to Lin (1997) and Hafner and Herwartz (2006) the VIRF is defined as the impact of a small perturbation of the ith market innovation on future predicted volatility. We use the estimates obtained from the BEKK model in the pre- and post- euro period to calculate the VIRF for 70 days after the shock. The vertical axis of these figures stands for $\partial h_{ii+s} / \partial e_{kt}^2$, that is the VIRF, and the horizontal axis represents the number of days beyond the shock.

In general it can be seen from Figures 4.5 and 4.6 that a shock arriving in the DM(EUR) is heavily transmitted to all other markets and lasts more than two months whereas, a shock arriving in each of the rest three markets is being transmitted to a lesser amount in the DM(EUR) market as its effect dissipates very fast in the DM(EUR) in both sub periods. This additional finding provides supporting evidence to our previous results that the DM(EUR) is the dominant currency in volatility transmission, as its volatility affects all other markets' volatility, and exerts an unidirectional persistent spillover effect on the GBP, CHF and JPY market's volatility, as a shock to the DM/EURO affects all other currencies' volatility for more than two months.

Figure 4. 11: Volatility Impulse Response Functions - Pre-Euro Period

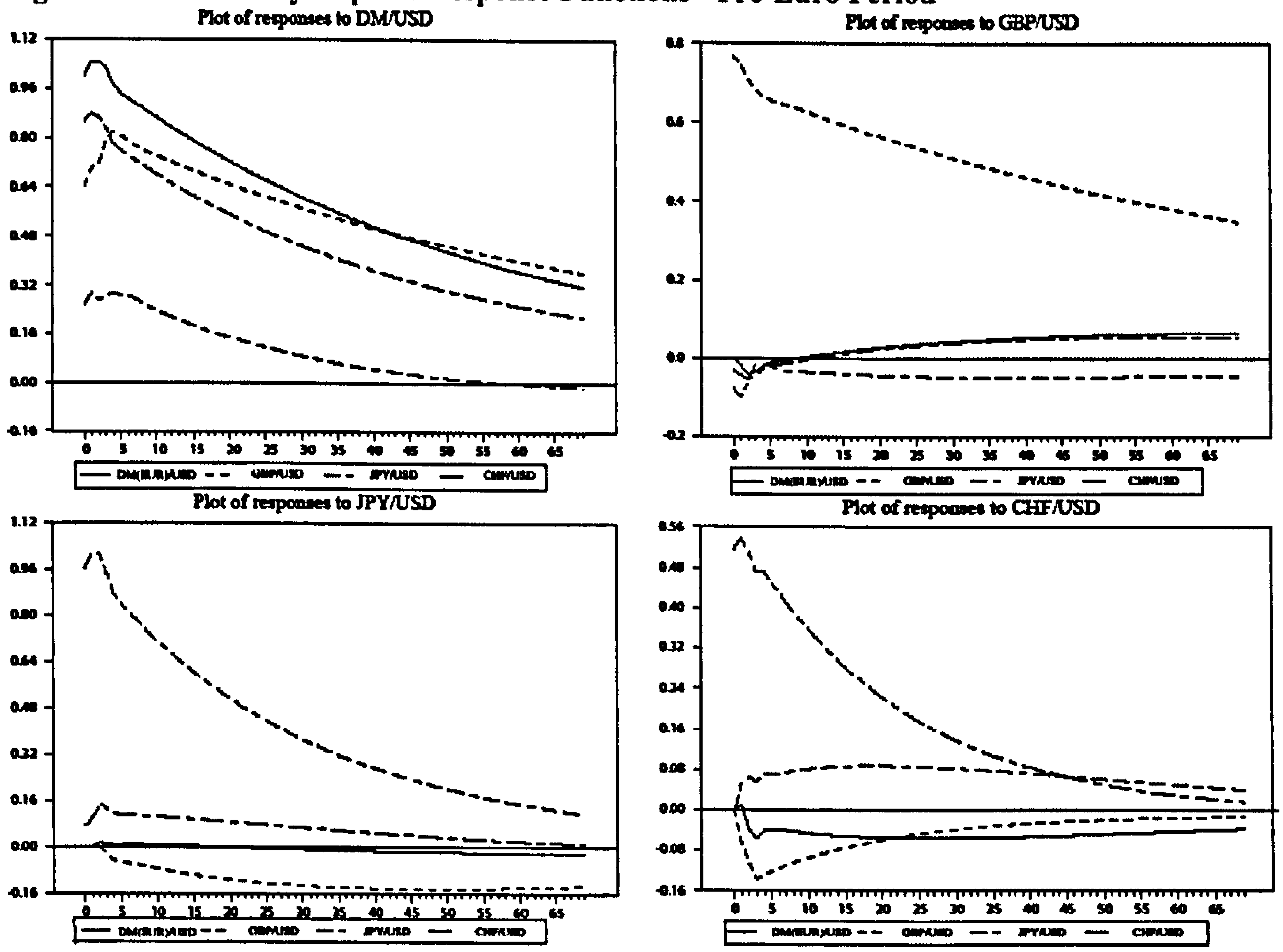
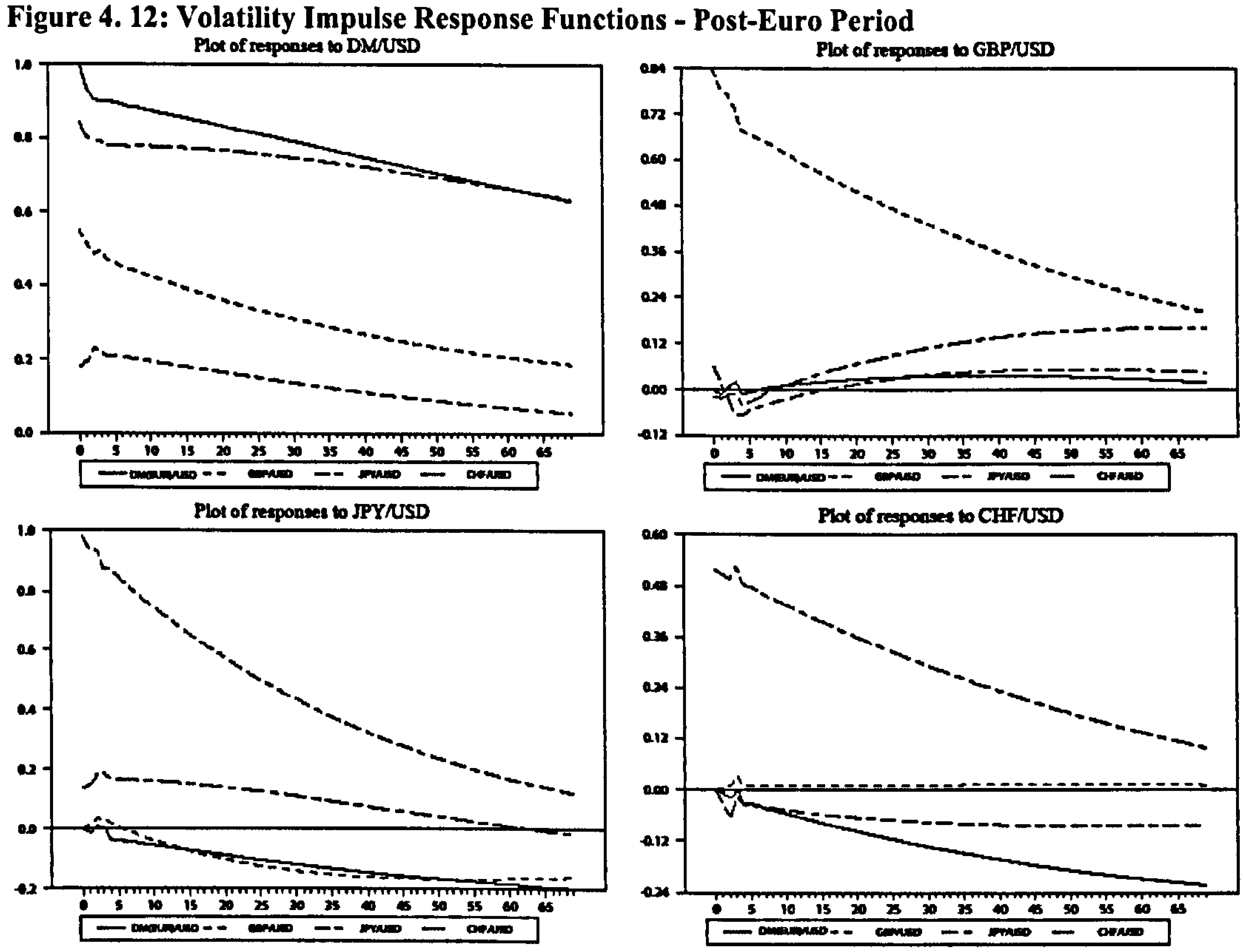


Figure 4. 12: Volatility Impulse Response Functions - Post-Euro Period



4.5 Conclusion

The launch of the Euro brought many debates about its future developments in terms of stability and spillovers in the euro and the functioning of global financial markets.

This chapter has examined exchange rate volatility comovements and spillovers for four highly traded currencies, specifically the euro, the British pound, the Japanese yen and the Swiss franc against the US dollar, for the period before and after the introduction of the euro. The paper contributes to the literature of exchange rate volatility spillovers and co-movements in two ways. Firstly, it examines volatility co-movements and spillovers in both the pre- and the post-euro period and extends the post-euro period sample with data up to 2007. Secondly, two flexible multivariate models were applied that allow conditional variances, co-variances and correlations to be time-varying rather than relying on the restrictive assumption of constant correlations. That assumption was clearly rejected by the data.

Both models based on diagnostic checking and misspecification tests performed equally well in the pre- and the post-euro period. According to these models, since the introduction of the euro conditional variances, co-variances and correlations declined significantly in magnitude. That is, volatility comovements and spillovers between the euro, pound, yen and the franc in general have a smaller impact in the post-euro period. This means that the launch of the euro coincided with greater stability in the euro and the global financial markets, which is in line with Mundell's (1998) claim of a decrease in volatility in the expansion of the euro due to the European's Central Bank commitment for price stability. It is essential to note that our results regarding the decline in exchange rate volatilities, co-movements and correlations since the launch of the euro may have occurred for reasons unrelated to the introduction of the euro. Thus, whether the volatility of the four currencies reflects the underlying volatility in the economic fundamentals of these regions is definitely an important avenue for future research. On these grounds, a paper from Gerlach and Hoffmann (2008) have found that since the launch of the euro, which was accompanied by better and more synchronised macroeconomic policies and increased consumption risk sharing, macroeconomic volatility (such as inflation, interest rates and consumption volatility) has been reduced. Therefore, the decline in exchange rate volatilities, co-movements and correlation reported in this chapter can be attributed to the decline in inflation and interest rate volatilities, the latter being a determinants of the former (Hausmann et al., 2006).

Moreover, the results showed that the euro(mark) is the dominant currency in volatility transmission, as its volatility significantly affects the volatility expectations of the franc, pound and the yen. This is in line with the results of Nikkinen et al., (2006). The authors, using daily data for the period between 2 January 2001 and 29 September 2003, found that the implied volatility of the euro significantly affects the volatility expectations of the pound and the franc. In this research, not only additional evidence of the dominant position of the euro volatility transmission to the yen is provided, but is also supported by a more extended sample. This fact has serious implications for portfolio diversification and risk management. For instance, a risk-averse trader who wishes to minimize risk should hold opposite positions between high positively correlated currencies.

In addition, it was found that the pound is the least volatile among these four currencies since the launch of the euro. As already pointed out, exchange rate volatility is just one aspect of the many which need to be considered before making any conclusive argument as to whether UK should replace the pound with euro or not. On these ground alone, this suggest that the UK may not be well advised to adopt the euro in the near future. The higher volatility of Euro than British pound has obviously important implications for many other financial markets and this particular finding definitely requires more research along this dimension before economists converge to any specific conclusion on this highly debated issue.

The analysis in this chapter was based on the assumption that shocks or news in one market affects that specific market and other markets symmetrically. This means that the impact of negative and positive shocks, of the same amplitude to exchange rate volatility, is the same. It would be of interest for further research to investigate whether the impact of news could have an asymmetric impact on exchange rate volatility.

Chapter 5

Official Central Bank Interventions in the Foreign Exchange Markets: A DCC Approach with Exogenous Variables

5.1 Introduction

This chapter investigates the impact of official central bank interventions (CBI) on exchange returns, their volatility and bilateral correlations. This investigation is based on the impact of the G4 (Fed, Bundesbank, Bank of Japan and Bank of England) officially announced CBIs rather than solely relying on the impact of the G3 G4 (Fed, Bundesbank and Bank of Japan) CBIs that has been thoroughly examined by the literature. The addition of information from a fourth central bank provides the opportunity to investigate coordinated interventions by up to three central banks, which has never been previously assessed.

It is now more than two decades since the Plaza Agreement signed on September 22, 1985 and the Louvre Accord on February 22, 1987.[63] These agreements were signed in order to induce US dollar depreciation and promote stability in currency markets, respectively. Economists, policy makers and central bank analysts still lack conclusive evidence on the impact of CBIs on exchange returns and especially on volatility. The majority of the empirical literature suggests that unilateral, and even

[63] The Plaza agreement was signed by the G5 countries, specifically France, West Germany, Japan, USA and UK, and the Louvre Accord by the G6 countries (Canada, France, West Germany, Japan, USA and UK). Italy was also an invited member in the Louvre Accord by declined to finalize the agreement.

coordinated intervention of two central banks, does not affect exchange returns and has in most of the cases the opposite outcome on volatility from that expected (among others see Beine, 2004; Beine et al., 2002; Fatum 2002; Humpage, 1999; Baillie and Osterberg, 1997; Bosner-Neal and Tanner, 1996; Catte et al., 1992). That is, interventions associated with the Louvre Accord appear to have been counterproductive since they led to an increase in volatility as opposed to the intended decrease.

The purpose of this chapter is to shed some light on the impact of official Central Bank Interventions (CBIs) on exchange rate returns, volatility and correlations of the DM (Euro after the 1999) and the JPY against the US dollar. This paper adds to the literature of CBIs in various respects. First, rather than relying only on G3 official CBIs, that is, the Bank of Japan, the Bundesbank (or the European Central Bank, ECB, after 1999) and the FED on the DM(EUR)/USD and the JPY/USD markets, as has already been investigated extensively in the literature, another major Central Bank is included, namely, the Bank of England (BoE). That is, the impact of the G4 official CBIs is examined. Such investigation will shed some more light to the argument that coordinated interventions are more powerful than unilateral ones (see Beine, 2004; Fatum 2002; Humpage, 1999; Catte et al., 1992).

The literature has so far not investigated the number of central banks engaged in intervention. One of the main questions this chapter tries to answer is whether the impact on exchange rate dynamics is more significant when two central banks intervene in coordination as opposed to three central banks. The approach adopted in this chapter explicitly allows the investigation of the impact of officially announced coordinated interventions of two and three central banks, since the Bank of England (BoE) intervened several times in coordination with another two central banks, and which was part of the G6 Louvre Accord (1987). Accounting for the BoE official interventions might more accurately assess the real impact of officially announced CBIs in the post-Louvre Accord period. Ideally, we would investigate the impact of officially announced central bank interventions of all the countries that were involved in the Louvre Accord. That is, including the Bank of Canada (BoC) and the

Bank of France (BoF), in addition to the Bank of England. However, since this paper examines the impact of officially announced CBIs, and since neither the BoC nor the BoF officially announce their interventions, at least for our sample period, they cannot be taken into account in this research.

The fact that the empirical studies provide such ineffective evidence of the G3 impact of CBIs on exchange rate returns and volatility might be attributed to several factors. One of which might be the omission of the Bank of England, which intervened several times in under our investigation sample, and which was part of the G6 Louvre Accord. Other factors include different sample periods and models used.

Moreover, as the empirical evidence suggests that intervention has been counterproductive, it raises several issues such as to why Central Banks keep conducting coordinated interventions when the result is the exact opposite from the expected one. That is, an increase as opposed to an anticipated decrease in exchange rate volatility. In other words the impact of CBIs is counterproductive. The inclusion of the BoE might provide more useful information on whether the impact of CBIs is counterproductive per se or is it due to the omission of other major central banks.

Whether is counterproductive per se or is it due to the omission of other major CBIs? Answers to such questions are of great importance for central banks decisions and the inclusion of the BoE might provide more useful information on this issue.

A third contribution of this paper is the application of the multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Dynamic Conditional Correlation (DCC) model of Engle (2002) extended with exogenous variables (in our case, CBIs). To my knowledge, the DCC has not been applied to modelling the effects of CBIs on returns, volatility and correlation of exchange rates. I argue that the DCC is more appropriate in exploring the effects of an extended set of CBIs on volatilities and correlations, as it overcomes certain numerical difficulties often arising in estimating multivariate GARCH models[64], such as the Vector Error Conditional Heteroskedasticity model (VECH) used by Beine (2004) to assess the impact of CBIs, and also because it enables the estimation of time-varying correlations.

This chapter investigates only the signalling channel through which CBIs might affect exchange rate dynamics and not the portfolio balance channel, since the empirical literature is not supportive of the latter.

The key findings are that unilateral CBIs are found to be more successful in influencing exchange returns than coordinated CBIs, when taking into account the interventions of the Bank of England. Coordinated CBIs could increase volatility as the number of central banks intervening in coordination increases. These results have implications for the effectiveness of Central Banks' intervention policy decisions.

The remainder of this chapter is organised as follows. Section 5.2 presents some basic definitions of the various respects of CBIs. Section 5.3 presents the literature review. Section 5.4 describes the methodology and data. Section 5.5 presents the empirical results and section 5.6 concludes.

5.2 Central Bank Interventions

Central bank interventions in the foreign exchange markets refer to the purchase or sale of a currency, domestic or foreign, by central banks in an attempt to influence exchange rate movements. For instance, the purchase of the JPY against the USD dollar by the Federal Reserve (FED) is such a central bank intervention. In addition, a central bank can intervene in the spot, forward or both exchange markets. The outcome will depend on the risk premium (according to the covered interest parity condition), whether intervention is sterilized or not and the source of shock. In the case of sterilized intervention –e.g. one that leaves the monetary base unchanged and thereby doesn't perturb the domestic money market- the outcome will be the same

[64] Such as the estimation of many parameters simultaneously, which makes it difficult to ensure the positive definiteness of the covariance matrix.

whether such an intervention is conducted on the spot or the forward exchange. In the case of unsterilized intervention in the spot exchange the effect on the monetary base and thus, on the exchange rate will be immediate whereas, in the forward exchange the effect will take place when the central bank's forward contracts come due at the delivery date.{footnote: It is worth mentioning that the potential role of the forward market intervention as a stabilizing instrument was first recognized by John Maynard Keynes (1936)}. Finally, in the case of a spot and forward intervention mix, no effects on fluctuations in the spot rate will be present if shocks do not directly perturb trade hedger's buying/selling forward exchange whereas, if shocks do directly perturb this hedging activity, forward market intervention can reduce fluctuations, as opposed to spot market intervention (Tseng, 1998). However, all central banks, at least throughout our sample period, claim to sterilize their interventions (see Beine, 2004) and conduct their intervention basically in the spot exchange rate. [65] Therefore, this chapter focuses solely on the impact of central bank interventions in the spot exchange market.

Central bank interventions can be conducted either unilaterally or in coordination. Unilateral CBIs are those conducted by one central bank, whereas coordinated CBIs are those conducted by at least two central banks on the same currency pair, direction and date. For instance, the sale of the JPY against the USD dollar by the Federal Reserve (FED) and the Bank of Japan (BoJ) on January 17, 1992 is a coordinated intervention on the JPY/USD market.

Within unilateral and coordinated interventions, one can distinguish two more types of intervention: 1) officially announced CBIs and 2) secret or reported CBIs. Officially announced interventions refer to intervention being directly available to the public from central banks' databases. On the other hand, secret interventions are the ones conducted without notification of the public. That is, information about CBIs is not directly revealed to the public. On the same grounds, reported

[65] See, for instance, FED's intervention process in http://www.newyorkfed.org/aboutthefed/fedpoint/fed44.html where it is mentioned that: *"The Fed historically has not engaged in forward or other derivative transactions."*

interventions refer to interventions that are not directly made available to the public from central banks but from newspapers reports or over the wire services. Hence, the choice of the type of intervention can alter their impact on exchange rate dynamics.

Moreover, each kind and type of such CBI can be either sterilized or non-sterilized. Sterilized intervention is defined as intervention where its effects on the domestic money supply are neutralised or 'sterilized' by the monetary authorities. For instance, a sterilized intervention occurs when the FED sells Japanese assets (that is, buying the JPY) and simultaneously buys US assets (that is, selling the USD) in order to induce an appreciation of the JPY/USD rate. The effects of such intervention are: an increase in the outstanding supply of Japanese assets and an equivalent decrease in the outstanding supply of US assets, while holding the money supply constant. That is, the effects of a change in official foreign asset holdings for domestic asset holdings on the monetary base are offset or sterilized. Had not the FED bought the equivalent amount (in US dollars terms) of US assets, the US money supply would have declined. An intervention of this nature is denoted as non-sterilized intervention because it alters the money supply.

Table 5.1: Monetary Authorities' Stylized Balance Sheet

Assets	**Liabilities**
Net Foreign Assets (NFA)	*Monetary Base (M)*
Gold	Total currency in circulation
Foreign	Reserve liabilities to commercial banks
Net domestic assets (NDA)	*Net worth (NW)*
Government securities	Spending surpluses
Loans to commercial banks	Net interest and capital gains from assets
other	

Source: Sarno & Taylor (2001).

Consider Table 5.1 taken from Sarno & Taylor (2001), which gives the monetary authority's balance sheet representation for a country. The monetary base (M) consists of total currency in circulation and reserve liabilities of the central banks. The financial authority's net worth (NW) contains spending surpluses, accumulated net interest payments and capital gains from holding domestic and foreign assets. It can be shown from Table 5.1 that:

$$M \equiv NFA + (NDA - NW) = NFA + DC \qquad (5.1)$$

where DC is equal to net domestic assets minus net worth ($DC \equiv NDA - NW$) and denotes the available domestic credit made by monetary authorities.

When foreign exchange market intervention occurs by the monetary authority, it involves the purchase or sale of foreign assets (normally against their own currency). In the case of non-sterilized official intervention, the purchase (sale) of foreign currency by monetary authorities leads to an increase (decrease) in net foreign assets and a corresponding increase (decrease) in the monetary base. Thus, the impact of non-sterilized intervention is the same as that of an open market operation, apart from the fact that, by the former, monetary authorities change M through a change in foreign assets whereas, according to the latter, this happens through a change in domestic asset holdings.

When official intervention is sterilized, it follows that:

$$\Delta DC = -\Delta NFA \qquad (5.2)$$

which means that the change in the domestic credit is equal to the change in net foreign assets of the opposite sign and thus:

$$\Delta M = \Delta NFA + \Delta DC = 0 \qquad (5.3)$$

where Δ denotes the change in a variable. That is, the effects of a sterilized official intervention do not have an impact on the monetary base.

Having provided some basic definitions of the CBI aspects, the following section presents the literature review.

5.3 Literature Review

5.3.1 Theoretical literature of CBI effects

The theoretical literature discusses three main channels through which the CBIs can influence spot exchange rates and their volatility. The first channel is through non-sterilized intervention operations, which involves direct purchases or sales of a foreign currency. This type of intervention affects the domestic monetary base and the relative interest rates and hence, causes a change in the level of the exchange rate. It is shown that non-sterilised interventions have a more significant impact on exchange returns compared to sterilized ones, where the latter have a minor impact on exchange returns only in the very short-run (see MacDonald, 2007 and Sarno & Taylor, 2001). However, the major central banks concede that most foreign exchange operations are fully-sterilized, especially CBI operations during the last two decades (Beine, 2004).[66] Thus, one would expect to find empirically a minor significant impact on exchange returns, measured on daily basis, when assessing CBIs conducted since the last two decades.

The other two channels, through which the literature suggests that CBIs might affect exchange rates, are based on sterilized interventions.

The second channel is through the portfolio-balance model of exchange rate determination. The main assumption of this model is that market participants regard bonds denominated in domestic and foreign currency as imperfect substitutes. According to the portfolio balance model, as long as foreign and domestic assets are imperfect substitutes, a sterilized intervention that alters the relative outstanding supply of domestic and foreign bonds will cause a change in the relative returns, resulting in a change in the exchange rate. The change in the exchange rate is generated by the adjustment of the risk premium required to balance demand and supply on international bonds markets. For instance, when the FED buys US bonds for Japanese bonds, the FED can alter the relative supply of domestic and foreign currency denominated bonds. If domestic and foreign bonds are imperfect substitutes, so that market participants are risk averse, such sterilized intervention requires agents to adjust the composition of their portfolios according to the change in the relative supply of bonds that took place. This adjustment gives rise to wealth

[66] The FED, the Bundesbank/ECB, the BoJ and the BoE claim to sterilize their foreign exchange interventions operations routinely.

and substitution effects. In the previous example, of the purchase of US bonds and the sale of Japanese bonds by the FED, these wealth and substitution effects necessitate a decrease in the risk premium paid for US denominated bonds in order to restore equilibrium in financial markets. Hence, the decrease in the risk premium caused by the sterilized intervention implies an increase in the relative attractiveness of US bonds, thus leading to an appreciation of the JPY/US dollar. Therefore, agents' portfolio reallocations indicate that sterilized central bank interventions can influence exchange rates.

Nevertheless, in the case where domestic and foreign assets are regarded as perfect substitutes (which seems to be the case for financial assets denominated in major industrialized countries' currencies, and in an integrated world of high-speed capital flows), sterilized central bank intervention through the portfolio balance model will have no significant effects on exchange rates. This is due to the fact that economic agents care only about the total amount of bonds and not the relative amounts of domestic and foreign bonds they are holding, and thus no adjustment in the composition of agents' portfolios is required. Returning to the above example of sterilized intervention (purchase of US bonds for Japanese bonds by the FED), under the assumption of perfect substitutability of domestic (US) and foreign (Japanese) bonds, agents will buy foreign bonds one for one with the decrease in supply of domestic bonds. Therefore, economic agents will buy the same amount of foreign currency (Japanese yen) that the authorities sold, thus leaving exchange rates unaffected.

In either case of imperfect or perfect substitutability the relative supply of assets (that is the exact amount of purchases or sales of domestic and foreign currency) is required to test the impact of CBI through the portfolio balance models.

The third channel is known as the signalling channel (Mussa, 1981 and Lewis, 1995). The signalling channel allows interventions to be interpreted as a means of information conveyed to the market which, if believed, will affect market participants' expectations, both in terms of the level and volatility of exchange rates.

Being more specific, even in the case where domestic and foreign assets are regarded as perfect substitutes, sterilized CBI through the signalling channel can still affect the future path of exchange rates. This is due to the fact that economic agents regard central bank intervention as a signal of the future evolution of economic policy. A key assumption of the signalling channel is that the exchange rate is regarded as an asset price and that economic agents utilize all publicly available information when pricing foreign exchange. Thus, a sterilized intervention may affect the exchange rate only if the central bank has an informational advantage over economic agents. When central banks intervene in the foreign exchange market, they reveal this information by sending 'signals'. Economic agents can in turn absorb this information and adjust their expectations regarding the future evolution of macroeconomic fundamentals, which means that CBI induces a change in the exchange rate (Mussa, 1981). The impact of intervention through this channel can be assessed with the use of dummy variables for CBI (which take the value of 1 when central banks intervene and 0 when not) that will serve as 'signals'.

5.3.2 Empirical literature of CBI effects

The empirical literature of the effects of CBIs on foreign exchange markets is ample and has not reached a unified conclusion. This can be attributed to different data and models used. These papers which can be divided into three groups are discussed in the following subsections.

5.3.2.1 The impact of CBI on exchange rate returns

In general, CBIs have been shown to have little or no effect on exchange returns (to mention few see Beine et al., 2009; Beine, 2004; Beine et al., 2002 and references therein), apart from some very limited evidence (Baillie and Osterberg, 1997). Beine (2004) uses daily data to examine the impact of the G3 official interventions (of the Bank of Japan, the FED, and the Bundesbank or ECB after 1999) on the DM(EURO) and the JPY currencies all against the USD. The author uses a VECH GARCH with daily data for the period of 1991-2001 to explore the signalling channel model. He finds that CBIs conducted either unilaterally or in coordination do not have significant impact on those two exchange returns. This result is in line with all studies examining the impact of CBI since the beginning of 1990's through the signalling channel. The signalling channel has recently attracted much more attention as opposed to the portfolio-balance model (for discussion, see for instance, Baillie at al., 2000, Beine et al. 2003; Beine, 2004).

Nevertheless, in another study of Baillie and Osterberg (1997) which also assesses the impact of the daily G3 official interventions for the period of 1985-1990 under the portfolio balance model finds that, using a two country inter-temporal asset pricing model under a GARCH formulation, intervention influences the risk premium in the foreign exchange market. However, the significant effects of CBI were found on the risk premium in the forward market, not on returns per se. In addition, before 1991 the BoJ did not officially announce their intervention and the authors had to use proxies for interventions reported on newspapers to construct 'official' intervention. This might also explain the presence of the significant effect of CBIs.

5.3.2.2 The impact of CBI on exchange rate volatility

Even so, attention has been steadily shifted to the CBI effects on the higher moments of exchange returns, such as the volatility. Besides, the main concern of the G6 Louvre Agreement in 1987 and thereafter, was the adoption of an adequate policy intervention that would stabilize exchange rate variations. In the case of the exchange rate volatility effects of CBIs, the literature provides less mixed evidence. Most of the papers suggest that CBIs tend to increase exchange rate volatility in the short-run (among others see e.g. Beine, 2004; Beine et al., 2002; Baillie and Osterberg, 1997; Bosner-Neal and Tanner, 1996) whilst other papers provide evidence of mixed effects (see Beine et al., 2003).

Beine et al., (2002) examine the short run effects of the G3 CBIs through the signalling channel on daily returns and the volatility of the DM and the JPY against the USD for the period of 1985-1995.[67] A FIGARCH model is used to measure volatility. They find that CBIs do not affect returns but increase volatility of exchange rates. Baillie and Osterberg (1997), under the methodology that previously discussed, also find that the G3 CBIs increases rather than decreases exchange rate volatility. Beine (2004) using a VECH GARCH model, provides additional supportive evidence that the G3 official CBIs increase exchange rate volatility.

Bosner-Neal and Tanner (1996) examine also the impact of CBI on exchange rate volatility but from a different perspective. They use implied (ex ante) volatilities extracted from currency option prices to examine the effects of official CBIs (through the signalling and the portfolio channels) of the Bundesbank and the FED on the DM and the JPY currencies against the USD between 1985 and 1991. They find that CBIs are generally associated with an increase in ex ante exchange rate volatility. Very limited support is found for the case the CBIs decrease volatility.

Nevertheless, Beine et al. (2003) find that, using a regime switching approach to examine the impact of official G3 CBIs (through the signalling channel) on weekly returns and volatilities of the DM and the JPY against the USD, interventions, depending on the prevailing volatility level, can lead to either an increase or decrease in volatility. That is, when the market is in a low-volatility (high-volatility) state, it is found that CBIs tend to increase (decrease) volatility.

Last but not least, the empirical literature provides evidence that the impact of coordinated CBIs on exchange rate volatility has a stronger impact as opposed to the unilateral ones (among others see Beine, 2004; Beine et al., 2002; Fatum 2002; Humpage, 1999; Catte et al., 1992). However, the empirical literature had examined the impact of coordinated interventions of a maximum two central banks, and not the impact of 3 CBIs. Hence, it would be interesting to assess how the impact of CBI changes when more central banks intervene in coordination.

[67] They have official CBI for the BB and the FED but not for the BoJ for which they used proxies of reported interventions on newspapers or over the wire services to construct them.

5.3.2.3 The impact of CBI on correlations: the spillover effect

Apart from the impact of CBIs on exchange rate returns and their volatility, the spillover effect of CBIs on volatility has also been assessed in a limited number of studies. This spillover effect allows the investigation of how CBIs in one market may affect volatility of other foreign exchange markets.

In the case of the impact of CBIs on correlations the literature is very limited but unified. Beine et al. (2009) assess the impact of the G3 official CBIs on the DM and the JPY against the USD using daily realized moments between 1989 and 2001. The authors find that interventions through the signalling channel, with the use of an ARFIMA model, do not affect returns, but significantly affect volatility, covariance, correlation and skewness. Beine (2004) obtained time-varying correlations from a VECH GARCH model finds that the impact of CBI on correlations is positive. However, a VECH GARCH model is rarely used for the estimation of more than 2 dependent variables (not mentioning the exogenous variables), as the parameters increase exponentially, raising difficulties in the estimation process.[68]

Another strand of the literature has examined how exchange rate volatility may affect central bank interventions through the use of central bank reaction functions (see Almekinders and Eijffinger, 1996). That is, rather than relying on the impact of CBI on exchange rate dynamics this approach assesses the opposite question. Even though this approach offers valuable insights into any strategic behaviour that monetary authorities may have and allows the derivation and construction of central bank reaction functions, it faces some drawbacks (Sarno and Taylor, 2001). According to Sarno and Taylor (2001) a key drawback is that "... *these models treat the central bank on the same terms as other market participants, who, therefore, do*

[68] The number of parameters in a VECH model is $[N(N+1)(N(N+1)+1)/2]+\mathrm{X}$, where N = number of dependent variables and X = number of exogenous variables. E.g. a VECH with N=2 and N=3, and without exogenous variables has 21 and 78 parameter estimates, respectively. Whereas, in a DCC model with $[(N+1)(N+4)/2]+\mathrm{X}$, the equivalent numbers of parameters are 9 and 19, respectively.

not have any informational gain from monitoring the actions of the central bank". Thus, this class of model will be left out of the scope of this research.

In addition, many papers have relied on the impact of secret or informally reported CBIs (Dominguez, 1998; Beine et al., 2002).[69] That was because of the unavailability of official CBI intervention data at that time. On these grounds some studies (Bonser-Neal and Tanner, 1996; Beine et al., 2002) have used secret or reported CBIs as proxies for official ones. However, it is argued that this approach could be quite misleading. Besides, quite recently, the Ministry of Finance in Japan made official intervention data available from 1991 onwards.[70] Hence, nowadays, one can examine the direct impact of official CBIs very conveniently.

Since secret interventions were mostly conducted between 1973 and 1990, and not after the 1990 (which is our investigation sample), since when central banks have tended to officially justify, at least ex post, their interventions in the FX market,[71] it is more appropriate to concentrate on official CBIs rather than covered ones.

The following section presents the methodology and data used in this chapter.

5.4 Methodology and Data

The data consists of daily observations of spot exchange rates of the Deutsche mark (Euro after 1999) and the Japanese yen, all against the US dollar, for the period of April 2, 1991 to October 19, 2001, obtained from the Bank of England online database.[72, 73] The CBI data consists of official interventions of the Federal Reserve (FED), the Bank of Japan (BoJ), the Bundesbank (BB) (European Central Bank,

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[69] That is, interventions that were not officially made available to the public.
[70] See http://www.mof.go.jp/english/e1c021.htm
[71] see e.g. FED's FX reports at http://www.ny.frb.org/markets/quar_reports.html and Japanese MoF's reports in footnote 61.
[72] http://www.bankofengland.co.uk/mfsd/iadb/index.asp?first=yes&SectionRequired=I&HideNums=-1&ExtraInfo=true&Travel=NIxRSx
[73] In order to make accurate comparisons, we use the same sample that Beine (2004) has used in his analysis.

ECB, after 1999) and the Bank of England (BoE).[74] Specifically, central bank purchases/sales of the Japanese yen and the Deutsche mark (Euro after 1999) measured in US dollars.

In order to assess the signalling channel, through which CBIs could influence exchange rates and their volatility, we use dummy variables that take the value of 1 when central banks intervene and 0 otherwise. In addition, we examine the impact of both unilateral and coordinated interventions of central banks. In the case of unilateral interventions, we use up to four dummies for the CBIs (capturing the impact of the G4 central banks included in our sample) on the JPY/USD and the DM(EUR)/USD. In the case of coordinated interventions, since each of the four banks intervened in both the DM(EUR)/USD and the JPY/USD (apart from the BB/ECB which intervened only on the DM(EUR)), it seems appropriate to use only two dummy variables reflecting the coordinated interventions of two central banks and one dummy for coordinated intervention of three central banks. Table 5.2 provides a definition of the dummy variables used.

As previously mentioned, in the literature review, coordinated interventions on exchange rate volatility are more effective as opposed to the unilateral ones (Beine, 2004; Fatum 2002; Humpage, 1999; Catte et al., 1992). However, the empirical literature has examined the impact of coordinated interventions of a maximum of two central banks. In this research, we provide results for coordinated interventions conducted by three Central Banks on the DM(EUR)/USD exchange rate.

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[74] These intervention data were obtained from the Federal Reserve: http://research.stlouisfed.org/fred2/categories/32145/downloaddata, the Japanese Ministry of Finance: http://www.mof.go.jp/english/e1c021.htm and the HM treasury http://www.hm-treasury.gov.uk/documents/uk_economy/exchange_equalisation_account_1999_to_2000/fx_intervention/ukexon_fx_intervention.cfm

Table 5. 2: Definition of exogenous (dummy) variables

Variable	Definition
Exogenous variables in the conditional mean equation	
$dFED_{DM}$	Unilateral interventions of the FED on the DM(EUR)/USD market.
$dBOJ_{JPY}$	Unilateral interventions of the BoJ on the JPY/USD market.
dBB_{DM}	Unilateral interventions of the BB(ECB) on the DM(EUR)/USD market.
$dBOE_{JPY}$	Unilateral interventions of the BoE on the JPY/USD market.
dCoDM	Coordinated interventions of 2 central Banks on the DM(EUR)/USD market.
dCoDM3	Coordinated interventions of 3 central Banks on the DM(EUR)/USD market.
dCoJPY	Coordinated interventions of 2 central Banks on the JPY/USD market.
Exogenous variables in the conditional variance equation	
δFED_{DM}	Unilateral interventions of the FED on the DM(EUR)/USD market.
δBOJ_{JPY}	Unilateral interventions of the BoJ on the JPY/USD market.
δBB_{DM}	Unilateral interventions of the BB(ECB) on the DM(EUR)/USD market.
δBOE_{JPY}	Unilateral interventions of the BoE on the JPY/USD market.
δCoDM	Coordinated interventions of 2 central Banks on the DM(EUR)/USD market.
δCoDM3	Coordinated interventions of 3 central Banks on the DM(EUR)/USD market.
δCoJPY	Coordinated interventions of 2 central Banks on the JPY/USD market.

The model used in this chapter is the DCC model of Engle (2002) described in detail in chapter 2, equation (2.23). The DCC model is estimated through a 1-step procedure using the Quasi-Maximum Likelihood (QML) estimator under a multivariate Student distribution (see Harvey, Ruiz, and Sentana, 1992 and Fiorentini, Sentana, and Calzolari, 2003). The multivariate Student distribution is applied as it is well known that the normality assumption of the innovations is rejected in most empirical applications dealing with daily exchange rate data. This adds an extra parameter to the estimation of each model, namely the degrees of freedom parameter, denoted by υ (see below). When υ tends to infinity, the Student distribution tends to the normal density. When it tends to zero, the tails of the density become thicker and thicker. The parameter value indicates the order of existence of the moments, e.g. if $\upsilon = 2$, the second moments do not exist, but the first moments exist. For this reason it is convenient to assume that $\upsilon > 2$, so that the conditional variance-covariance matrix H_t is always interpretable as a conditional covariance matrix. Under this assumption, the Student density can be defined as:

$$g\langle z_t | \theta, \upsilon \rangle = \frac{\Gamma\left(\frac{\upsilon+n}{2}\right)}{\Gamma\left(\frac{n}{2}\right)\left[\pi(\upsilon-2)\right]^{\frac{n}{2}}}\left[1+\frac{z_t' z_t}{\upsilon-2}\right]^{-\frac{n+\upsilon}{2}} \tag{5.4}$$

where $\Gamma(.)$ is the Gamma function. The density function of y_t (exchange returns) is easily obtained by applying:

$$f\langle y_t | \theta, \Omega_{t-1} \rangle = |H_t|^{-1/2} g\langle H_t^{-1/2}(y_t - \mu_t | \upsilon \rangle \tag{5.5}$$

where $|H_t|^{-1/2}$ is the Jacobian that arises in the transformation from the innovations to the observables.

5.4.1 The effect of CBI

In order to assess the impact of CBIs on exchange returns, volatility and correlations the DCC model of Engle (2002) in equation (2.23) can be easily extended to incorporate exogenous variables such as:

$$\begin{aligned} & y_t = \mu_t(\theta) + d_t X_t + \varepsilon_t, \text{ where } \varepsilon_t | \Omega_{t-1} \sim N(0, H_t) \\ & \varepsilon_t = H_t^{1/2} u_t, \text{ where } u_t \sim N(0, I) \\ & H_t = D_t R_t D_t \end{aligned} \tag{5.6}$$

where d_t is the *n x 1* vector of parameters entering the mean equation and X_t is a *n x 1* vector of exogenous variables that denote the set of central bank interventions at time *t*. The specification for the proposed model has a different evolution for Q_t that enters the R_t (the $t \times \left(\frac{n(n-1)}{2}\right)$ matrix containing the time-varying conditional correlations), and the latter enters the conditional variance/covariance matrix H_t according to:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha u_{t-1}u'_{t-1} + \beta Q_{t-1} + \delta_{t-1}X_{t-1} \qquad (5.7)$$

where δ_t is the *n x 1* vector of parameters entering the conditional variance equation and X_t is a *n x 1* vector of exogenous variables that denote the set of central bank interventions at time *t*.[75] I focus on the impact of both unilateral and coordinated CBIs, on both the exchange returns, variances and correlations. The following section presents these results for the various definitions of the dummy variables.

5.5 Empirical results

In this section we begin by presenting the descriptive statistics of our data followed by the empirical results of the CBI impact under a DCC specification.

5.5.1 Descriptive statistics

Table 5.3 presents descriptive statistics of the mark(euro), and the yen returns series for the period of April 2, 1991 to October 19, 2001. The returns are calculated by taking the first logarithmic differences in exchange rates as denoted in equation (2.1). The means show the DM(EUR) and JPY with small positive and negative returns. The daily unconditional standard deviations of the JPY/USD return is greater than that for the DM exchange return, indicating that volatility is greater in the JPY as opposed to the DM returns. The excess kurtosis parameter estimate is significantly greater than zero for each returns series indicating non-normality of returns.[76] In addition, it is more than double than that for the JPY exchange rate, indicating that extreme episodes (such as currency crises) are more than twice likely to occur in the JPY than in the DM(EUR) market. In addition, the Jarque-Bera statistic confirms that exchange returns are, as expected, not normally distributed since the null hypothesis

[75] More precisely, the dummy variables for CBIs equal to 1 when central bank(s) intervene in the purchase or sale of US dollars and to 0 otherwise. See Table 5.2 for a specific definition of the dummy variables used.

[76] The excess kurtosis is defined as: $K = \frac{E\left[(y-\mu)^4\right]}{\sigma^4} - 3$. A distribution with positive excess kurtosis is said to have heavy tails, implying that the distribution puts more mass on the tails of its support than a normal distribution does. If returns are normally distributed, then the excess kurtosis coefficient should be zero.

of normally distributed returns is persuasively rejected and the data are clearly skewed.

Table 5.3: Descriptive Statistics of Returns – 02.04.1991-19.10.2001

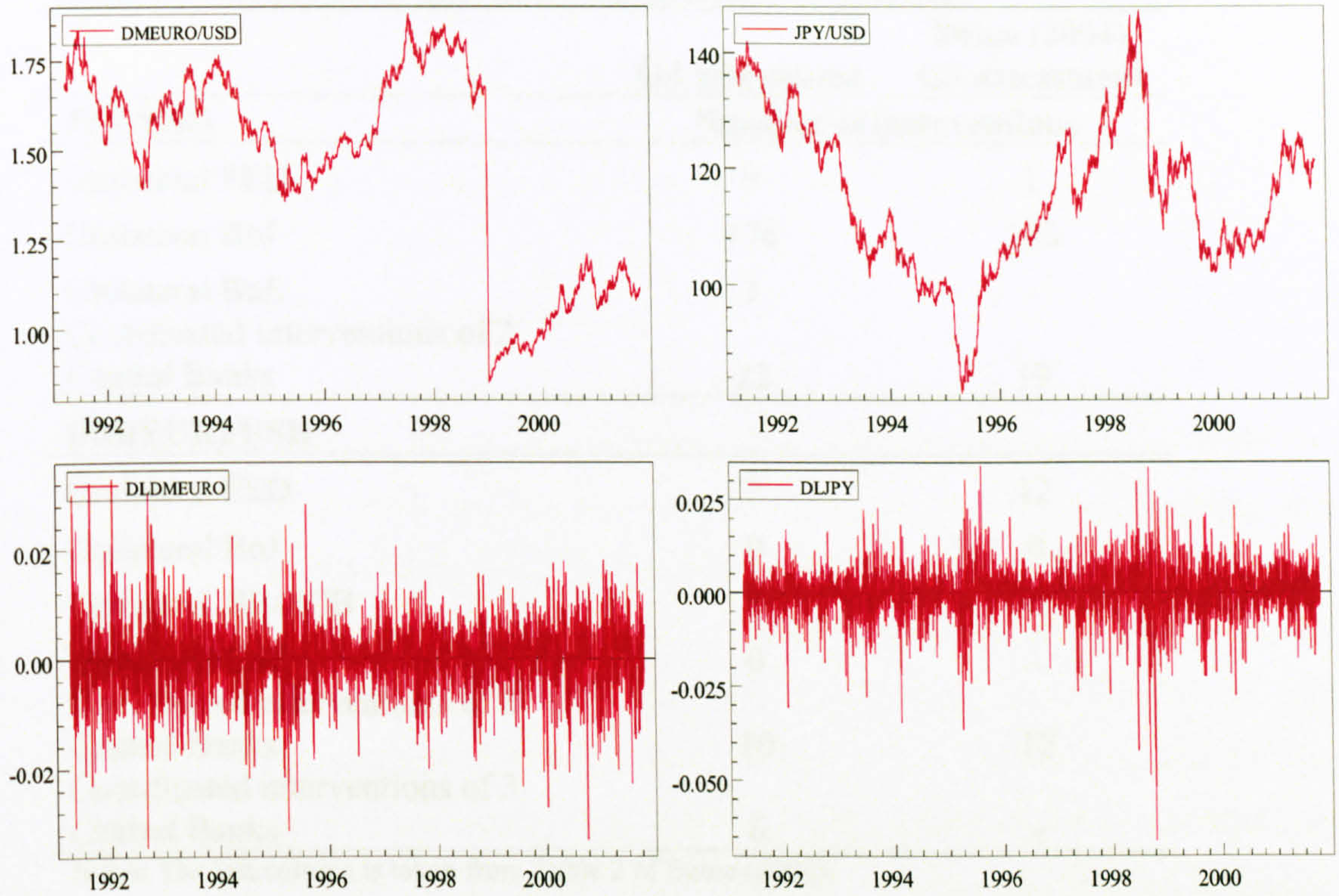
	DM (EUR)	JPY
Mean	0.000096	-0.000057
Standard Deviation	0.0068	0.0073
Skewness	-0.129 [0.01]**	-0.703 [0.00]**
Excess Kurtosis	2.119 [0.00]**	5.750 [0.00]**
Normality Test (JB)	507.1 [0.00]**	3898 [0.00]**
Q(10)	18.88 [0.04]*	20.75 [0.02]*
$Q^2(10)$	143.9 [0.00]**	288.6 [0.00]**
ARCH(5)	12.59 [0.00]**	27.49 [0.00]**

Notes: [] denote p-values. Q(10) and $Q^2(10)$ is the Ljung-Box statistic for serial correlation in raw series and squared returns, respectively. * 5% significant; ** 1% significant.

The Ljung-Box Q statistic tests the null hypothesis of no serial correlation and is calculated using up to 10 lags for both daily returns and the squared returns series. A significant Q statistic rejects the null hypothesis of no serial correlation in returns, while a significant Q statistic for the squared returns series rejects the null hypothesis of homoskedastic squared returns. Table 5.3 reports the Q statistics to be significant at 10 lags across each returns series at the 5% level of significance. This indicates that all exchange rates cannot be characterized as random walk processes. The Q statistic in the squared returns is significant for each returns series indicating strong non-linear dependencies. This is also supported by Engle's ARCH-LM statistic. The last row of Table 5.3 clearly shows the presence of ARCH effects in returns up to 5 lags. The null hypothesis of no ARCH effects is rejected for each series at the 1% level of significance.

Figure 5.1, plots the exchange rates and returns series for the DM(EUR) and the JPY, all against the USD. One can clearly observe the introduction of the Euro at the beginning of 1999. Focusing on the returns plots on the lower part of Figure 5.1, one can see the phenomenon of volatility clustering, that is, large (small) changes tend to be followed by large (small) changes of either sign.

Figure 5.1: Plots of Exchange Rates and Returns series



The findings of higher order serial correlation, non-normality, non-linear dependency and volatility clustering support the decision to model exchange rate volatility using a GARCH-type process under the student-t distribution.

Columns 1 and 2 in Table 5.4 present the number of days that CBIs were carried out under the G4 assessment and under Beine's (2004) G3 assessment (which serve as the base for our comparisons), respectively. As previously mentioned, and as can be seen from Table 5.4, the number of interventions for the variables in common among this research and Beine's is different due to the intervention definitions in this research.[77]

[77] By definition, in this research, the classification of CBIs differs. For instance, when the dummy variable that represents coordinated interventions conducted by 3 central banks in a currency and on a specific date is equal to 1, then instantaneously the dummy for coordinated interventions conducted by 2 central banks is equal to zero for that specific intervention and date. In addition, the dummy variables that represent the unilateral interventions for each of the 3 central banks are equal to zero on that date. For instance, consider the sell of the DM/USD on August 19th, 1991 by the BoJ, the BB and BoE. Under Beine's (2004) framework and the rest of the papers that examined CBIs under the G3 assessment (that is without the BoE assessment) the construction of the intervention dummy variables

Table 5.4: Official Central Bank Interventions: 02.04.1991-19.10.2001

	G4 assessment	Beine (2004) G3 assessment
JPY/USD	**Number of interventions**	
Unilateral FED	0	1
Unilateral BoJ	176	180
Unilateral BoE	1	-
Coordinated interventions of 2 Central Banks	22	19
DM(EUR)/USD		
Unilateral FED	7	12
Unilateral BoJ	0	0
Unilateral BB/ECB	5	6
Unilateral BoE	0	-
Coordinated interventions of 2 Central Banks	10	12
Coordinated interventions of 3 Central Banks	6	-

Notes: The last column is taken from Table 2 of Beine (2004).

Among the G4 Central Banks, the Bank of Japan (BoJ) was by far the most active, as it intervened 176 times unilaterally in the JPY/USD market. The FED has conducted its interventions unilaterally only in the DM(EUR)/USD market. In addition, the FED relied solely on coordinated interventions with the BoJ in the JPY/USD market, whereas in the DM(EUR)/USD market it intervened with the BoJ, the BB/ECB and/or the BoE since 1995. The Bundesbank (BB) (or the European Central Bank, ECB, since 1999) has deployed its interventions solely in the DM(EUR)/USD market. A very interesting feature of Table 5.4 is the nature of the Bank of England's (BoE) interventions. The BoE has intervened several times in coordination with at least one another central bank in both markets, and unilaterally once in the JPY/USD market. Moreover, it has intervened six times in coordination with another two Central Banks in the DM(EUR)/USD as shown in the last row of column 1 in Table

for that date implies that these dummies are equal to zero for unilateral interventions by the BoJ and the BB, and equal to 1 for coordinated interventions of 2 central banks. In my classification, the dummy variables for unilateral intervention by the BoJ, the BB, the BoE and coordinated interventions of 2 central banks are equal to zero. However, the dummy variable for coordinated intervention of 3 central banks in this research equals to 1. That is why in this classification there are fewer interventions in the case of unilateral and coordinated interventions by 2 central banks.

2. The availability of official intervention data for the BoE motivates the examination of how the impact of CBIs on exchange returns, volatility and correlation changes when the BoE is also taken into account.

The following section, presents the results of the DCC model performance.

5.5.2 The DCC model performance

Table 5.5 presents the results of the DCC model performance described in equation (2.23). The DCC model seems to perform very well in terms of capturing the DM(EUR) /USD and the JPY/USD exchange rate dynamics: (1) Both exchange returns exhibit heteroskedasticity, based on the significant estimated coefficients of the individual GARCH models. (2) The conditional correlations of the DM(EUR)/USD and the JPY/USD returns are highly persistent as shown by the significant parameter estimates of the DCC GARCH model. (3) The Li and McLeod (1981) test (which is a multivariate version of the Box-Pierce/Ljung-Box portmanteau test statistic for serial correlation) cannot reject the null hypothesis of no serial correlation on both standardized and squared standardized residuals, up to 20 lags. (4) The DCC model indicates that the correlations between these two returns are indeed time-varying. This can also be clearly seen in Figure 5.2, which plots the dynamic conditional correlation of the estimated DCC model in Table 5.5. The correlations during April 2, 1991 to October 19, 2001 vary between -0.05 to 0.8. Beginning from 1991, correlations between those two markets gradually declined till 1994, then there was an increasing trend till the mid-1995 followed by a declining trend till the end of 2000 when they became negative. Since the beginning of 2001, correlations varied around -0.05 to 0.2.

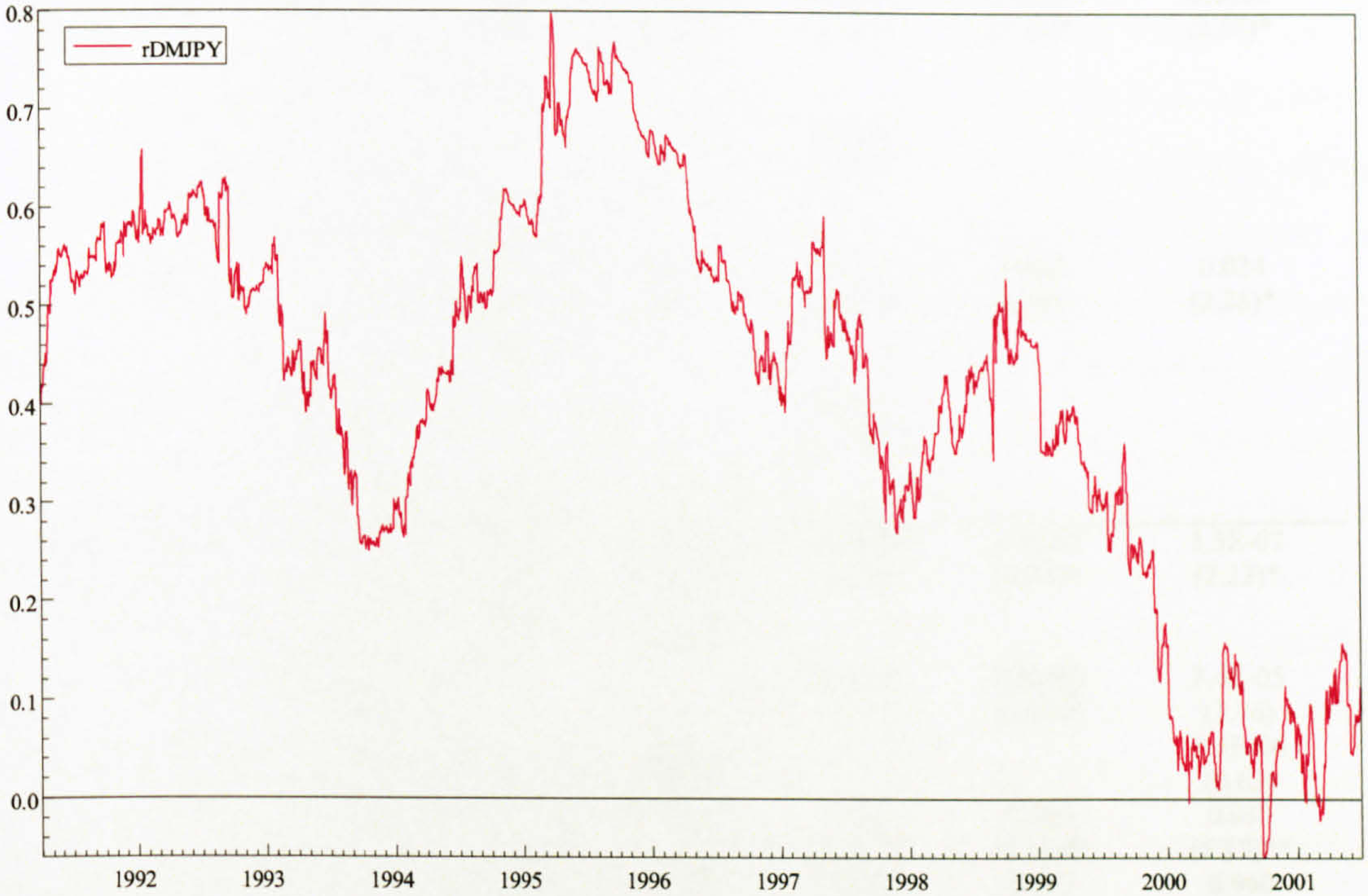
Table 5.5: DCC Model of DM(EUR) and JPY returns

	Dependent Var.	Explanatory Var.	(a)
Conditional Mean	DM(EUR)	Constant	0.000 (1.99)*
	JPY	Constant	0.024 (2.41)*
Conditional Var.	DM(EUR)	Constant	0.000 (2.10)*
		a DM	0.035 (5.74)**
		b DM	0.959 (131)**
	JPY	Constant	0.004 (2.70)**
		a JPY	0.042 (6.73)**
		b JPY	0.946 (135)**
		DCC a	0.013 (261)**
		DCC b	0.985 (967)**
		df	5.77 (13.2)**
		Log Lik.	7454.6
Standardized Residuals		Q(20)	79.96 [0.45]
Based Tests		Qsq(20)	87.44 [0.20]

Note: t-statistics and p-values in parenthesis and square brackets, respectively. * and ** denote 5% and 1% significance, respectively.

Having evaluated the good performance of the DCC model for the DM(EUR)/USD and JPY/USD exchange returns dynamics, the results of the DCC, extended with exogenous variables to incorporate the impact of both unilateral and coordinated officially announced interventions will be presented in the following sections.

Figure 5.2: Dynamic Conditional Correlations of the DM(EUR)/USD and the JPY/USD Returns



5.5.3 The impact of Coordinated Interventions

The analysis begins with the impact of coordinated interventions on exchange rate returns, variances and correlations under the G4 assessment. These results are presented in Table 5.6. Columns (a) and (b), (c) and (d), and (e) present the results for coordinated interventions of 2 central banks in the DM(EUR)/USD and the JPY/USD markets, of 3 central banks in the DM(EUR)/USD market, and for 3 central banks in the DM(EUR)/USD market together with the coordinated interventions of 2 central banks in the JPY/USD market, respectively.

Table 5.6: Coordinated CBI – Signalling Channel Analysis of DM(EUR) and JPY

	Dep. Var.	Explan. Variab.	(a)	(b)	(c)	(d)	(e)
Cond. Mean	DM	Constant	0.0002 (2.30)*	0.0002 (2.30)*	0.0002 (2.12)*	0.0002 (2.13)*	0.0002 (2.07)*
		dCoDM	0.002 (0.49)				
		dCoDM3			0.006 (1.62)		
		dCoJPY	0.00003 (0.02)				
	JPY	Constant	0.023 (2.33)*	0.023 (2.24)*	0.025 (2.51)*	0.025 (2.36)*	0.024 (2.28)*
		dCoDM	0.186 (0.77)				
		dCoDM3			0.119 (0.64)		
		dCoJPY	-0.002 (-0.01)				
Cond. Var.	DM	Constant	3.4E-07 (2.26)*	3.4E-07 (2.09)*	3.2E-07 (2.29)*	3.3E-07 (2.45)*	3.3E-07 (2.23)*
		δCoDM	7.2E-06 (0.90)	7.4E-06 (0.88)			
		δCoDM3			2.1E-05 (1.57)	0.00002 (2.14)*	2.4E-05 (1.76)
		δCoJPY	-3.3E-07 (-0.09)	-2.1E-07 (-0.06)			2.3E-06 (0.63)
		a DM	0.035 (5.78)**	0.035 (5.72)**	0.033 (5.78)**	0.033 (5.17)**	0.033 (5.19)**
		b DM	0.959 (135)**	0.959 (130)**	0.961 (140)**	0.961 (133)**	0.960 (126)**
	JPY	Constant	0.004 (2.34)*	0.004 (2.49)*	0.004 (2.34)*	0.004 (2.49)*	0.004 (2.25)*
		δCoDM	-0.069 (-3.05)**	-0.074 (-1.73)			
		δCoDM3			0.012 (0.284)	0.018 (0.513)	0.023 (0.576)
		δCoJPY	0.108 (2.31)*	0.112 (2.37)*			0.095 (1.98)*
		a JPY	0.039 (5.66)**	0.040 (6.30)**	0.042 (6.30)**	0.042 (6.08)**	0.041 (6.19)**
		b JPY	0.952 (112)**	0.952 (126)**	0.951 (121)**	0.951 (123)**	0.950 (115)**
		DCC a	0.019 (4.99)**	0.019 (4.93)**	0.018 (4.91)**	0.018 (4.91)**	0.019 (5.01)**
		DCC b	0.979 (229)**	0.979 (227)**	0.980 (233)**	0.980 (232)**	0.980 (225)**
		df	5.847 (14.06)**	5.847 (13.29)**	5.854 (12.85)**	5.877 (13.29)**	5.960 (13.36)**
		Log Lik.	7461.2	7460.6	7460.1	7458.9	7461.6
Standardized Residuals Based Tests							
		Q(20)	78.62 [0.49]	78.73 [0.49]	77.76 [0.52]	76.26 [0.57]	75.75 [0.58]
		Qsq(20)	87.28 [0.20]	86.35 [0.22]	93.55 [0.10]	97.12 [0.06]	92.56 [0.11]

Note: Parentheses and brackets are the t-statistics and p-values, respectively. * and ** denote 5% and 1% significance, respectively. See Table 5.2 for definitions of the exogenous (dummy) variables.

When coordinated interventions are conducted by only 2 central banks in the DM(EUR)/USD and the JPY/USD markets, they have a significant impact only on the JPY volatility. However, no significant impact on exchange returns is evident. That is, coordinated interventions do not affect the exchange rate levels. This is in line with the empirical literature that coordinated interventions do not affect exchange rates (Beine, 2004 and references therein). These results are presented in columns (a) and (b) on Table 5.6. Under specification (a), the dummy variables for coordinated CBIs that enter in both the mean and variance equations, attract significant coefficients only in the latter equation. Specifically, coordinated interventions in the DM(EUR)/USD market significantly decrease the JPY volatility whereas, coordinated interventions in the JPY/USD market significantly increase the JPY volatility. In addition, coordinated CBIs in the DM(EUR)/USD and the JPY/USD markets do not have a significant impact on the DM(EURO) volatility. After dropping the dummy variables for the coordinated CBIs on returns, as they were found insignificant, the new specification under column (b) reports reduced impact of coordinated interventions on volatility. Now, coordinated CBIs in the DM(EUR)/USD markets do not significantly decrease the JPY volatility. The estimated parameter $\delta CoDM$ is now significantly negative only at the 10% level. The signs and significance of the rest of the parameter estimates remain similar to those under specification (a). That is, when exactly two central banks intervene in coordination they can significantly affect the volatility of returns, although sometimes in the correct direction. Under (a) and (b) specifications, the Li and McLeod (1981) test reports no evidence of serial correlation on both standardized and squared standardized residuals, up to 20 lags. These results under the G4 assessment are partly in line with the empirical literature on the G3 assessment that shows that coordinated interventions can significantly affect only volatility, but in a positive way (see Beine 2004; Beine et al., 2002; Bosner-Neal and Tanner, 1996 and references therein). We find instances that coordinated interventions of two central banks under the G4 assessment in the DM(EUR)/USD market to significantly increase JPY volatility.

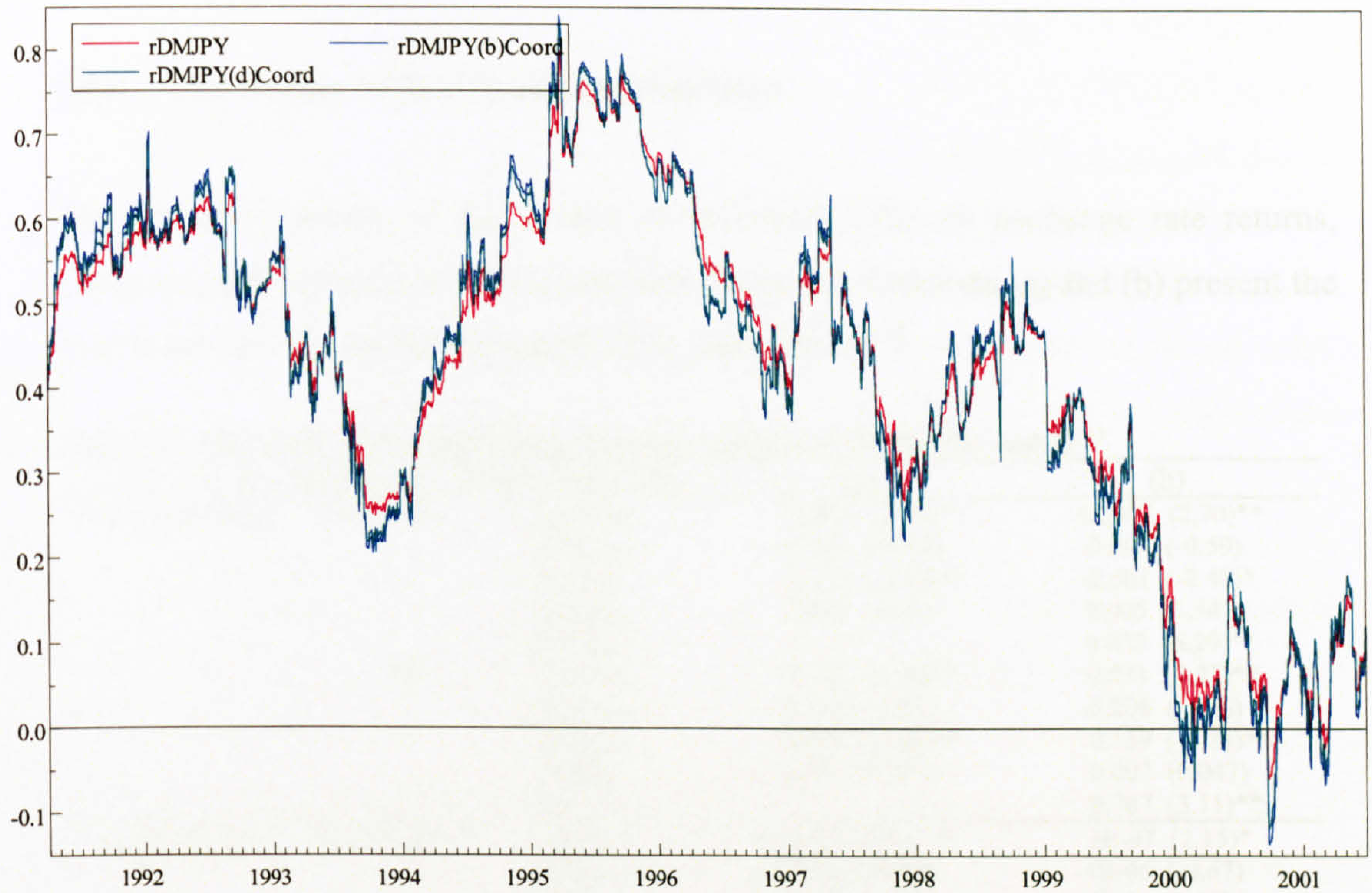
In addition, the existing literature suggests that coordinated interventions have a more significant impact on volatility as opposed to unilateral ones (Beine, 2004; Fatum 2002; Humpage, 1999; Catte et al.1992). The results recorded in the next section, which assesses the impact of unilateral interventions under the DCC model, are in line with this finding. However, there is no paper, to my knowledge, that examines the impact of a greater number of two central banks intervening in coordination. If the previous argument is correct, then coordinated interventions of three central banks should increase even more the impact on exchange rate volatility compared to interventions of one or two central banks.

According to Table 5.4, the Bank of England (BoE) intervened six times in our investigation sample in coordination with another two central banks in the DM(EUR)/USD market. Thus, it would be of interest to see how our results change when three central banks coordinate their interventions. Besides, apart from the FED, the BoJ and the BB/ECB, the BoE was among the G6 that signed the Louvre Accord in 1987 (and which officially announces its interventions). As previously mentioned, the aim of the Louvre Accord was to stabilize the turbulent international currency markets. Hence, the post-Louvre period performance of the impact of a greater number of central banks intervening in coordination on exchange rate dynamics is of great interest.

The results for coordinated interventions of three Central Banks in the DM/USD market are presented under columns (c) and (d) on Table 5.6. Since there were not any coordinated interventions conducted by three central banks in the JPY/USD market, we can only examine the impact of coordinated interventions of three central banks in the DM(EUR)/USD market. Under column (c) the dummies representing the coordinated interventions of three Central Banks in the DM(EUR)/USD market enter both in conditional mean and variance equations, whereas under column (d) they enter only in the conditional variance equation.

It is found, under column (c), that the impact of coordinated CBIs of three central banks is dramatically different to the impact of coordinated interventions of two central banks. Specifically, coordinated interventions of three Central Banks in the DM/USD market do not have a significant impact on exchange returns and volatilities. However, when the insignificant impact of three Central Banks in the DM/USD in the conditional mean equation has been removed, the results show that coordinated interventions of three central banks significantly increased the DM(EURO) volatility. The robustness of these results is strengthened even when coordination of three Central Banks in the DM(EUR)/USD market are modelled together with the coordination of two Central Banks in the JPY/USD market. These results are shown in the last column (e) of Table 5.6. That is, a greater number of Banks engaging in coordinated interventions does not necessarily increase the effectiveness on volatility. On the contrary, when more than two Central Banks intervene in coordination they can only increase exchange rate volatility. The DCC model under the various specifications in Table 5.6 do not suffer from serial correlation as the Li and McLeod (1981) test reports no evidence of serial correlation on both standardized and squared standardized residuals up to 20 lags. Figure 5.3, which plots the dynamic conditional correlations of the DCC model without exogenous variables (specification in Table 5.5), together with the ones from the DCC with exogenous variables in the estimations (b) and (d) of Table 5.6, shows that the magnitude of correlations is slightly intensified due to coordinated interventions.

Figure 5.3: Dynamic Conditional Correlations of the DM(EUR)/USD and the JPY/USD Returns, including the ones from estimations (b) and (d) from Table 5.6



These results could be of great importance for central banks' decisions on conducting coordinated interventions in a currency. According to these results if central banks wish to decrease exchange rate volatility, then it is preferable to intervene in coordination with only one another central bank and not in coordination with another two central banks; if it intervenes with another two central banks it will only increase volatility. If a central bank wishes to affect its exchange returns it should not intervene in coordination. Intervening in coordination with at least another central bank will have no impact on exchange returns, as the vast majority of the literature suggests (see Beine et al., 2009; Beine, 2004; Beine et al., 2002 and references therein). However, these results are specific to our G4 assessment of official CBIs and evidently further research is needed to determine whether the more coordination between central banks the less effective the outcome on exchange returns and volatility is.

5.5.4 The impact of Unilateral Interventions

The empirical results of the impact of unilateral CBIs on exchange rate returns, variances and correlations are presented in Table 5.7. Columns (a) and (b) present the results for the G3 and G4 unilateral CBIs, respectively.[78]

Table 5.7: Unilateral CBI – Signalling Channel Analysis of DM(EUR) and JPY

Dependent Var.		Explanatory Var.	(a)	(b)
Conditional Mean	DM(EUR)	Constant	0.0003 (2.96)**	0.0002 (2.70)**
		$dFED_{DM}$	-0.001 (-0.56)	-0.001 (-0.59)
		$dBOJ_{JPY}$	-0.001 (-2.88)**	-0.001 (-2.48)*
		dBB_{DM}	0.005 (1.79)	0.005 (1.54)
		$dBOE_{JPY}$		0.032 (6.29)**
	JPY	Constant	0.031 (3.39)**	0.031 (3.27)**
		$dFED_{DM}$	-0.209 (-1.01)	-0.208 (-1.28)
		$dBOJ_{JPY}$	-0.139 (-3.91)**	-0.139 (-3.23)**
		dBB_{DM}	0.006 (0.047)	0.007 (0.047)
		$dBOE_{JPY}$		0.767 (3.11)**
Conditional Var.	DM(EUR)	Constant	0.00001 (40.6)**	3E-07 (2.15)*
		δFED_{DM}	-4E-06 (-0.77)	-4E-06 (-0.67)
		δBOJ_{JPY}	1E-06 (2.15)*	1E-06 (1.60)
		δBB_{DM}	1E-06 (0.14)	-1E-06 (-0.11)
		δBOE_{JPY}		-2.2E-06 (-0.08)
		a DM	0.034 (8.16)**	0.034 (5.70)**
		b DM	0.958 (252)**	0.959 (129.)**
	JPY	Constant	0.004 (2.69)*	0.004 (2.24)*
		δFED_{DM}	-0.002 (-0.04)	-0.003 (-0.05)
		δBOJ_{JPY}	0.002 (0.37)	0.002 (0.28)
		δBB_{DM}	-0.085 (-4.76)**	-0.085 (-3.58)**
		δBOE_{JPY}		-0.028 (-0.34)
		a JPY	0.039 (6.71)**	0.039 (5.93)**
		b JPY	0.954 (136)**	0.953 (117)**
		DCC a	0.019 (7.21)**	0.018 (4.58)**
		DCC b	0.979 (327)**	0.979 (213)**
		df	5.741 (14.1)**	5.759 (22.9)**
		Log Lik.	7467.5	7474.8
Standardized Residuals		Q(20)	78.49 [0.50]	78.28 [0.50]
Based Tests		Qsq(20)	84.89 [0.25]	86.36 [0.22]

Note: Parenthesis and brackets are the t-statistics and p-values, respectively. * and ** denote 5% and 1% significance, respectively. See Table 5.2 for definitions of the exogenous (dummy) variables.

[78] The dummy variables used in the evaluation of the impact of the G3 and G4 CBIs are based on those in column 1 of Table 5.4. That is, these dummies are based on those under the G4 assessment. In the following section which involves robustness analysis we present the results of the impact of unilateral interventions according to the dummies used in Beine's (2004) paper under the G3 assessment.

Under the G3 assessment, the results of the DCC model extended with exogenous variables in columns (a) in Table 5.7 provide evidence that unilateral interventions have little impact on both mean returns and variances. Only CBIs conducted by the BoJ in the JPY/USD market significantly affect both the JPY and DM(EUR) returns. Specifically, unilateral interventions of the BoJ cause a depreciation of the US dollar. Unilateral interventions of the FED and the BB do not have a significant impact on the two returns. These results partially contradict the empirical literature that denotes unilateral interventions have no impact on returns (see among others, Beine 2004; Beine et al., 2002; Bosner-Neal and Tanner, 1996) as the BoJ interventions in the JPY/USD market significantly affects the DM(EUR) and JPY returns.

Another interesting feature of column (a) on Table 5.7 is that unilateral interventions of the BoJ and the BB(ECB), even though increase their own exchange rate volatility, albeit insignificantly, have a significantly negative and positive externality impact on the JPY/USD and the DM(EUR)/USD markets, respectively.[79] That is, unilateral interventions of the BoJ in the JPY/USD market significantly increase the DM(EUR) volatility and unilateral interventions of the BB(ECB) in the DM(EUR)/USD market significantly reduce the JPY volatility. The unilateral intervention impact of the FED on volatility of both returns is correctly negatively signed but insignificant. These results are in line with the empirical literature that indicates that unilateral interventions have a mixed effect on volatility (see Beine 2004; Beine et al., 2002; Bosner-Neal and Tanner, 1996).

Including the BoE's unilateral interventions under our G4 assessment, the results seem to be clearer. Column (b) on Table 5.7, which presents these results, shows that, there is no evidence that any of the unilateral official central bank interventions significantly increases volatility, which is in line with Central Banks' intentions. That is, the impact of the BoJ intervention in the JPY/USD market on the DM(EURO) volatility now becomes insignificantly positive and the BB(ECB) intervention in the DM(EUR)/USD market on the DM(EURO) volatility is now correctly negatively signed, although insignificant. The impact of interventions of the BoE in the

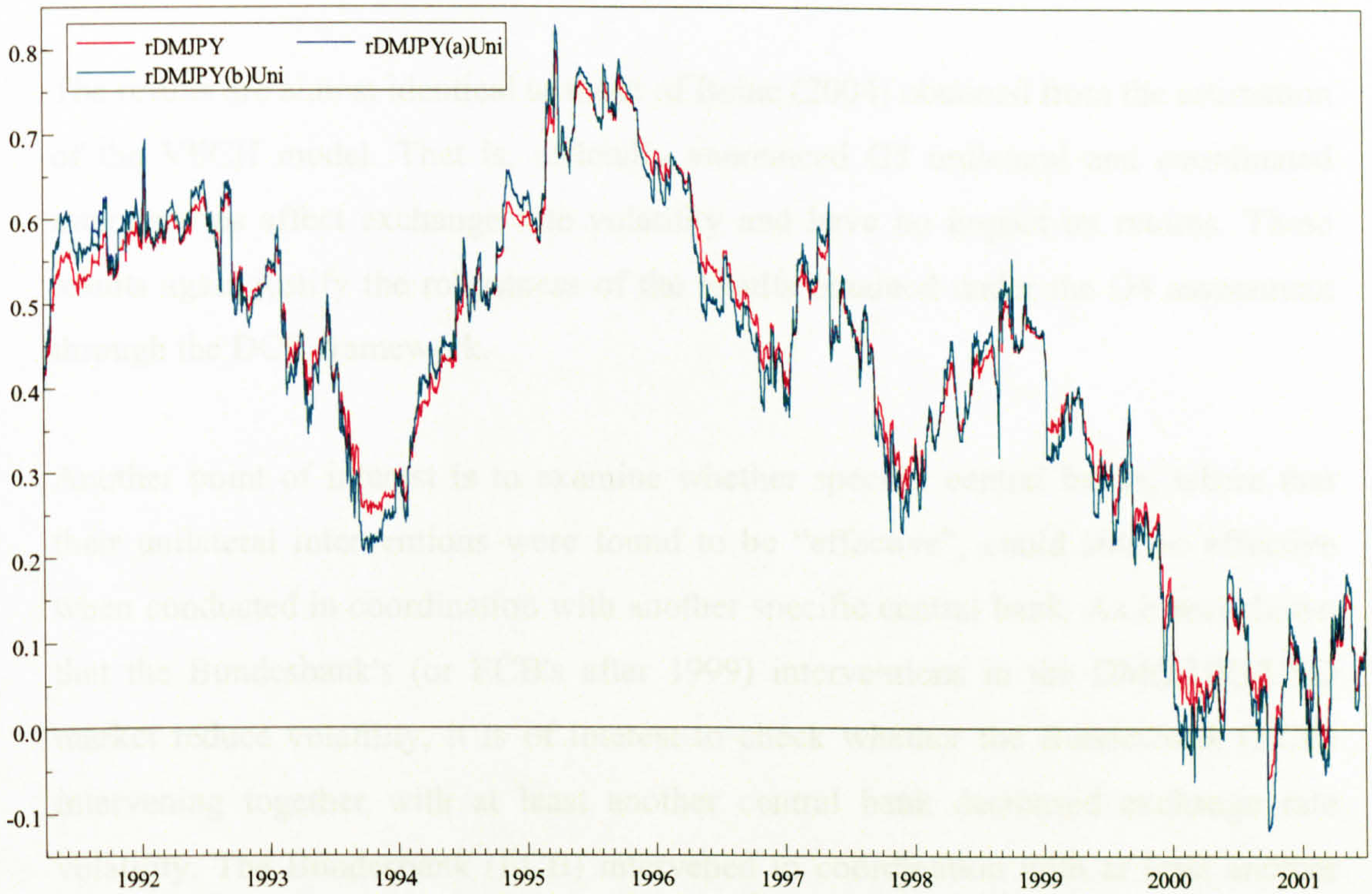
[79] See Table 5.2 for full definition of exogenous (dummy) variables.

JPY/USD market on both returns' volatility is also correctly signed, although insignificant.

In addition to the previous results, under column (a) on Table 5.7, of the impact of the G3 CBIs on exchange returns (with the use of dummies under the G4 assessment), unilateral interventions of the BoE significantly affect both DM/USD and JPY/USD returns, under column (b) on Table 5.7. That is, taking into account unilateral interventions of the BoE it is found that unilateral interventions have a significant impact on returns and reduce volatility. These results contradict the empirical literature that finds that unilateral interventions have no impact on returns (see Beine 2004; Beine et al., 2002; Bosner-Neal and Tanner, 1996). Morever, the empirical literature, in most of cases, suggests that unilateral interventions significantly increase volatility, indicating that the intervention should be considered ineffective (see Beine 2004 and references therein). One major point of central banks' decisions to intervene is to decrease rather than increase exchange rate volatility. In this research we provide evidence that unilateral interventions are effective (or to be more precise, are productive), as their impact on mean returns is significant, and on volatility is correctly negatively signed and significant in the case of the BB(ECB) interventions in the DM(EUR)/USD market on the JPY volatility. No evidence that any of the unilateral interventions significantly increases volatility is reported, which is in line with Central Banks' intentions.

The conditional correlations of the DM(EUR) and JPY returns are highly persistent as shown by the significant estimated a and b parameters of these two DCC models on Table 5.6 indicating that correlation between these two returns are indeed time varying and driven by unilateral CBIs. Figure 5.4, which plots the dynamic conditional correlations of the DCC without exogenous variables (specification shown in Table 5.5), together with the ones from the DCC with exogenous variables from (a) and (b) in Table 5.7 shows that unilateral interventions increase the magnitude of correlations.

Figure 5.4: Dynamic Conditional Correlations of the DM(EUR)/USD and the JPY/USD Returns, including the ones from specifications (a) and (b) from Table 5.7



Last but not least, the DCC model is well specified as the Li and McLeod (1981) test reports no evidence of serial correlation on both standardized and squared standardized residuals, as it cannot reject the null hypothesis of no serial correlation on both standardized and squared standardized residuals, up to 20 lags.

5.5.5 Robustness Analysis

Having found evidence that unilateral interventions are more successful as opposed to coordinated interventions of 2 or 3 central banks under the G4 assessment, since the former affect returns and in minor cases reduce volatility, in this section several robustness checks are being performed.

In order to check the robustness of the results of the impact of the officially announced G4 unilateral and coordinated CBIs, dummy variables representing the impact of officially announced G3 CBIs were constructed. That is, we omitted the BoE's interventions, and replicated Beine's (2004) analysis by using the same dates and variables but under the DCC framework.[80] These results are presented in columns (a) and (b) on Table 5.8.

The results are almost identical to those of Beine (2004) obtained from the estimation of the VECH model. That is, officially announced G3 unilateral and coordinated interventions affect exchange rate volatility and have no impact on returns. These results again justify the robustness of the results obtained under the G4 assessment through the DCC framework.

Another point of interest is to examine whether specific central banks, where that their unilateral interventions were found to be "effective", could still be effective when conducted in coordination with another specific central bank. As it was shown that the Bundesbank's (or ECB's after 1999) interventions in the DM(EUR)/USD market reduce volatility, it is of interest to check whether the Bundesbank (ECB) intervening together with at least another central bank decreased exchange rate volatility. The Bundesbank (ECB) intervened in coordination with at least another central bank in the DM(EUR)/USD market 15 times. This specific choice of central banks intervening in coordination might shed light on the counterproductive evidence of coordinated interventions.

[80] The dummy variables used for the G3 assessment were constructed based on the number of CBIs shown in the last column of Table 5.2.

Table 5.8: Replication of Beine (2004) estimation under the G3 impact through the DCC model

		Coordinated interventions		Unilateral Interventions	
Dependent Var.	Explanatory Var.	(a)	(b)	(c)	(d)
Conditional Mean DM(EUR)	Constant		0.0002 (2.21)*		0.0002 (2.35)*
	dCoDM	0.0035 (1.44)			
	dCoJPY	-0.0001 (-0.07)			
	$dFED_{DM}$			0.0003 (0.17)	
	dBB_{DM}			0.0050 (1.76)	
JPY	Constant		0.0236 (2.48)*		0.0239 (2.49)*
	dCoDM	0.1451 (0.90)			
	dCoJPY	0.0333 (0.17)			
	$dBOJ_{JPY}$			-0.0655 (-1.73)	
	$dBoJ_{DM}$			0.0280 (0.00)	
Conditional Variance DM(EUR)	Constant	4E-07 (2.01)*	4E-07 (2.39)*	4E-07 (2.48)*	4E-07 (41.84)**
	δCoDM	0.00001 (1.82)	2E-05 (2.06)*		
	δCoJPY	-1E-06 (-0.18)	-1E-06 (-0.15)		
	δFED_{DM}			-4E-06 (-0.82)	-4E-06 (-0.82)
	δBOJ_{JPY}			1E-06 (1.69)	1E-06 (2.14)*
	δBB_{DM}			1E-06 (0.15)	3E-06 (0.27)
	a DM	0.0334 (5.37)**	0.0330 (5.29)**	0.0344 (6.10)**	0.0341 (26.79)**
	b DM	0.9588 (116.4)**	0.9592 (127)**	0.9579 (137)**	0.9585 (866)**
JPY	Constant	0.0042 (2.35)*	0.0042 (2.51)*	0.0036 (2.91)**	0.0037 (8.28)**
	δCoDM	-0.0123 (-0.4949)	-0.0090 (-0.32)		
	δCoJPY	0.1009 (1.99)*	0.1021 (1.99)*		
	δFED_{DM}			-0.0019 (-0.04)	-0.0032 (-0.07)
	δBOJ_{JPY}			0.0022 (0.36)	0.0022 (0.45)
	δBB_{DM}			-0.0825 (-3.87)**	-0.0842 (-3.86)**
	a JPY	0.0404 (5.92)**	0.0406 (5.76)**	0.0392 (7.14)**	0.0400 (30.63)**
	b JPY	0.9496 (112)**	0.9495 (108)**	0.9539 (148)**	0.9528 (831)**
	DCC a	0.0190 (4.46)**	0.0196 (4.90)**	0.0183 (4.84)**	0.0184 (19.2)**
	DCC b	0.9791 (209)**	0.9784 (216)**	0.9795 (227.7)**	0.9793 (874)**
	df	6.0272 (12.8)**	5.9500 (13.1)**	5.8488 (14.6)**	5.7838 (17.7)**
	Log Lik.	7460.2167	7462.4958	7460.6221	7461.1064
Standardized Residuals	Q(20)	77.8420 [0.52]	76.0561 [0.57]	78.6535 [0.49]	79.4615 [0.46]
Based Tests	Qsq(20)	88.8644 [0.17]	92.9871 [0.10]	83.1936 [0.29]	86.4296 [0.22]

Note: Parenthesis and brackets are the t-statistics and p-values, respectively. * and ** denote 5% and 1% significance, respectively. See Table 5.2 for definitions of the exogenous (dummy) variables.

Table 5.9 presents the empirical results for coordinated CBIs wherein the BB(ECB) is involved.

Table 5.9: Coordinated CBIs of BB(ECB) with at least another CB

	Dependent Var.	Explanatory Var.	Coordinated interventions
Conditional Mean	DM(EUR)	Constant	0.0002 (2.25)*
		dCoDM	0.00339 (1.53)
	JPY	Constant	0.0241 (2.55)*
		dCoDM	0.1340 (1.08)
Conditional Variance	DM(EUR)	Constant	3.62E-07 (2.64)*
		δCoDM	0.00001 (1.80)
		a DM	0.0330 (5.57)**
		b DM	0.9593 (139)**
	JPY	Constant	0.0038 (2.53)*
		δCoDM	-0.0052 (-0.19)
		a JPY	0.0427 (6.57)**
		b JPY	0.9501 (120)**
		DCC a	0.0185 (5.22)**
		DCC b	0.9794 (242)**
		df	5.8490 (13.9)**
		Log Lik.	7459.8
Standardized Residuals		Q(20)	78.32 [0.50]
Based Tests		Qsq(20)	93.82 [0.09]

Note: Parenthesis and brackets are the t-statistics and p-values, respectively.
* and ** denote 5% and 1% significance, respectively.

As can be clearly seen, coordinated interventions involving the BB(ECB) neither significantly affect exchange returns nor volatility. Hence, even when a central bank, whose unilateral interventions are found to be successful, intervenes in coordination with another central bank, its impact on exchange returns and volatility diminishes.[81] This is in line with the empirical literature and which strengthens our previous results that coordinated CBIs are counterproductive. Clearly, further investigation needs to be done in order to find out why interventions are so counterproductive when conducted in coordination.

[81] Other combinations of coordinated CBIs were investigated and the results were of the same qualitative nature. These results are not presented but can be obtained from the author upon request.

Another interesting feature is to assess whether there exist any asymmetries, that is to investigate whether the purchase of US dollars has a different impact than the sale of US dollars in the foreign exchange markets. One would expect that the purchase and the sale of US dollars to be associated with an appreciation and depreciation of the USD, respectively. In addition, if successful, CBIs should significantly decrease volatility.

In order to assess whether any asymmetries exist whenever a CBI takes place, two sets of dummy variables were constructed. The one set of dummies involves dummies that are equal to one when a central bank purchases US dollars and zero otherwise, and the other set involves dummies that are equal to one when a central bank sells the US dollars and zero otherwise. The specific amounts of purchases and sales of US dollars by each central bank are presented in Table 5.10. The BoJ again is once more the most active central bank with 149 purchases and 27 sales of US dollars during our data sample.

Table 5.10: Purchase and sale of USD, 02.04.1991-19.10.2001

	Purchase of USD	Sale of USD
JPY/USD	**Number of interventions**	
Unilateral FED	0	0
Unilateral BoJ	149	27
Unilateral BoE	0	1
Coordinated interventions of 2 Central Banks	18	4
DM(EUR)/USD		
Unilateral FED	6	2
Unilateral BoJ	0	0
Unilateral BB/ECB	0	0
Unilateral BoE	0	0
Coordinated interventions of 2 Central Banks	6	4
Coordinated interventions of 3 Central Banks	5	2

The estimation results for the purchase and sale of USD are presented in Table 5.11 and 5.12, respectively. According to Table 5.11, coordinated purchases of US dollars do not significantly affect returns. Even though they are correctly positively signed (appreciation of the US dollar) when coordinated intervention is conducted on the DM(EUR)/USD market, they are found to be insignificant. In addition, coordinated purchases of USD in general increase volatility, the greater the number of central banks involved. In the case of unilateral CBIs, purchases of USD are associated with a significant appreciation of the US dollar and decreased volatility when interventions are conducted by the BoJ.[82] That is, unilateral purchases of US dollars are found to be more productive than coordinated ones in terms of their effect on returns, as they are associated with the intended appreciation of the US dollar.

[82] Unilateral FED interventions are also found to cause an appreciation of the US dollar however, the estimated parameters are insignificant.

Table 5.11: The impact of purchase of USD

			Coordinated interventions		Unilateral Interventions
Dependent Var.		Explanatory Var.	(a)	(b)	(c)
Conditional Mean	DM(EUR)	Constant	0.0002 (2.33)*	0.0002 (2.16)*	0.0003 (2.78)**
		dCoDM	0.010 (0.41)		
		dCoDM3		0.002 (0.50)	
		dCoJPY	-0.001 (-0.64)		
		$dFED_{DM}$			0.003 (1.53)
		$dBOJ_{JPY}$			0.001 (2.76)**
	JPY	Constant	0.023 (2.51)*	0.025 (2.47)*	0.031 (3.19)**
		dCoDM	0.003 (0.24)		
		dCoDM3		0.024 (0.12)	
		dCoJPY	-0.091 (-0.36)		
		$dFED_{DM}$			0.295 (1.91)
		$dBOJ_{JPY}$			0.174 (3.92)**
Conditional Var.	DM(EUR)	Constant	0.000 (2.16)*	3.00E-07 (2.33)*	3.00E-07 (40.1)**
		$\delta CoDM$	0.000 (0.40)		
		$\delta CoDM3$		0.00002 (2.82)**	
		$\delta CoJPY$	0.000 (0.19)		
		δFED_{DM}			-1.23E-07 (-0.65)
		δBOJ_{JPY}			1.00E-06 (1.99)*
		a DM	0.037 (5.75)**	0.032 (5.73)**	0.036 (25.9)**
		b DM	0.957 (124)**	0.962 (144)**	0.957 (792)**
	JPY	Constant	0.003 (2.37)*	0.004 (2.43)*	0.003 (7.06)**
		$\delta CoDM$	0.0265 (0.16)		
		$\delta CoDM3$		0.026 (2.65)**	
		$\delta CoJPY$	0.091 (1.22)		
		δFED_{DM}			-0.016 (-0.34)
		δBOJ_{JPY}			0.010 (2.71)**
		a JPY	0.041 (5.66)**	0.042 (6.60)**	0.040 (27.8)**
		b JPY	0.951 (115)**	0.951 (127)**	0.952 (742)**
		DCC a	0.018 (5.12)**	0.018 (4.55)**	0.019 (17.0)**
		DCC b	0.979 (243)**	0.980 (222)**	0.978 (729)**
		df	5.822 (13.8)**	5.840 (14.4)**	5.710 (17.5)**
		Log Lik.	7462.1	7458.9	7463.5
Standardized Residuals		Q(20)	77.48 [0.53]	76.99 [0.54]	79.97 [0.45]
Based Tests		Qsq(20)	86.48 [0.21]	93.95 [0.09]	83.05 [0.30]

Note: Parenthesis and brackets are the t-statistics and p-values, respectively. * and ** denote 5% and 1% significance, respectively. See Table 5.2 for definitions of the exogenous (dummy) variables.

In the case of sales of US dollars the results remain almost the same. These results are presented in Table 5.12. Coordinated sales of USD conducted by two central banks do not significantly affect returns and can only significantly decrease volatility in the JPY/USD (when conducted on the DM(EUR)/USD market). However, when coordinated sales of USD are conducted by three central banks, they still do not have a significant impact on returns but significantly increase volatility. In the case of unilateral interventions the estimated parameters accounting for sales of USD are correctly associated with a depreciation of the US dollar (negatively signed), and are significant when conducted by the BoJ and BoE. In the case of the impact on unilateral sales of US dollars on exchange rate volatility, one can see that, each of the unilateral interventions is associated with decreased volatility (as the estimated parameters are negatively signed), but are significant only when conducted by the BoJ.

In conclusion, even when asymmetries are taken into account the results remain the same as those obtained from our main analysis, which strengthens our results. That is, the more coordination of central banks in the foreign exchange markets, the more counterproductive their impact on returns and volatility. Specifically, unilateral purchases and sales of US dollars affect returns in the intended direction and can significantly reduce exchange rate volatility only when conducted by the BoJ; however, coordinated interventions conducted by two central banks and, especially by three central banks, do not have the intended outcome on both returns and volatility.

Table 5.12: The impact of sale of USD

Dependent Var.	Explanat. Var.	Coordinated interventions (a)	(b)	Unilateral Interventions (c)	(d)
Conditional Mean	Constant	0.0002 (2.40)*	0.0002 (2.21)*	0.0002 (2.46)*	0.0002 (2.39)*
DM(EUR)	dCoDM	0.011 (1.47)			
	dCoDM3		0.018 (1.51)		
	dCoJPY	0.001 (0.39)			
	$dFED_{DM}$			-0.001 (-0.13)	-0.002 (-0.16)
	$dBOJ_{JPY}$			-0.001 (-0.81)	-0.001 (-1.97)*
	$dBOE_{JPY}$				-0.032 (-6.27)**
JPY	Constant	0.024 (2.64)**	0.024 (2.29)*	0.024 (2.56)*	0.024 (2.44)*
	dCoDM	0.594 (1.53)			
	dCoDM3		0.486 (1.27)		
	dCoJPY	0.335 (1.17)			
	$dFED_{DM}$			-0.405 (-0.91)	-0.412 (-0.96)
	$dBOJ_{JPY}$			-0.030 (-0.34)	-0.030 (-2.39)**
	$dBOE_{JPY}$				-0.774 (-3.43)**
Conditional Var.	Constant	4.00E-07 (2.49)*	3.00E-07 (2.17)*	3.00E-07 (2.35)*	3.00E-07 (2.23)*
DM(EUR)	δCoDM	8.00E-05 (0.58)			
	δCoDM3		1.00E-05 (2.56)**		
	δCoJPY	-1.00E-05 (-1.16)			
	δFED_{DM}			1.00E-05 (0.53)	1.00E-05 (0.45)
	δBOJ_{JPY}			-1.00E-07 (-0.08)	-1.00E-07 (-2.10)**
	δBOE_{JPY}				-1.00E-05 (-0.34)
	a DM	0.035 (5.86)**	0.034 (5.49)**	0.035 (6.14)**	0.035 (5.82)**
	b DM	0.959 (132)**	0.960 (122)**	0.959 (140)**	0.960 (133)**
	Constant	0.003 (3.23)**	0.004 (2.44)*	0.004 (2.97)**	0.004 (2.83)**
JPY					
	δCoDM	-0.110 (-3.11)**			
	δCoDM3		0.064 (1.879)*		
	δCoJPY	-0.035 (-0.55)			
	δFED_{DM}			-0.101 (-1.20)	-0.105 (-1.26)
	δBOJ_{JPY}			-0.020 (-2.56)*	-0.021 (-2.40)*
	δBOE_{JPY}				-0.099 (-1.39)
	a JPY	0.039 (7.57)**	0.041 (6.00)**	0.039 (6.78)**	0.039 (6.08)**
	b JPY	0.955 (182)**	0.951 (116)**	0.954 (141)**	0.953 (128)**
	DCC a	0.018 (4.71)**	0.011 (2962)**	0.018 (5.54)**	0.018 (4.45)**
	DCC b	0.980 (232)**	0.987 (1173)**	0.980 (264)**	0.980 (212)**
	df	5.789 (14.1)**	5.810 (13.7)**	5.773 (14.7)**	5.786 (13.8)**
	Log Lik.	7461.7	7454.1	7459.4	7467.1
Standardized	Q(20)	77.57 [0.52]	80.29 [0.44]	80.63 [0.43]	80.62 [0.43]
Residuals Based Tests	Qsq(20)	89.10 [0.16]	78.76 [0.42]	89.04 [0.16]	88.94 [0.17]

Note: Parenthesis and brackets are the t-statistics and p-values, respectively. * and ** denote 5% and 1% significance, respectively. See Table 5.2 for definitions of the exogenous (dummy) variables.

5.6 Conclusion

Two decades since the Plaza Agreement on September 22, 1985 and the Louvre Agreement/Accord on February 22, 1987, that were signed in order to induce a US dollar depreciation and promote stability in currency markets respectively, economists, policy makers and central bank analysts still do not have conclusive evidence of the impact of CBIs on exchange returns and volatility, especially in relation to coordinated CBIs. Most of the empirical literature suggests that CBIs conducted, either unilaterally or in coordination, do not affect exchange returns and have an opposite or ineffective outcome on volatility (among others see Beine, 2004; Beine et al., 2002; Fatum 2002; Humpage, 1999; Baillie and Osterberg, 1997; Bosner-Neal and Tanner, 1996; Catte et al., 1992). That is, there is an increase in volatility as opposed to the decrease which was the aim of the Louvre Accord.

In order to shed some light on the effectiveness of official CBIs, this chapter examined the signalling channel through which official CBIs, conducted unilaterally or in coordination with two and three central banks, could affect exchange returns, their volatility and correlations. A novel contribution of this study is the assessment of the impact of the G4 CBIs on exchange returns, volatility and correlations. Specifically, in addition to the G3 CBIs impact of the Federal Reserve (FED), Bank of Japan (BoJ) and the Bundesbank or European Central Bank (BB/ECB), after 1999, on the DM(EUR)/USD and the JPY/USD markets, that has been systematically examined in the literature, this paper provided contributory results on the G4 interventions by adding the Bank of England (BoE). This investigation was extended with the application of the DCC model of Engle (2002) that recently has used when modelling exchange returns dynamics because of its flexible structure and the specification of time-varying conditional correlations. This is another contribution of this paper, as the DCC has never been employed before to study the impact of CBIs on exchange rate dynamics. The DCC model performed very well in the various specifications and showed that CBIs intensify the DM(EUR)/USD and the JPY/USD dynamic conditional correlations.

Under the G4 assessment, it was found that official CBIs can significantly affect exchange returns only when these are conducted unilaterally. In the case of the impact of CBIs on volatility, it was found that unilateral interventions, in some cases, decrease volatility. However, coordinated interventions are more counterproductive the greater the number of central banks intervening in coordination.

Our results of the impact of the G4 CBIs under the DCC assessment are strengthened by various robustness checks, such as re-examining the established G3 assessment, accounting for coordinated interventions by specific central banks that were found to be successful unilaterally, and by accounting for asymmetries.

Based on our results, unilateral CBIs can influence returns in the intended direction, whereas coordinated CBIs do not have a significant impact on returns. In terms of the impact of CBIs on exchange rate volatility the results are as follows. Unilateral or even coordinated interventions of 2 central banks can, in minor cases, significantly decrease volatility. However, coordinated interventions of 3 central banks in the same currency can only increase volatility, which is the exact opposite of the central banks' intentions. These results have important implications for the effectiveness of Central Banks' intervention policy decisions. That is, if central banks wish to influence exchange rates and/or volatility, they should intervene unilaterally. The more central banks intervene in coordination the less, or the opposite from the, anticipated would be the generated outcome.

Moreover, CBIs in one market are found to positively increase correlations between foreign exchange markets. That is, CBIs conducted either unilaterally or in coordination in one market intensify volatility in other foreign exchange markets. This is true in a world of highly integrated financial markets and might be the reason why these CBIs, and especially coordinated ones, increase volatility in these markets in most of the cases.

However, a limitation of the results obtained in this chapter is captured by the following question: had not central banks intervened, would the impact on returns and volatility have been different? This is a rather difficult question to address. Nonetheless, a recent growing literature has focused on the impact of official statements and speeches of central banks on foreign exchange markets prior to intervention (see, for instance, Beine, Janssen and Lecourt, 2009, and references therein). Using this approach, our analysis could be extended to answer the above question.

In addition, the analysis in this chapter was solely based on the investigation of the signalling channel through which CBIs could affect exchange returns, volatility and correlations using daily data under the DCC model. That is, the portfolio-balance channel was not examined. Hence, it would be of interest in further research to investigate how the impact of the G4 CBIs, in the context of the portfolio-balance model, changes.

Chapter 6

Conclusion

6.1 Overview

This thesis has explored several important issues relating to foreign exchange markets: i) the modelling and forecasting performance of various exchange rate volatility models in developing and industrialised countries; ii) the Euro's impact on major financial markets by examining exchange rate volatility comovements and spillovers since the Euro's launch, and comparing these with the results with the pre-Euro period; and iii) the impact of the G4 countries' CBIs on exchange returns, their volatility and bilateral correlations. The objective of this thesis has been to extend the existing literature and provide potential explanations for the contradictory results reported in the existing literature, thus contributing to the empirical foundations in the exchange rate volatility area.

6.2 Summary of key findings and implications

Chapter 2 provided an overview of the widely used methods used to capture exchange rate dynamics, and the various forecast criteria, in order to assess their forecasting performance. Given the large number of alternative models and empirical specifications, synthesizing them is a contribution in itself.

Chapter 3 assessed the modelling and forecasting performance of various conditional volatility models in developing and industrialised countries. The key contribution of this study was the novel results regarding daily exchange rate volatility modelling and forecast evaluation in developing countries. Specifically, it was found that modelling both long memory and volatility clustering properties resulted in substantial gains in out-of-sample forecasting performance. In the case of developing countries the IGARCH model proposed by Engle and Bollerslev (1986) was found to be superior in both in-sample estimation and out-of-sample forecast evaluation, whereas in industrialised countries, and in line with the empirical literature, the FIGARCH model proposed by Baillie, Bollerslev and Mikkelsen (1996) was found to fit the data best, and provide superior forecasting performance. Even under a one-day ahead VaR forecasting assessment, supporting evidence of the superiority of the FIGARCH and IGARCH models in industrialised and developing countries, respectively, was also provided. It was shown that the FIGARCH and IGARCH models in industrialised and developing countries, respectively, outperform the various alternative models in terms of correctly forecasting the failure rates at any given level. These findings have implications for various groups of agents. For instance, such models could be used effectively by central banks and other groups of agents to manage and measure currency risk exposure in these two sets of countries in an attempt to reduce their vulnerability to major exchange rate movements, especially after the currency crisis episodes of the last two decades.

Chapter 4 examined exchange rate volatility comovements and spillovers of four major financial markets for the period before and after the introduction of the euro in an attempt to assess the Euro's dependencies with these major markets. The key contributions of this chapter can be summarized as follows. It examined volatility comovements and spillovers in both the pre- and the post-euro period by extending the analysis to eight years of data for both sub-periods and to a larger number of financial markets involved. The results of the empirical analysis showed that significant volatility spillovers and comovements across the four exchange rates' volatility exist, but their magnitude has declined since the introduction of the euro. These findings suggest that the launch of the euro itself coincided with greater stability in the global financial markets. Moreover, the results showed that DM(EUR) is the dominant currency in volatility transmission, as its volatility affects all other markets' volatility, and exerts an unidirectional and persistent spillover on the GBP, CHF and JPY volatility. An additional finding is that sterling has become the least volatile currency in the group since the launch of euro. The latter finding has implications for the prolonged discussion of whether Great Britain should replace the pound with the euro, volatility being one of the main aspects that need to be considered in the above discussion.

Chapter 5 investigated the impact of official central bank interventions on exchange returns, their volatility and correlations. This investigation was based on the impact of the G4 officially announced CBIs rather than solely relying on the impact of the G3 CBIs that has been previously examined in the literature. The addition of information regarding a fourth central bank, which was the key contribution of this chapter, provided the opportunity to investigate coordinated official interventions by up to three central banks, which has never been assessed. In common with the existing literature, the results demonstrated that CBIs intensify exchange rate correlations. However, under the G4 assessment, unilateral CBIs are shown to have a significant impact on returns and in minor cases reduce volatility as opposed to the results in the existing literature. This is another contribution of this chapter. In addition, the impact of coordinated bilateral interventions was less clear than the existing literature has suggested. Last but not least, we find that instances of official coordination between three central banks tend to coincide with increased volatility. The latter results lead us to question the conclusions of earlier studies and caution against the belief that coordinated intervention is necessarily beneficial. Such results have important implications for central banks' intervention decisions in the foreign exchange markets. Based on our results, if central banks wish to influence exchange rates and/or volatility, they should intervene unilaterally. Intervening in coordination will not generate the anticipated outcome.

6.3 Future research

The validity of the obtained results and policy implications suggested throughout this thesis was based on the assumptions made, and on the data and models employed. The limitations suggest avenues for future research.

In the case of developing countries, the results of the superiority of the IGARCH model were obtained only for a selection of developing countries and models. Further work along these lines is called for, to check whether our results are specific to the particular data set and/or the specification of the volatility process. For instance, it would be of great interest to check whether our results for the selection of the four developing countries can be generalised to the rest of the developing countries. In addition, our results are based on a single regime model, so do not consider any possible structural changes in the volatility process over time. Diebold and Inoue (2001) argue that the apparent finding of long-memory in volatility persistence, such that captured by the FIGARCH or the IGARCH models, could be due to the existence of regime switching in the volatility process. Hence, our finding of the superiority of the IGARCH model in developing countries, and the FIGARCH model confirmation of other studies in preference of industrialised countries' return series, might be explained by the presence of structural breaks rather than long memory (slow mean reversion) in the conditional variance dynamics of exchange rate returns series. Therefore, it would be of interest to see whether the key findings stand up to consideration of a regime switching model in the estimation process.

The finding that the launch of the euro coincided with greater stability in the euro area and the global financial markets are in line with Mundell's (1998) claim of a decrease in volatility arising from the expansion of the euro due to the European Central Bank commitment to price stability. However, the conclusions reached in chapter 4 alone cannot prove causality. Thus, whether the volatility of the four currencies reflects the underlying volatility in the economic fundamentals of these regions is definitely an important avenue for future research. In addition, the documented evidence of euro's dominance in volatility transmission to the Swiss franc, British pound and the Japanese yen was reported till the end of 2007. The recent credit crunch that spread to the global financial markets has not been assess under our analysis. Thus, it would serve as an interesting future research to check whether our previous results hold during periods of turmoil, such as those experienced from 2008.

Moreover, the fact that, since the launch of the euro, the British pound is found to be the least volatile among the four currencies assessed suggests that, on these grounds, the UK may not be well advised to adopt the euro in the near future. However, as already pointed out by Malik (2005) and many others, exchange rate volatility is just one feature of the many that have to be considered before considering whether UK should replace pound with euro or not.

Last but not least, the analysis in this chapter was based on the assumption that shocks or news in one market affect that specific market and other markets symmetrically. This means that the impact of negative and positive shocks of the same amplitude as exchange rate volatility is the same. It would be of interest for further research to investigate whether the impact of news could have an asymmetric impact on exchange rate volatility.

Turning to the results associated with central bank intervention, there is an important avenue for future research. Our results obtained in chapter 5 were based on the analysis of official CBIs in the post-Louvre period under the G4 assessment. Not all official CBIs of the G6 countries that had signed the Louvre Accord were assessed. That was because the Bank of Canada and France did not officially announce their interventions under our investigation sample. However, it is argued that the more credible central banks are, in terms of interventions, the more effective the outcome on returns and volatility is (see, for instance, Sarno and Taylor, 2001). Thus, we argue that central banks should officially announce their interventions. An investigation of CBIs under the G6 assessment would shed more light on the prolonged counterproductive impact of coordinated CBIs reported in the literature.

Another question this chapter did not address is whether the impact on returns and volatility would be different had not central banks intervened. This is a rather difficult question to address. Nonetheless, a recent growing literature has focused on the role of official statements and speeches of central banks which might influence foreign exchange markets prior to intervention (see, for instance, Beine, Janssen and Lecourt, 2009, and references therein). Our analysis could be extended to answer the above question, to check whether statements and speeches under the G4 assessment have a different impact on returns and volatility or not.

In addition, the analysis in chapter 5 was solely based on the investigation of the signalling channel through which CBIs could affect exchange returns, volatility and correlations using daily data under the DCC model. That is, the portfolio-balance channel was not examined. Hence, it would be of interest for further research to investigate the impact of the G4 CBIs in the context of a portfolio-balance model.

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Appendix

Figure A.1: Conditional Variances of BEKK model – Pre-Euro (05.01.90-31.12.98)

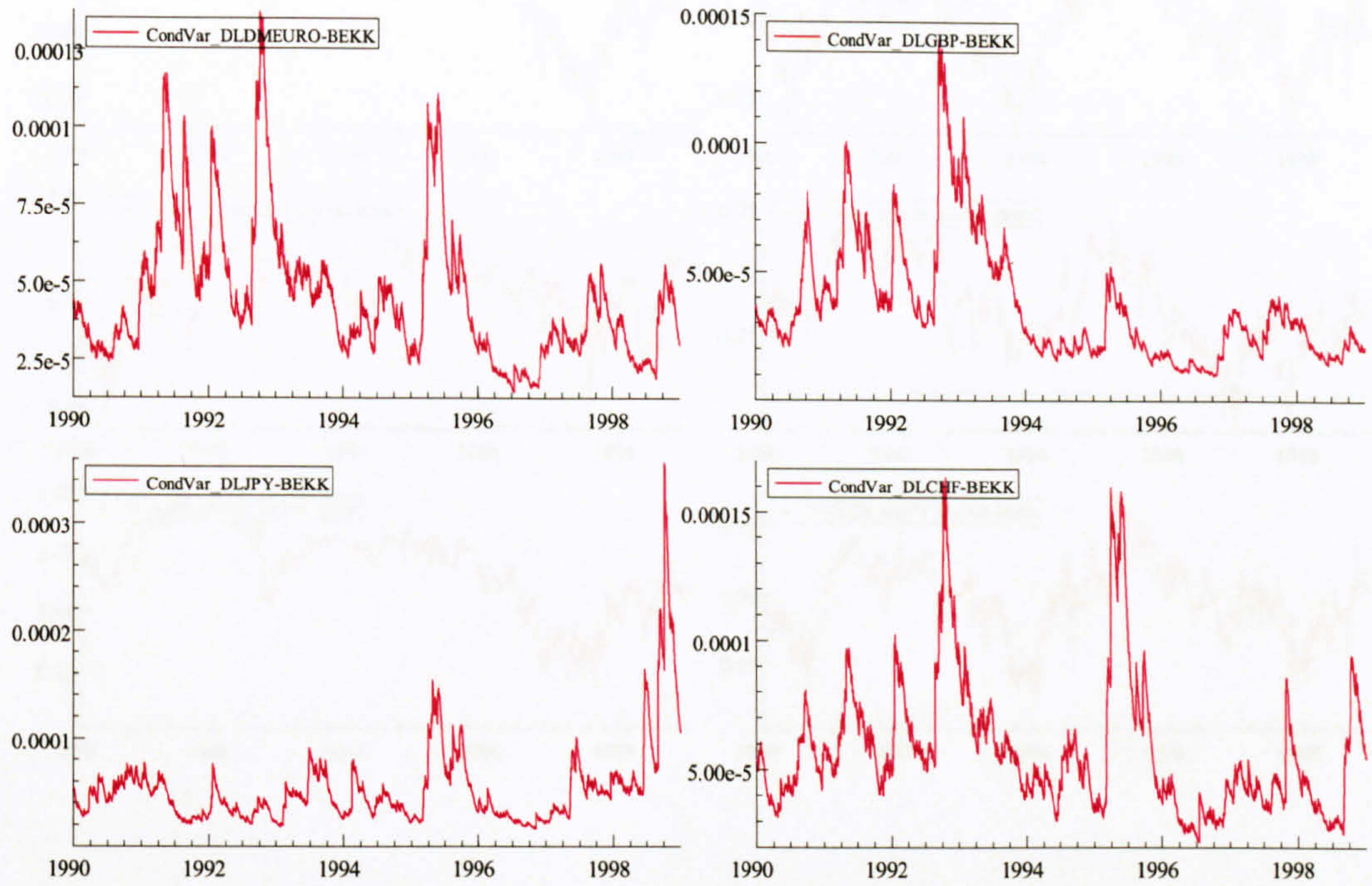

Figure A. 2: Conditional Covariances of BEKK model – Pre-Euro (05.01.90-31.12.98)

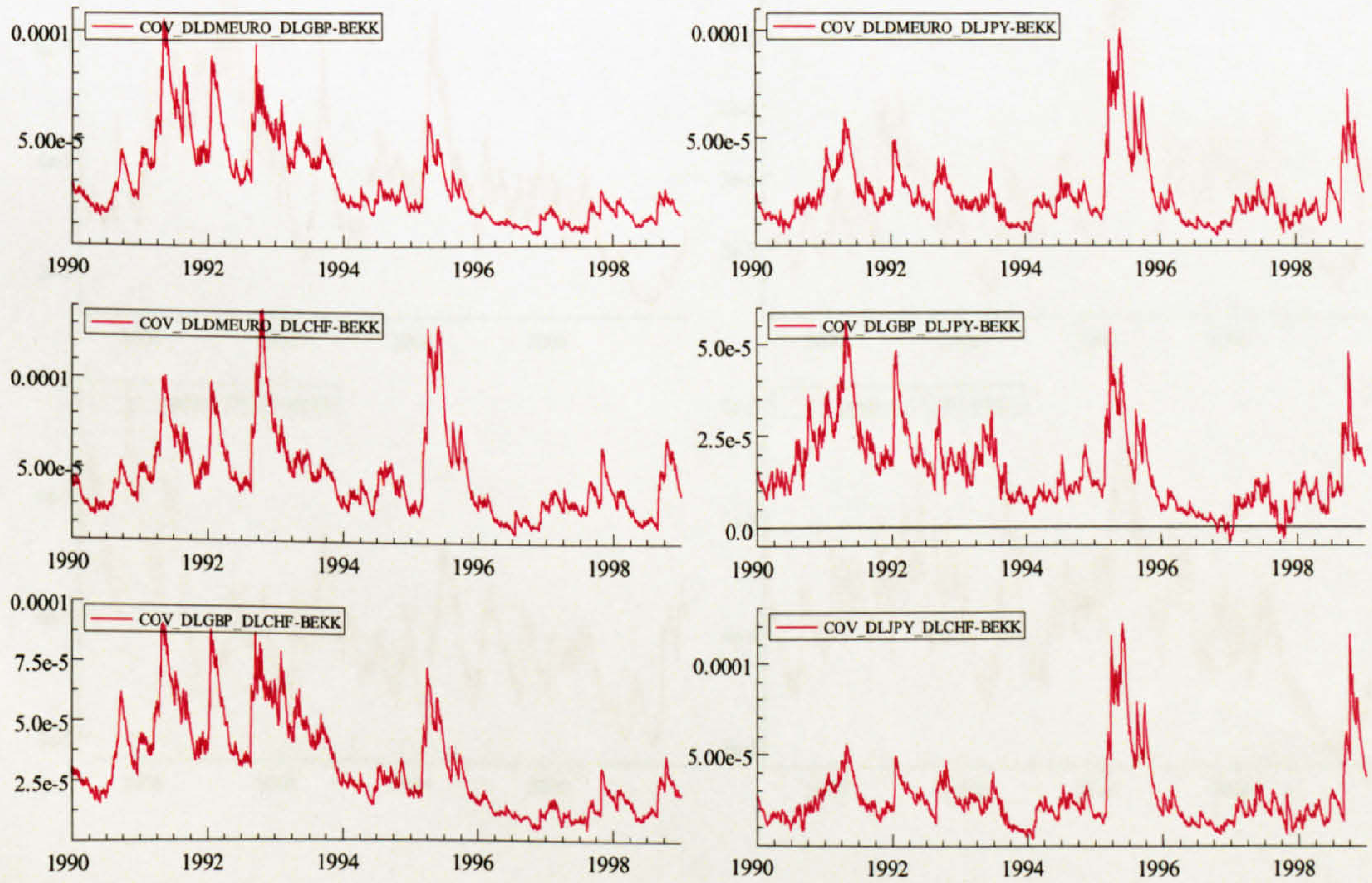

Figure A.3: Conditional Correlations of BEKK model – Pre-Euro (05.01.90-31.12.98)

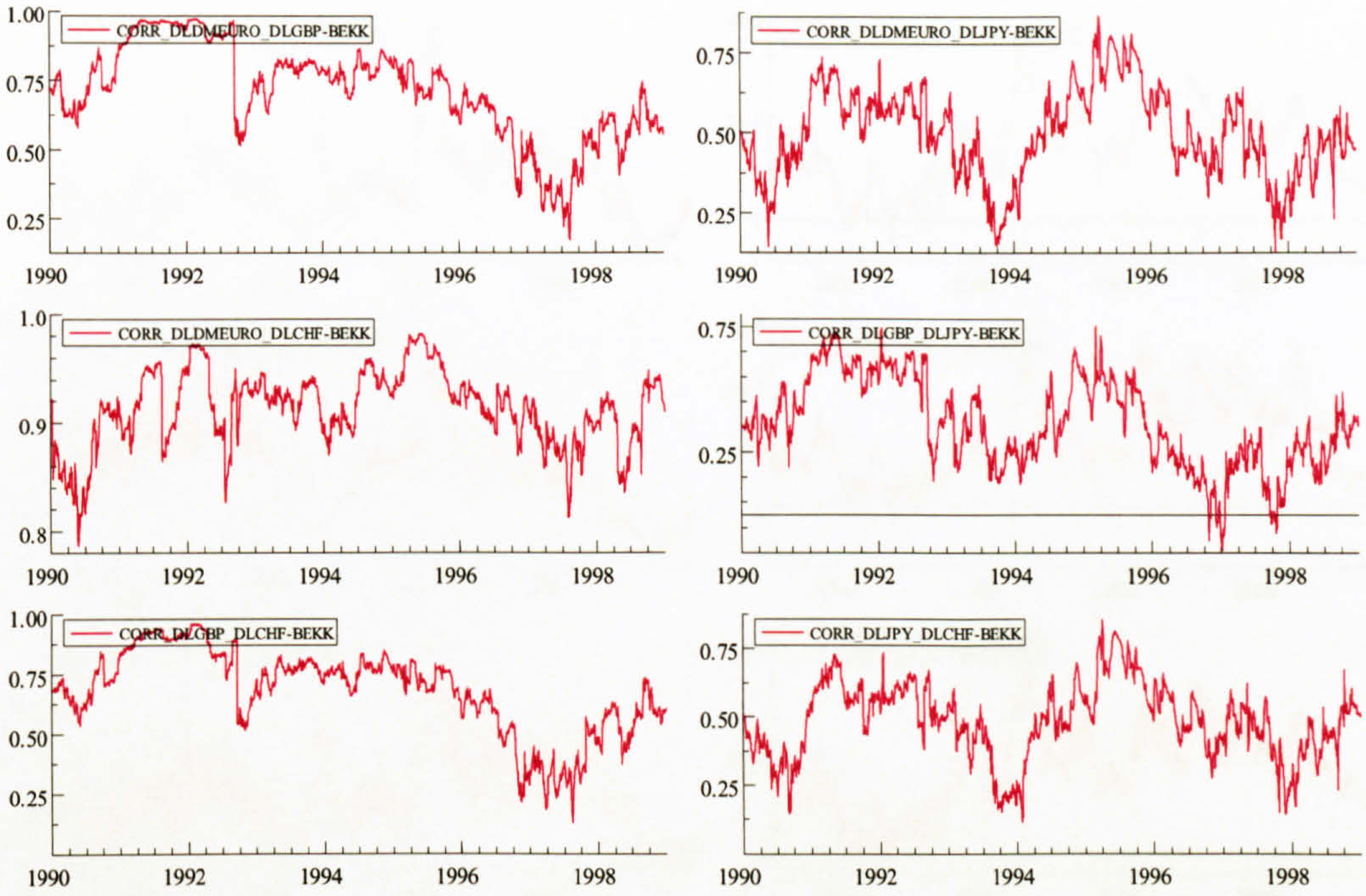

Figure A.4: Conditional Variances of BEKK model – Post-Euro (05.01.99-31.12.07)

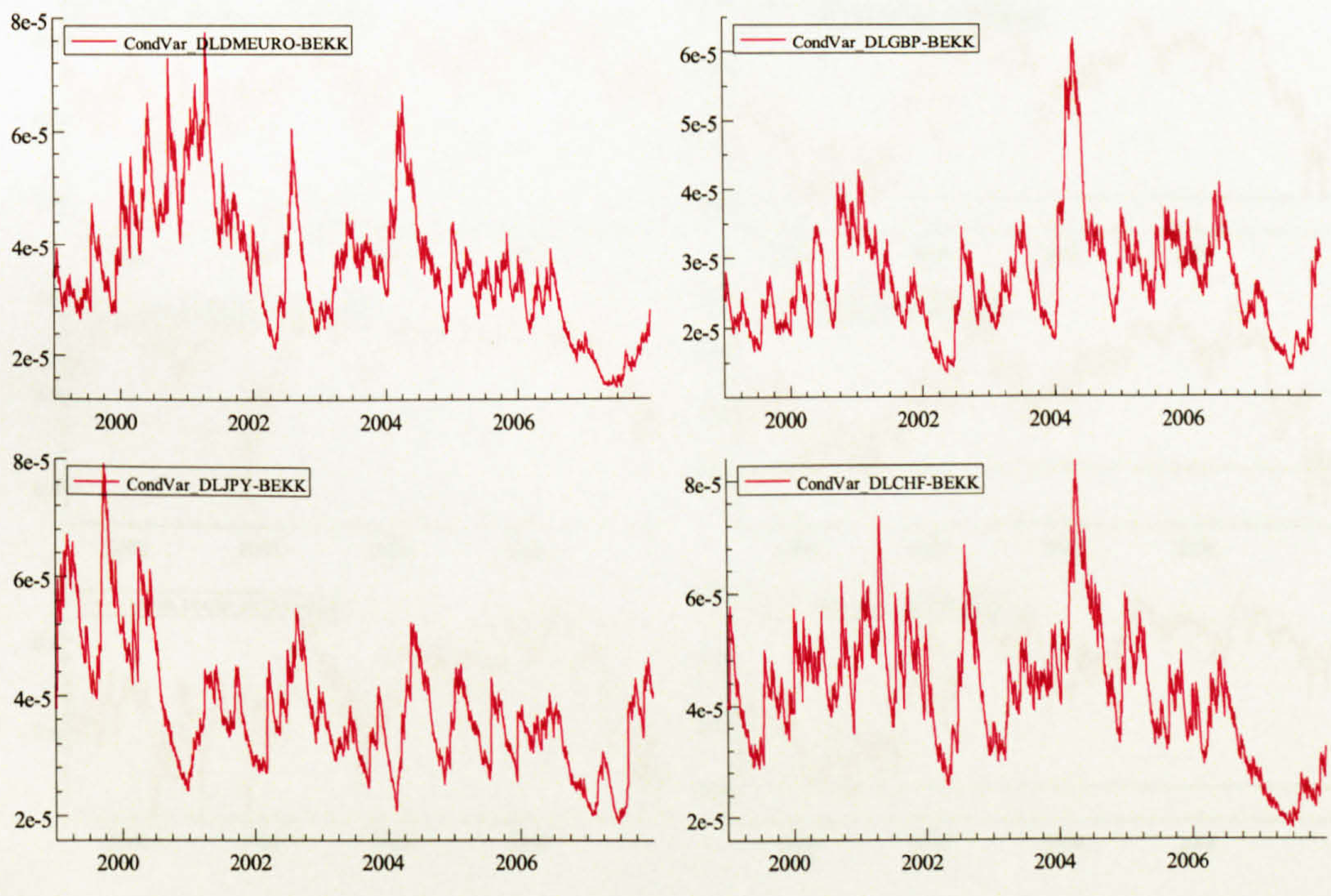

Figure A.5: Conditional Covariances of BEKK model – Post-Euro (05.01.99-31.12.07)

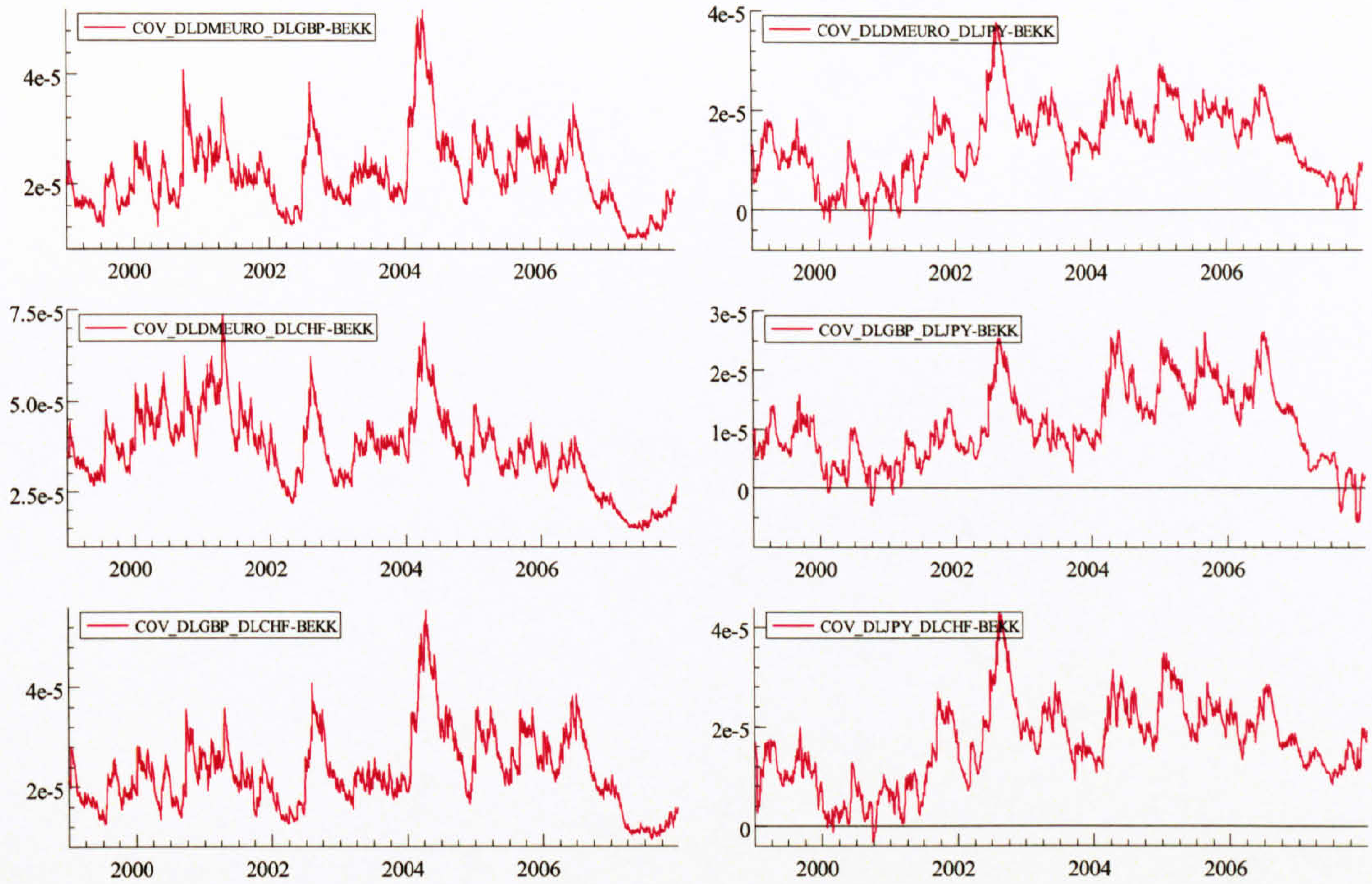

Figure A.6: Conditional Correlations of BEKK model – Post-Euro (05.01.99-31.12.07)