Investors Dilemma: The Volatility of the New Zealand Exchange Rate: Short Term Performance of the NZ Dollar versus the US Dollar

Klaus E. Buhr
Department of Commerce, Massey University at Albany, New Zealand

Lawrence C. Rose
Department of Commerce, Massey University at Albany, New Zealand

Xiaoming Li
Department of Commerce, Massey University at Albany, New Zealand

Phone: 0064 9 4439799 ext 9253
Fax: 0064 9 441 8177
E Mail: k.buhr@massey.ac.nz

Key words: Forecasting the volatility, exchange rate return, ARCH, GARCH, GARCH-M, EGARCH and TGARCH

Massey University at Albany
Department of Commerce
Private Bag 102-904, NSMC
Auckland, New Zealand
Contact: k.buhr@massey.ac.nz

Abstract:

Investors trade around the clock to capitalize on market movements in the foreign exchange market. An investor has to bear the relative risk while pursuing a return however; they must employ appropriate investment methods. Being a prudent investor, it is wise to take both the expected return and the exposed risk into account.

Forecasting the volatility of exchange rate return is of great interest to individual and institutional investors. In this research, we used five GARCH models (ARCH, GARCH, GARCH-M, EGARCH and TGARCH) to forecast the volatility of the return of the New Zealand Dollar. Our research found that the GARCH-M model outperformed other models in describing the return series. The New Zealand Dollar returns time series is highly persistent and leptokurtic. No obvious asymmetric effects were found in the return time series.

1. Introduction

The trend of deregulation and globalization in financial markets allows investors to do around the clock trading to capitalize on market movements. Three main categories of factors affect the fluctuation of a currency. First are the fundamental factors, including economic performance, interest rate levels, government fiscal policy as well as central banks' monetary policies, which are regarded as fundamental as they can cause medium to long-term price movements of the currency. The second category is that of technical movements and financial performance is sometimes found to, repeat past performance. Some analysts believe that some regulations could be found from historical data to forecast its future behaviour. The third category is market focus and market sentiment. A sudden event will exert pressure on a currency in the short and long term, (such as political and economic events). The market sentiment will also affect the attractiveness of a currency. A country may have all the right fundamentals, but finds its currency depreciating simply because the market is focusing on several factors or events at that time.

All these factors affect the performance of the exchange rate integrative, and form the daily performance series of the exchange rate. The short-term and long-term performance, therefore, may be revealed by the data of the daily performance series.
As a sophisticated investor, it is important to consider seriously the expected return from trading activity, as well as the risk that one incurs. Risk-averse investors will wish to reduce their exposure during periods of high volatility, and improvements in risk-adjusted performance depending upon the accuracy of volatility predictions. Employing a suitable model to forecast volatility is, therefore, of high concern to academics and practitioners. As emphasized by Engle and Patton (2001). "A volatility model must be able to forecast volatility; this is the central requirement in almost all financial applications."

In the literature, there are wide ranges of methods and models of quantitative forecasting techniques and raises the issue of choosing the appropriate forecasting technique. As pointed out by Anderson and Bollerslev (1998), "accurate measures and good forecasts of volatility are critical for implementation and evaluation of asset and derivative pricing theories as well as trading and hedging strategies".

In this paper, the most important consideration is whether the forecasts can lead to a better result; therefore, possibly helping investors to make better decisions.

The aim of this research is to analyze the historical performance of the New Zealand dollar exchange rate performance, employing several types of ARCH (Engle 1982) and GARCH (Bollerslev 1986) models. We will try to find an appropriate model to predict the short-term performance of NZD versus USD and test its predictive ability.
To achieve the above aim, the research will pursue the following objectives:

- An overall review of the literature concerning the ARCH and GARCH models, with specially emphasis on the different characteristics of different GARCH models, to find a benchmark for choosing linear GARCH models, or nonlinear GARCH models, to predict the short-term volatility of NZD.
- Using several different GARCH models to predict the short-term volatility of the exchange rate.
- Test whether the volatility properties are shown in the New Zealand Exchange Rate return.
- Analyze the predictive ability of different ARCH and GARCH models in forecasting the future short-term movements in the exchange rate
- Compare the forecast results and test the significance, validity and application of this forecast in the foreign exchange market.

3. LITERATURE REVIEW

The foreign exchange market is affected by various factors and uncertainties, which raises a major issue in the financial literature; volatility. Volatility is the conditional variance of the underlying asset return. In the foreign exchange rate market, volatility has attracted growing attention and now plays an important role.

3.1 Characteristics of return volatility

In the literature, consensus has been reached that volatility in asset returns has the following basic characteristics,

- Volatilities are clustered. For certain time periods volatility may be high, and for other periods volatility may be low. This characteristic is demonstrated by both Mandelbrot (1963) and Fama (1965). It indicates large return changes tend to be followed by large changes, while small changes tend to be followed by small changes. This implies that volatility shocks today will influence the expectation of volatility for some time in the future.
- Asset returns often show leptokurtosis, which means that the distribution of the returns are thick-tailed. Mandelbrot (1963) and Fama (1965) documented this empirical property. Their research led to a large body of literature on modelling the excess kurtosis. Hsieh (1989) and Baillie and Bollerslev (1989) also addressed the theory that exchange rate series show leptokurtosis.
- Volatility seems to be affected asymmetrically by positive and negative returns. Some researchers ascribed this asymmetry to a leverage effect or a risk premium effect. Specifically, although the stock returns exhibit some degree of asymmetry in their conditional variances, this property of asymmetries is less likely in the foreign exchange market, as it is of a two-sided nature. Black (1976), Christie (1982), Nelson (1991) and Engle and Ng (1993) all find evidence of volatility being negatively related to equity returns, but this has not been found for exchange rates.

These characteristics of volatility provide important information in the development of a model to forecast volatility. Researchers have devoted much effort to the modelling of these characteristics of volatility. The most successful models are the Autoregressive Conditional Heteroscedastic model (ARCH) of Engle (1982), and the generalized Autoregressive Conditional Heteroscedastic model (GARCH) by Bollerslev (1986

According to the ARCH model, the conditional error distribution is normal, but with conditional variance equal to a linear function of past squared errors. Thus, there is a tendency for extreme values to be followed by other extreme values, but of an unpredictable sign. The variances are usually not constant, autoregressive conditionally heteroscedastic (ARCH) models can reflect the pattern of volatility in series. If a series is modelled using an ARCH (p) or a GARCH (p,q) model, the series will look like white noise but its variance is not constant.

3.3 ARCH & GARCH Application in foreign exchange rate volatility

Exchange rate returns are found to be unconditionally symmetric but highly leptokurtic. The return of foreign exchange data is slightly different from some other types of speculative return, such as stock returns. The property of asymmetry is less likely in the foreign exchange market, as the foreign exchange market is of a two-sided nature, but it is found to be of size bias asymmetry response (Hsieh 1989). The distribution of the exchange rate returns are, therefore, not only unconditionally, but are also to a lesser extent conditionally leptokurtic.

3.3.1 The ARCH Effect

Mussa (1979) and Friedman and Vandersteel (1982) pointed out that traditional time series models have not been able to characterize short-run exchange rate movements, such as the contiguous periods of volatility and stability together with the leptokurtic unconditional distribution. The ARCH effect is highly significant in regards to the daily and weekly foreign exchange data.

In 1988, Hsieh argued that the conditional distributions of the daily nominal returns of the exchange rate are changing through time, since the squared returns are significantly autocorrelated to a high degree. He pointed out that a multivariate linearly declining lag structure can present the data well. This finding is also reported by Diebold (1988) and Diebold and Nerlove (1989). Hsieh (1989a,b) confirmed this finding using a GARCH (1,1) model. Similar conclusions are reached in studies by Taylor (1986) and Kugler and Lenz (1990).

Diebold and Nason (1990) used a detailed nonparametric analysis of ten weekly USD exchange rates, and found that these nonparametric estimates did not improve the forecast accuracy. This complies with the idea that any significant dependencies in short-run exchange rate movements work through the conditional variance and higher even-ordered conditional moments only. On the contrary, Taylor (1990b) argued that the conditional mean can be predicted well enough to obtain net trading profit forecasts.

It is noted that the ARCH effects tend to weaken with less frequently sampled data (Baillie and Bollerslev 1989). They used the average Ljung-Box portmanteau test across six currencies, and found that the daily data is highly significant in autocorrelations while the monthly data is insignificant. As pointed out by Drost and Nijman(1991), this weakening effect may be explained by aggregation effects.

3.3.2 Non-normal conditional densities

Various researchers have argued that a simple symmetric linear GARCH model may be a good description of most exchange rate series. The property of excess kurtosis of the exchange rate series cannot be explained by a simple symmetric linear GARCH model, as this model assumes conditional normality. (Hsieh 1989a and Baillie and Bollerslev 1989).Other researchers explicitly attempted to model the thick-tailed conditional distributions, including, for example, Bollerslev (1987), Engle and Gonzalez-Rivera (1991) and Hansen (1994). Based on the proposed GARCH model (Bollerslev 1986), Bollerslev (1987) extends the GARCH model by specifying conditionally t-distributed errors. Comparing the normal distribution, the t-distribution distinguishes a larger proportion of outliers, which is commonly regarded as "thick tailed". Bollerslev argued that this t-distribution might provide a superior fit of the time series data than conditional normal distribution, and he tested it on the daily US-British and US-German exchange returns series data over 5 years (1980-1985). He concluded that the results of his test verified that the GARCH-t model is better in describing the data than the standard GARCH model.

Baillie, Bollerslev and Lastrapes (1989) estimated deviations from normality in the standardized residuals from estimated linear GARCH (p, q) models. They characterized these deviations by some parametric leptokurtic density. Baillie and Bollerslev (1989) employed the student-t distribution, which is better than the power exponential and can reflect the excess kurtosis for most of the rates. Lastrapes (1989) argued that including dummy variables (which represents the information of changes in policy) in the conditional variance would reduce the degree of leptokurtosis in the standardized residuals and the degree of persistence of the conditional variance. Gallant, Hsieh and Tauchen (1989), employed a nonparametric procedure to explore the characteristics of non-normality. As stated by Bolleslev (1992) in the ARCH review, the leading term in the expansion for the conditional density resembles the conventional linear ARCH model. Contrary to other speculative prices, the response of the conditional variance to negative and positive surprises is virtually symmetric.

3.3.3 Volatility persistence

Engle and Bollerslev (1986) demonstrated that the persistence of volatility shocks in the foreign exchange market is also very high. This is consistent with the findings in studies on other speculative returns. This persistence of volatility suggests an IGARCH type behaviour may be suitable in describing this property. Various researchers reported similar results. These studies include those by Bollerslev (1987), McCurdy and Morgan (1987, 1988), Hsieh (1988a) and Taylor (1990a).

Bollerslev and Engle (1990) extend the idea of persistence of volatility across foreign exchange markets. They illustrated that within the context of a bivariate GARCH (1,1) model, most of the persistence in different rates (towards the USD) derived from some common set of underlying forcing variables, while the cross rates had much less persistent volatility shocks.

3.3.4 Size Biased Asymmetry Effect

Hsieh (1989); Byers and Peels (1995); Tse and Tsui (1997); and Hu, Jiang and Tsoukalas (1997) argued that the standard ARCH type model might not capture the evidence that large shocks produce a proportionately larger response from the market while smaller shocks produce smaller responses, which is a biased size asymmetry effect. They found that unlike the stock market, which exhibit both sign and size bias responses, the asymmetry found in foreign exchange market data showed only the size bias effect.

3.3.5 Applications of ARCH type model in the Foreign Exchange Market

Bollerslev and Engle (1990) used IGARCH to forecast the cross rate between the Deutschemark and the British pound. Ito, Lin (1990a) explored the intraday observations on the Japanese Yen to the USD, and demonstrated that volatility is transmitted through time and different market locations. Kam (1995), Kim (1998), and McKenzie (1997) applied ARCH models to the Australian exchange rate market and the results verify that the conditional variance of the exchange rate series is well modelled by an ARCH-type process.

Diebold and Pauly, Baillie and Bollerslev (1990); McDonald, Kendall and Ridley (1993) used ARCH models to test the stablility of foreign exchange risk premium and

Aseery and Peel 1991, Gagnon 1993 and Mckenzle and Brooks 1997 used univariate ARCH models to quantify the exchange rate volatility, while Lin (1989) applied a multivariate factor GARCH model for intra daily volatility in the foreign exchange market. Kendall and McDonald (1989) used a GARCH(1,1)-M model for the Australian/USD.

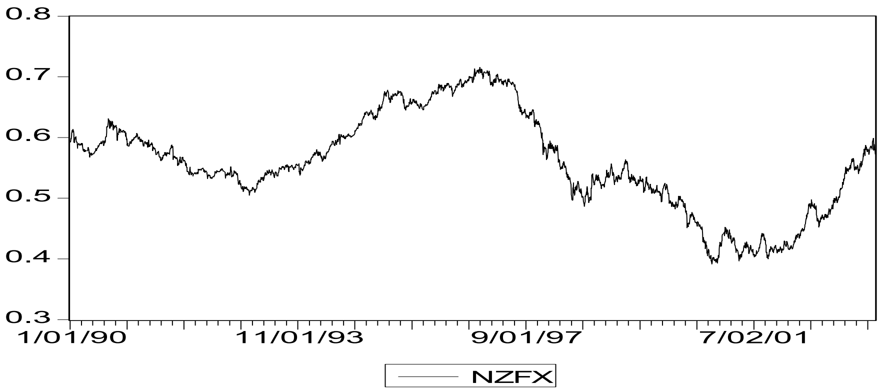
In the application of multivariate GARCH models, Kroner and Lastrapes, 1993, Qian and Varangis, 1994, and Caporale and Doroodian , 1994, used the MGARCH model to test the impact of exchange rate volatility on trade flows. Kroner and Lastrapes (1993) used a three-equation MGARCH system to study the relationship between exchange rate volatility and multilateral export volumes.

4. Research Data and Methodology

The data, taken from DataStream International, consists of the daily spot exchange rates for the NZD to the USD. The daily data covered the period of January 1, 1990 to June 30, 2003, with 3520 observations for this analysis.

Figures 1 plots the NZFX series. It represents a multiplicative time series with exponential trend and cyclical properties. From January 1, 1990, the NZFX fluctuated often and reached its peak at nearly 0.7161 late in 1996. It then declined dramatically during the period of 1997 to 2001, and recorded its lowest point of 0.3921 during the sample period in October 2000. Thereafter, the NZFX increased gradually and reached nearly 0.60 at the end of the sample period. It should be noted that the fluctuation range of NZFX is very large, the gap between the highest point and the lowest point during the sample period amounts to 0.342.

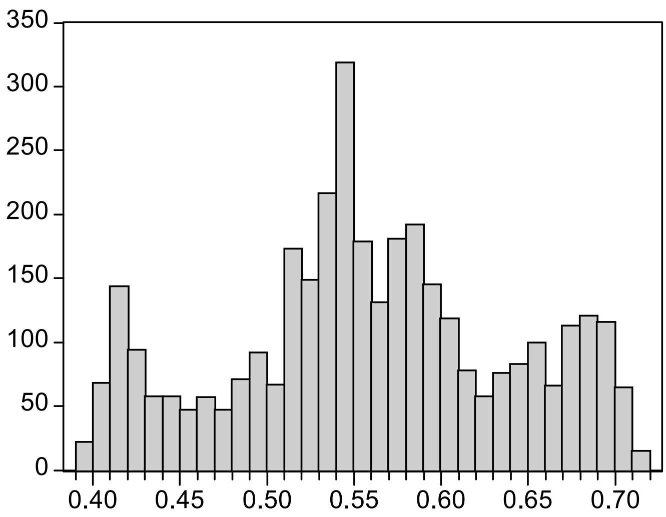
Figure 1: **The Daily New Zealand Dollar versus U.S. Dollar (NZFX series) ,**



The sample covers January 1st, 1990 through May 31st, 2003 [1]

Source: Author

Figure 2 Statistic histogram chart of the NZFX



The sample covers January 1st, 1990 through May 31st, 2003

Data Source: Author

Table 1: Descriptive Statistics of Raw Data of NZFX

The NZFX series			
Mean	0.558862	Maximum	0.716100
Median	0.553150	Minimum	0.392100
Std. Dev.	0.080197	Skewness	-0.071219
Kurtosis	2.350008	Jarque-Bera	64.95915
P-value	0		

[1] Data source: Data Stream

Sample range: January 1, 1990 to May 31, 2003
Data Source: Author

The mean value of the NZFX is 0.558862, while the standard deviation is 0.080197. It could be noted that the skewness parameter shows that the raw data NZFX is negative exhibiting non-normal left skewness distribution. The histogram plot shows obvious fat-tail characteristics indicating that there are a greater number of observations in the tails than there would be in a normal distribution.

All these statistics show that the distribution of the raw data of the NZFX does not have a normal distribution. It is not enough to simply use the mean and standard deviation to describe the raw data; some relative data processing would be necessary in order to describe the series. The first step is to test whether the NZFX series is stationary.

There are two general approaches to test for stationarity:

- Utilize Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the lagged time series over time. If the ACF plot shows no significant decay after 4-5 lags, and the PACF plot has a significant spike at a lag of 1, the underlying time series is likely to be non-stationary
- Perform the formal stationarity tests, which include the Dickey-Fuller test (DF) and the Augmented Dickey-Fuller test (ADF). The second is considered superior as it accommodates the possible serial correlation of the residual term.

One of the major drawbacks of the DF test is that the statistic does not follow any standard tabulated distribution either in finite or asymptotic samples (Holden and Thompson 1992). The special values must be produced by simulation methods, so this study utilizes the critical values provided in Patterson (2000).

One of the main problems with the standard version of the DF test is that it implicitly assumes serial independence of the error term u_t. Should serial correlation in fact be present, this is likely to negatively impact upon the reliability of the coefficient α and again affect the critical value for the test. To address this problem Dickey and Fuller (1981) proposed a modified version of the test, which attempts to remove this serial correlation by including the lagged values of Δx_t in the equation . This notion can be generalized to any number of lag terms.

As shown in the plot of the NZFX series in Figure 1, there is not an obvious trend in the NZFX series, but there are cyclical properties. This means that only intercepts need to be included in the test process.

Table 2 Unit Root Test Results on Raw Data of NZFX

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.161490	0.6931
Test critical values:	1% level	-3.432021	
	5% level	-2.862164	
	10% level	-2.567146	

*MacKinnon (1996) one-sided p-values.

Sample range: January 1st, to May 31st, 2003

Source: Author

It could be concluded that the raw data series is non-stationary as the p-value is 0.6931, showing a unit root exists.

Since the series of the NZFX is non-stationary, transformation processes are needed to make the NZFX series stationary. A log transformation and first difference processes are performed . This is a common method in obtaining the return series. The daily returns on the NZFX are, obtained by differencing the logarithmic NZFX series. The daily returns of the New Zealand Dollar Exchange Rate (r_t) are then calculated as:

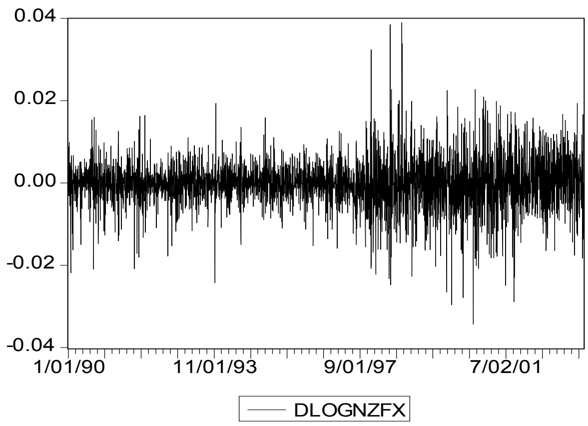
$$r_t = log\ (P_t) - log\ (P_{t-1})$$

where: Pt is the daily exchange rate at time t.

It is noted that the log $(P)_t$-log$(P)_{t-1}$ equals to Log$[(P_t)/(P_{t-1})]$, which is the logarithmic return of the NZFX.

Figure 2 illustrates the returns on the NZFX over the sample period.

Figure 2: Returns on the NZFX



The sample range: January 1st, 1990 to May 31st, 2003

Source: Author

The plot in Figure 2 indicates that the NZFX returns are fluctuating around the zero horizontal line, indicating that the mean return is close to zero. It shows obviously the properties of volatility clustering throughout most of the sample period.

The descriptive statistics for the return series are showed in Table 3.

Table 3 Summary of Descriptive Statistics of NZFX Return Series

The Returns Series of NZFX

Mean	2.96E-06	Maximum	0.0393035
Median	0	Minimum	-0.034182
Std. Dev.	0.005857	Skewness	-0.072461
Kurtosis	6.991545	Jarque-Bera	2339.837
P-value	0		

Sample range: January 1st, 1990 to May 31st, 2003

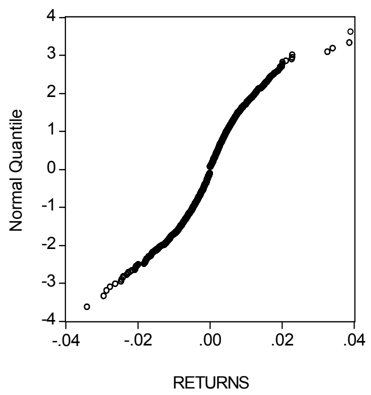
Source: Author

As shown in Table 3, the returns of NZFX had a small negative average return of about 0.00296% per day. The skewness coefficient is -0.072461. This indicates that the returns distribution is nearly symmetrical, and slightly negative skew. This confirms the findings in the literature that foreign exchange returns seldom display asymmetry compared with stock return.

The Kurtosis coefficient, which measures the thickness of the tails of the distribution, is 6.99, which is much higher than a Gaussian distribution with a kurtosis of 3. This is consistent with the finding in the literature that exchange rate returns have leptokurtic characteristics. In addition, the Jarque-Bera test is 2339.837 with a p-value equal to 0, which clearly rejects a normal distribution.

In order to see whether the return is non-normally distributed, a Quartile Quartile plot (Q-Q Plot) is computed as shown in Figure 3 below. This also confirms the distribution of the NZFX is non-normal.

Figure 3 Q-Q Plot of the Return Series of NZFX

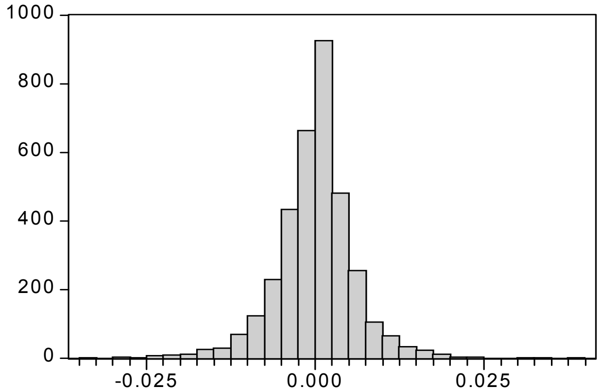


Sample range: January 1st,1990 to May 31st,2003

Source: Author

Figure 4 is the histogram chart of the statistics of return volatility. From this chart, it is obvious that the volatility of the NZFX is of a leptokurtic nature, but is quite symmetrical. This confirms that the redistribution of the NZFX returns are non-normal.

Figure 4: Histogram of statistics of NZFX returns



Sample range: January 1, 1990 to May 31, 2003

Source: Author

4.2.3.3 Augmented Dickey Fuller test on the returns series

In order to build a suitable model to describe the NZFX, the Augmented Dickey Fuller (ADF) test is employed to test whether the returns series is stationary.

As shown in the plot of the return series in Figure 2, the returns series have a zero mean and no obvious trend. There is no need to include lagged differenced terms. A test for unit root in the absence of an intercept or trend is conducted. Table 4 shows the result as:

Table 4 ADF stationary test for NZFX

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-44.57861	0.0001
Test critical values:	1% level	-2.565620	
	5% level	-1.940914	
	10% level	-1.616639	

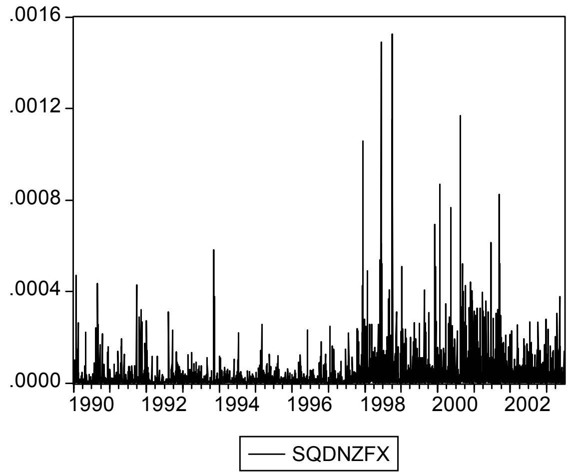
Sample range: January 1st, 1990 to May 31st, 2003

Source: Author

From the return plots of the NZFX in Figure 2, it is obvious that the volatility clustering effect exists and that an ARCH effect may exist. To confirm whether an ARCH effect is presented, two kinds of test are employed. One is to explore the plot of the square returns, and the other is the ARCH-LM test.

Figure 5 plots the Square Returns of NZFX (shown below). The plot of the squared return presents obvious evidence that large changes are followed by large changes (especially during the period of 1998 to 2000) while small changes follow small changes. This demonstrates the volatility clustering effect.

Figure 5, Square Returns of NZFX



Sample range: Jan 1st, 1990 to May 31st, 2003

Source: Author

4.2 Fitting a suitable GARCH type model for the NZFX

ARCH effects are presented in the return data of the NZFX and it appears that characterising the returns series using the ARCH process to specify the conditional variance could be suitable.

Since there is a wide range of ARCH type models in the literature, it is challenging to choose a suitable processes. To test for this finding and for the purposes of forecasting comparison, we will allow the variance of the NZFX returns series to follow two stages of the ARCH process. The first part involves linear ARCH models, including ARCH (p), GARCH (1, 1) and the GARCH-Mean process; the second part involves non-linear ARCH processes, including EGARCH and TARCH models, which allow asymmetry effects. Thus, a total of five ARCH processes are employed to estimate and forecast the NZFX returns series.

- **Model 1: ARCH (5) model**

An ARCH-LM test in lag 1 presents a significant ARCH effect. To find out the suitable lag for the ARCH (p) model, lags are added to the ARCH-LM test, and significant coefficients are obtained when a lag of up to 5 is specified. When lags are added to 6, the coefficient p-value is insignificant. An AR (6) model is, therefore, over-parameterised. Table 6 summarizes the ARCH –LM test results from lag 1 to 6.

Table 6 ARCH-LM Test For ARCH Effects in returns of NZFX

Variable		lag1	lag2	lag3	lag4	lag5	Lag 6
C	coefficient	3.00E-05	2.74E-05	2.39E-05	2.26E-05	2.17E-05	2.13E-05
	Prob.	0.00000	0.00000	0.00000	0.00000	0.00000	0.99960
$RESID^2(-1)$	coefficient	0.125139	0.11423	0.103186	0.09597	0.09379	0.093046
	Prob.	0.00000	0.00000	0.00000	0.00000	0.00000	0.42050
$RESID^2(-2)$	coefficient		0.08691	0.072395	0.068234	0.06369	0.0626
	Prob.		0.00000	0.00000	0.00010	0.00020	0.00110
$RESID^2(-3)$	coefficient			0.127509	0.121602	0.11899	0.116478
	Prob.			0.00000	0.00000	0.00000	0.68640
$RESID^2(-4)$	coefficient				0.056968	0.05332	0.052142
	Prob.				0.00080	0.00170	0.47080
$RESID^2(-5)$	coefficient					0.03778	0.036075
	Prob.					0.02540	0.60520
$RESID^2(-6)$	coefficient						0.01955
	Prob.						0.98370

Sample Range: January 1st,1990 to May 31st,2003

Source: Author

Table 6 illustrates that an ARCH (5) appeared to be a suitable ARCH (p) model to describe the returns series. An ARCH (5) is fitted to the returns data, as shown in Table 7.

Table 7: ARCH (5) Models On NZFX Returns Series

(p)	C	ARCH(1)	ARCH(2)	ARCH(3)	ARCH(4)	ARCH(5)
Coefficient	1.38E-05	0.137414	0.108073	0.126155	0.12366	0.180753
Std. Error	5.17E-07	0.014453	0.014273	0.014912	0.015159	0.015739
z-Statistic	26.69809	9.50778	7.571647	8.460099	8.157308	11.48418
Prob.	0	0	0	0	0	0

Sample Range: January 1st, 1990 to May 31st, 2003

Source: Author

The significant p-values on the parameters showed that this is a reliable model The Akaike Information Criterion (AIC) of ARCH (5) model is -7.554921; and Schwarz Criterion (SC) statistics is -7.542597. The sum of the parameters amounts to 0.676055. We will compare these statistics after the five proposed model have been obtained.

We requested a correlogram test on the squared series of the returns and results are shown in *Appendix 3*. The PACF has spikes at lags one to five and illustrates that the ARCH (5) model selected above was reasonable.

- **Model 2: GARCH (1,1) model**

The correlogram test on the squared return shown in *Appendix 3* suggests that there is also a possibility that GARCH (1, 1) could be a good process for the return series, because the decay on the ACF and PACF suggests that an ARMA could be used to model the squared series.

A GARCH (1, 1) model is fitted to the NZFX returns data. All the p-values on the parameters are significant and indicates that this is a reliable model. Table 8 illustrates the model as:

Table 8:

GARCH (1,1) Models On NZFX Returns Series

	ω	α	β
Coefficient	2.36E-07	0.040204	0.953336
Std. Error	3.24E-08	0.003192	0.003654
z-Statistic	7.264804	12.59555	260.8888
Prob.	0.00000	0.00000	0.00000

Sample Range: January 1st,1990 to May 31st,2003

Source: Author

The AIC =-7.617752 and the SC =-7.612497. The sum of α+β =0.99354, which implies quite a long memory persistence in the returns volatility. In addition, it is significantly less than one, which shows the properties of mean reversion of the volatility.

- **Model 3: GARCH-Mean model**

A GARCH-Mean model distinguished from other models by adding a regressor of the conditional variance into the mean equation. In our process, a variance is added in the mean. All the p-values on the parameters are significant. This is a reliable model and the AIC Statistics of GARCH-M model amounts to -7.616994, the Schwarz criterion equals to -7.608191. Table 9 illustrates the result of the G ARCH-Mean Model:

Table 9:

GARCH-Mean Models On NZFX Returns Series

	ω	α	β
Coefficient	2.33E-07	0.03984	0.953677
Std. Error	3.22E-08	0.003186	0.003637
z-Statistic	7.236118	12.50556	262.2367
Prob.	0.00000	0.00000	0.00000

Source: Author

The sum of α+β equals to 0.9935170, which also implies a long memory persistence in the returns volatility and is significantly less than one.

Model 4: TARCH Model

We employed the Threshold Autoregressive (TARCH) model (Tong 1990, Zakoian 1990 and Glosen et al 1993) to the Returns Series of the NZFX to test whether a non-linear model can give a better description of the series. The TARCH model defines the variance as a linear piecewise function and allows volatility to react differently to different signs and magnitudes of shocks. Table 10 illustrates the TARCH Model.

Table 10:

TARCH Models On NZFX Returns Series

	ω	α1	β1	Lev Term
Coefficient	2.33E-07	0.03984	0.953677	0.1143
Std. Error	3.22E-08	0.003186	0.003637	0.005047
z-Statistic	7.236118	12.50556	262.2367	2.265287
Prob.	0.00000	0.00000	0.00000	0.02350

Sample Range: January 1st,1990 to May 31st,2003

Source: Author

All the p-values on the parameters are significant and indicate that this is a reliable model. The sum of α+β equals to 0.96177, which is significantly less than one and indicates the volatility persistence and mean reversion properties. The Akaike Info Criterion (AIC) is -7.617452, Schwarz Criterion statistics equals to -7.610409.

Model 5: EGARCH Model

The exponential GARCH (EGARCH) (Nelson 1991) is another non-linear ARCH type models used in our analysis, Table 11 illustrates the EGARCH model on the NZFX returns data.

Table 11:

Table 11: EGARCH Models On NZFX Returns Series

	ω	α1	β1	asy-commponent
Coefficient	-1.43195	0.040235	0.93179	-0.018053
Std. Error	0.014654	0.005254	0.001155	0.00371
z-Statistic	-9.771466	15.27231	758.6147	-4.869934
Prob.	0.00000	0.00000	0.00000	0.00000

Sample Range: January 1st,1990 to May 31st,2003

Source: Author

All the p-values on the parameters are significant and indicates that this is a reliable model. The sum of α and β equals to 0.972025, significantly less than one, which is consistent with volatility persistence and mean-reversion properties. The Akaike Info Criterion (AIC) is -7.614637, Schwarz Criterion statistics equals to -7.607595.

4.3.2 Summarizing the statistics of five employed ARCH type models.

In the above section, five ARCH type models have been fitted to the returns data of the NZFX. There is no exact theoretical or empirical guidance in choosing which model could be an optimal model. In this section, we summarise and compare the statistics of these five different ARCH type models and test whether the properties of the volatility are presented by these models. Table 12 summarizes the estimated test statistics of Akaike info criterion, the Schwarz criterion and the sum of the α and β.

Table 12:

Summary of some statistics of the five selected model

	AIC	SC	$\alpha+\beta$
ARCH(5)	-7.554921	-7.542597	0.676055
GARCH(1, 1)	-7.617752	-7.612497	0.99354
GARCH-M	-7.616994	-7.608191	0.9935170,
TARCH	-7.617452	-7.610409	0.96177
EGARCH	-7.614637	-7.607595	0.972025

Source: Author

Table 12 illustrates that all the five models present the persistency properties of the return volatility, as all the sums of α and β are less than 1. Among these sums, the GARCH (1, 1) model and GARCH-M model show the strongest volatility persistence characteristics, which are nearly equal to 1. For the GARCH (1, 1) model, the sum of α and β amounts to 0.99354 and implies that a volatility half-life of about 106 days indicating that the volatility of NZD is highly persistent.

From Table 12, it is noted that the GARCH (1, 1) model provides the lowest value in both AIC and SC, which is consistent in t[2] with the literature that the GARCH (1, 1) model appears to present a better description on the return of exchange rates. The ARCH (5) model, however, gives the highest result in the test statistics of AIC and SC. Both the ARCH (5) model and the GARCH (1, 1) model are linear models but show contrary ranks.

As pointed out by Pagan and Schwert (1990), it might be inappropriate to use the AIC and SC for selecting a suitable ARCH model. As ARCH models are centred, the analysis in the second moment while AIC and SC are centred on the first moment. As we cast the critical assessment on the forecasting ability of the models, we use these five fitted to forecast the short-term volatility of the NZFX. The forecast results are presented in *Appendices 4* to *8*. We compare the results of the forecasting and their accuracy and forecasting ability.

Appendix 4 to 8 presented the forecast results using the selected five ARCH type models. To compare the accuracy of the forecast, four kinds of forecast error statistics measures are used. These are the root mean square error (RMSE), the mean absolute error (MAE), the mean absolute percentage error and the Theil Inequality Coefficient statistic function.

Both the RMSE and MAE are measures, which depend on the scale of the dependent variable. They can be regarded as relative measures in comparing the same series through different models. The smaller the error, the better the forecast will be.
The root mean square error is a powerful measure to test the forecasting performance of a model. It is defined as:

$$RMSE = \sqrt{\sum_{t=t+1}^{t+h} (\hat{y}_t - y_t)^2 / h}$$

[2] The half-life volatility is computed as $-Ln(2)[Ln(\alpha+\beta)]^{-1}$, which was presented by Anderson and Bollerslev (1998).

The MAE is also a popular measure because of its simplicity of calculation. It is computed as,

$$MAE = \frac{1}{I}\sum_{i=1}^{1}\left|\hat{\sigma}_i^{\ 2} - \sigma_i^{\ 2}\ \right|$$

The Theil Inequality Coefficient statistics defined the forecast error as the standardized error from the random walk forecast. The advantage of it is that it is invariant to scale transformation, it always lies in the range 0 to 1, with 0 indicating a perfect forecast. It can be computed as

$$Theil = \frac{\sqrt{\sum_{t=t+1}^{t+h}(\hat{y}_t - y_t)^2 / h}}{\sqrt{\sum_{t=t+1}^{t+h}\hat{y}_t^2 / h} + \sqrt{\sum_{t=t+1}^{t+h} y_t^2 / h}}$$

The Mean Absolute Percentage Error is also a measure invariant to scale transformation. It could be defined as:

$$100\sum_{t=r+1}^{r+h}\left|\frac{\hat{y}_t - y_t}{y_t}\ \right| / h$$

After computing the results of the measures, it is possible to compare the forecast performances and rank the measures.

In our comparison, we will compare the RMSE & MAE statistics of these five models and rank them separately. The results are as shown in Table 13.

Table 13

Forecasting Performance Evaluating by the RMSE & MAE

			RMSE		
	ARCH(5,0)	GARCH(1,1)	GARCH-M	TARCH	EGARCH
	0.004626	0.004635	0.004617	0.00464	0.00464
rank	2	3	1	4	5
			MAE		
	ARCH(5,0)	GARCH(1,1)	GARCH-M	TARCH	EGARCH
	0.003685	0.003702	0.003665	0.003708	0.003703
rank	2	3	1	5	4

Forecasting Range: June 1^{st}, 2003 to June 30^{th}, 2003

Source: Author

Table 14

Forecast Comparison by MAPE & TIC

	ARCH(5,0)	GARCH(1,1)	GARCH-M	TARCH	EGARCH
Mean absolute percentage error	0.679466	0.682736	0.675895	0.683786	0.682915
RANK	1	3	2	5	4
Theil inequality coefficient	0.004261	0.004269	0.004253	0.004272	0.00427
RANK	2	3	1	5	4

Forecasting Range: June 1^{st}, 2003 to June 30^{th}, 2003

Source: Author

From the comparison of Table 13 and Table 14, it can be noted that all the statistic measures indicate that the ARCH –M model provides the most accurate forecast. The ARCH (5, 0) and the GARCH (1,1) models rank second and third. Except the RMSE measure, the other three measures indicate that the EGARCH model has a superior performance than TARCH, but both are ranked lower than GARCH-M, ARCH (5, 0) and GARCH (1, 1) models.

5.3 Empirical Results

From the comparison results, we have concluded the following points:

5.3.1 Linear versus Non-linear

The linear model (represented by the GARCH-Mean model, ARCH (5,0) and GARCH (1,1)), out-performs the non-linear model (represented by TARCH and EGARCH). This is consistent with the findings in the literature, that there is no obvious asymmetry effect in exchange rate volatility.

5.3.2 ARCH (5, 0) versus GARCH (1, 1) and GARCH-M

Although there are only tiny differences, all the measures indicate that for the returns of the NZFX, the GARCH –Mean model provides a better forecast than the 5 lag ARCH model and the traditional GARCH (1, 1) model. Since the GARCH-Mean process allows the mean of a series to be dependent, at least in part on the conditional variance of the series, it appears that the mean of the NZFX is partly dependent on its conditional variance.

5.3.3 TARCH and EGARCH

It appears that TARCH is not as good as EGARCH in forecasting the volatility performance of the NZFX return. As compared above, these two models have been given a relatively lower ranking than the linear model. As the EGARCH model does not require a nonnegative constraint, as in linear ARCH and GARCH model, it was expected to give a better result. Indeed, the lower ranking shows that whether ε_{t-1} is negative or not will not affect the forecast of the returns of the NZFX. The same result could be concluded for the TARCH model, as the TARCH is also distinguished by its ability to reflect the leverage effects. This means that when there is no obvious leverage effect in the return series of the NZFX, it does provide better performance qualities than the symmetric linear ARCH type models.

6 Conclusion

It is widely accepted that the volatility of asset prices show properties of considerable persistence. Large movements in prices tend to be followed by larger movements. This characteristic leads to positive serial correlation in the square returns of a time series. Future volatility, therefore, can be forecasted by using the past and current volatility. Since the proposition of the Autoregressive Conditional Heteroscedastic Model (ARCH) presented by Engle (1982), the ARCH type models have been applied widely in modelling the volatility of financial time series.

This paper has attempted to use ARCH type models in forecasting and capturing the volatility of the New Zealand Dollar Daily Exchange Rate. The characteristics of the return of foreign exchange rates are analysed. We test whether the characteristics of the volatility are presented by the return series of the New Zealand Dollar (NZFX).

The daily New Zealand Exchange rate over approximately thirteen years, is explored in this report and we found that the conditional volatility of the NZFX is highly persistent. There is obvious volatility clustering characteristics in the returns series of NZFX We have also proved that although the distribution of its volatility is not asymmetric, it did show the characteristics of leptokurtic. By using an ARCH-LM test, we have proved that the returns series of NZFX represents obvious ARCH effects.

In exploring these characteristics, five ARCH class models were used to forecast the performance. It is found that the linear GARCH models out-performed the non-linear ARCH models; this indicates that there are no obvious asymmetric characteristics of the volatility of NZFX. A non-linear ARCH model, which allows for asymmetric effects, cannot provide better forecasting abilities compared to linear GARCH models. This is consistent with the finding in the literature. The GARCH-Mean model, which added the standard deviation as a regressor of the conditional variance into the mean equation, provides the best forecast. This implies that in the forecasting of the volatility of NZD, the GARCH-Mean model established a direct relationship between the risk and the return of the exchange rate, and leads to more accurate forecasting.

All the forecasts are out-of-sample. The reported forecast-error statistics are not significantly different from each other and a formal test such as the Modified Diebold and Mariano test statistic of Harvey, Leybourne and Newbold (1999) needs to be performed to compare the accuracy of the forecast error statistics.

7. **Bibliography**

1. Andersen, T.G. and T. Bollerslev (1998), "Answering the Skeptics: Yes, Standard
2. Volatility Models do Provide Accurate Forecasts", *International Economic Review,vol. 39, no. 4, 885-905*
3. Baillie and Bollerslev, 1989. R.T. Baillie and T. Bollerslev , The message in daily exchange rates: a conditional variance tale. *Journal of Business and Economic Statistics* 7 (1989), pp. 297–306.
4. Baillie and Bollerslev, 1991. R.T. Baillie and T. Bollerslev , Intra-day and inter-market volatility in foreign exchange rates. *Review of Economic Studies* 58 (1991),
5. Baillie R T, Bollerslev T and Mikkelsen H O 1996 fractionally integrated generalized autoregressive conditional heteroskedasticity *J. Econometrics* 74 3-30
6. Black, F. 1976, '*Studies of Stock Price Volatility Changes*' Proceedings of the 1976 Meetings of the Business and Economics Statistics Section, American Statistical Association, pp177-81
7. Bollerslev, Tim, 1987, A conditional heteroskedastic time series model for speculative prices and rates of return, *Review of Economics and Statistics* 69, 542-547.
8. Bollerslev T, Chou R. Y. and Kroner K.F. (1992) ARCH model in finance, a review of the theory and empirical evidence. *Journal of Econometrics* 52 (1992) 5-59. North-Holland.
9. Bollerslev, T., Engle, R.F. and Wooldridge, J.M. 1988, A capital Asset Pricing Model with Time Varying covariances, *Journal of political economy*, vol, 95, pp.116-31
10. Bollerslev, Tim (1986): "Generalized autoregressive conditional heteroskedasticity", Journal of Econometrics 31, 1986, p. 307-328.

11. Campbell, John Y. and Ludger Hentschel, 1990, No news is good news: An asymmetric model of changing volatility in stock returns, *unpublished manuscript* (Princeton University, Prince-ton, NJ).
12. Cai, J. (1994), A Markov Model of Unconditional Variance in ARCH, *Journal of Business and Economic Statistics,* 12, 309-316
13. Cao C.Q and R.S. Tsay (1992) Nonlinear time series analysis of stock volatilities.
14. Chou R Y 1988 Volatility persistence and stock valuations: some empirical evidence using GARCH, *Journal of Financial Quantitative Analysis* vol. 31, p. 85-107
15. Christie, A.1982, The Stochastic Behaviour of Common Stock Variances: Value, Leverage And Interest Rate Effects, *Journal of Financial Economics,* vol. 10, pp. 407-32
16. Ding, Z., Granger, C.W.J., and Engle, R.F. 1993, A long Memory Property of Stock Market Returns and a new Model, *Journal of Econometrics*, Vol. 73. 185-215
17. Diebold, 1986. F.X. Diebold , Testing for serial correlation in the presence of ARCH. In: *Proceedings of the Business and Economics Statistics Section of the American Statistical Association* (1986), pp. 323–328.
18. Diebold, Francis X., 1988, Empirical modeling of exchange rate dynamics, Springer Verlag, NewYork. NY.
19. Diebold, Francis X. and Mark Nerlove. 1989, The dynamics of exchange rate volatility: A multivariate latent factor ARCH model, *Journal of Applied Econometrics* 4, 1-21.
20. Diebold, Francis X. and James M. Nason, 1990, Nonparametric exchange rate prediction, *Journal of International Economics 28,* 3155332.
21. Drost, Feike C. and Theo E. Nijman, 1991, Temporal aggregation of GARCH processes, Unpublished manuscript (Department of Economics, Tilburg University, Tilburg).

22. Engle, Robert F. and Victor K. Ng, 1990, *An examination of the impact of volatility shocks on the short end of the term structure based on a factor-ARCH model for treasury bills,* Unpublished manuscript (School of Business Administration, University of Michigan, Ann Arbor, Ml).
23. Engle, Robert F. and Gloria Gonzalez-Rivera, 1991, Semiparametric ARCH models, J*ournal of Business and Economic Statistics* 9, 345-360.
24. Engle, Robert F.(1982): Autoregressive conditional heteroscedasticity with estimates of the variance of the United Kingdom inflation, *Econometrica* 50, 1982, p.987-1007.
25. Engle, R.F.,Granger, C.W. J. and Kraft, D. 1984, Combining Competing Forecasts of Inflation using a Bivariate ARCH Model, *Journal of Economic Dynamics and Control*, vol. 8 pp. 151-65.
26. Engle, Robert F. and Tim Bollerslev, 1986, Modeling the persistence of conditional variances, *Econometric Reviews 5*, l-50, X1-87.
27. Engle, R.F., Lilien, D.M. and Robins, R.P. 1987, Estimating Time varying Risk Premia in the Term Structure: The GARCH-M model, *Econometrica*, vol. 55, pp.391-407
28. Engle, R.F. and Mustafa, C. 1992 Implied ARCH Models from Options Prices, *Journal of Econometrics,* vol.52, pp 289-311.
29. Engle, R, F and Patton A. J, 2001, What good is a volatility model? *Quantitative Finance*, Vol. 1, p237-245
30. Eugene F. Brigham 2001, Financial Management, theory and practice, 10the edition,
31. Fama, E.F.1965, The Behavior of Stock Market Prices, *Journal of Business,* vol.38, pp.34-105
32. Fleming, J., C. Kirby and B. Ostdiek (2001), "The Economic Value of Volatility Timing," *Journal of Finance*, 56, 329-352.
33. Franses P.H. and D. Van Dijk (1996) Forecasting stock market volatility using (non-linear) Garch models, *Journal of Forecasting*, 15, 3, 229-235.

34. Franses, P.H and K. van Griensven, 2000, non-linear time series models in empirical finance, Cambridge
35. French, K.r. and Roll, R.(1986), “Stock Return Variances: The Arrival of Information and the Reaction of Traders”, *Journal of financial Economics*, 17, 5-26
36. Friedman, Daniel and S. Vandersteel, 1982, Short-run fluctuations in foreign exchange rates, *Journal of International Economics 13*, 171-126.
37. Granger, C.W.J 1992, Forecasting Stock Market Prices: Lessons for Forecasters, *International Journal of Forecasting,* vol.3, pp 3-13.
38. Gencay, 1999. R. Gencay , Linear, non-linear and essential foreign exchange rate prediction with simple trading rules. *Journal of International Economics* 47 (1999), pp. 91–107.
39. Giannopoulos, K. 1995, Estimating the Time varying components of International stock markets risks*, European Journal of finance,* vol. 1, pp. 129-64
40. Gonzales-Rivera, G. 1996, Time Varying Risk the case of the American Computer Industry, *Journal of Empirical Finance*, vol. 2, pp 333-42
41. Hamilton, James D., 1989, A new approach to the economic analysis of nonstationary time series and the business cycle*, Econometrica* 57, 357-384.
42. Hansen, Bruce E., 1994, GARCH (l,l) processes are near epoch dependent, Unpublished manuscript ,University of Rochester, Rochester, NY.
43. Hsieh, David A., 1988, The statistical properties of daily foreign exchange rates: 1974-1983, *Journal of International Economics 24*, 129-145.
44. Hsieh, David A., 1989a, Modeling heteroskedasticity in daily foreign exchange rates, Journal of *Business and Economic Statistics 7*, 307-317.
45. Hsieh, David A. 1989b, Testing for nonlinear dependence in daily foreign exchange rate changes, *Journal of Business 62,* 339-368.
46. Hsieh, 1989. D.A. Hsieh, Modelling heteroskedasticity in daily foreign exchange rates *Journal of Business and Economic Statistics* 7 (1989), pp. 307–317.
47. Johansen S. (1991), Estimation and Hypothesis testing of cointegration vectors in Gaussian vector autoregressive models, *Econometrica,* 59: 1551-1580

48. Kendall, Jon D. and A. David McDonald, 1989, Univariate GARCH-M and the risk premium in a foreign exchange market, Unpublished manuscript Department of Economics, University of Tasmania, Hobart.
49. Kugler, Peter and Carlos Lenz, 1990, Chaos, ARCH and the foreign exchange market: Empirical results from weekly data, *Unpublished manuscript* ,Volkswirtschaftliches Institut, Zurich.
50. Lastrapes, William D., 1989, Weekly exchange rate volatility and U.S. monetary policy regimes: An application of the ARCH model, Journal of Money, Credit and Banking 21, 66-77.
51. Leblang, D. 1996, ARCH and GARCH models, handouts of University of Colorado.
52. Lin, Wen-Ling, 1989, The sources of intra daily volatility in the foreign exchange market: A multivariate factor GARCH approach, Unpublished manuscript, Department of Economics, University of Wisconsin, Madison, WI.
53. Mandelbrot, B. 1963, The Variation of Certain Speculative Prices, *Journal of Business,* vol. 36, pp.394-419
54. McCurdy, Thomas H. and Ieuan Morgan, 1987, Tests of the martingale hypothesis for foreign currency futures with time varying volatility, *International Journal of Forecasting* 3, 131-148.
55. McCurdy, Thomas H. and Ieuan Morgan, 1988, Testing the martingale hypothesis in Deutschemark futures with models specifying the form of the heteroskedasticity, *Journal of AppliedEconometrics 3,* 187-202.
56. Meyer, D. 2003, Time Series Analysis for Researchers, *161.774 Study Guide*, College of Science, Massey University
57. Meyer, D. 2002. Time series Analysis for Researchers (Albany) lecture handouts.
58. Mussa, Michael, 1979, Empirical regularities in the behavior of exchange rates and theories of the foreign exchange market, in: K. Brunner and A.H. Meltzer, eds., *Carnegie-Rochester series on public policy,* Vol. 11 (North-Holland, Amsterdam).
59. The National Bank of New Zealand Limited website, http://www.nationalbank.co.nz/economics/exchange/nzdusd.htm

60. Nelson, Daniel B., 1989, *Modeling stock market volatility changes,* 1989 Proceedings of the American Statistical Association, Business and Economic Statistics Section, 93-98.

61. Nelson, D.B.1991, Conditional Heteroscedasticity in Asset Returns: A New Approach, *Econometrica,* vol. 59, pp347-370

62. Nelson, Daniel B. and C.Q. Cao, 1991, A note on the inequality constraints in the univariate GARCH model, *Journal of Business and Economic Studies*, forthcoming.

63. Schwet G W 1989 why does stock market volatility change over time? *Journal of Finance* vol. 44, p1115-53

64. Shumway and professor Alan D.R. McQuarrie of North Cakota State University. 2002, *Applied Statistical Time series Analysis,* The Readers.

65. Pagan, Adrian R. and G. William Schwert, 1990, Alternative models for conditional stock volatility, *Journal of Econometrics* 45, 267-290.

66. Patterson, K. (2000). An Introduction to Applied Economics: a time series approach. London: Macmillan Press Ltd

67. Phillips, P.C.B. (1987). Time series regression with a unit root. *Econometrica.*, 277-302.

68. Ramanathan, R. (1998). Introductory Econometrics. (4^{th} ed.). Orlando: The Dryden Press.

69. Sentana, Enrique, 1990, Identification and estimation of multivariate conditionally heteroskedastic latent factor models, *Unpublished manuscript* (London School of Economics, London).

70. Taylor, Stephen J., 1986, Modelling financial time series (Wiley, New York, NY).

71. Taylor, Stephen J., 1990a, Modelling stochastic volatility, Unpublished manuscript (Department of Accounting and Finance, University of Lancaster, Lancaster).

72. Taylor, Stephen J., 1990b, Efficiency of the yen futures market at the Chicago Mercantile Exchange, in: B.A. Gross, ed., Rational expectations and efficiency in futures markets (Routledge) forthcoming.

73. Tong,H.1980 Threshold Autoregressive, limit cycles and cyclical data. *Journal of Royal Statistical Society,* 42

74. Zakoian J. M.(1990) Threshold Heteroskedastic Models, manuscript, crest, Insee, Paris.

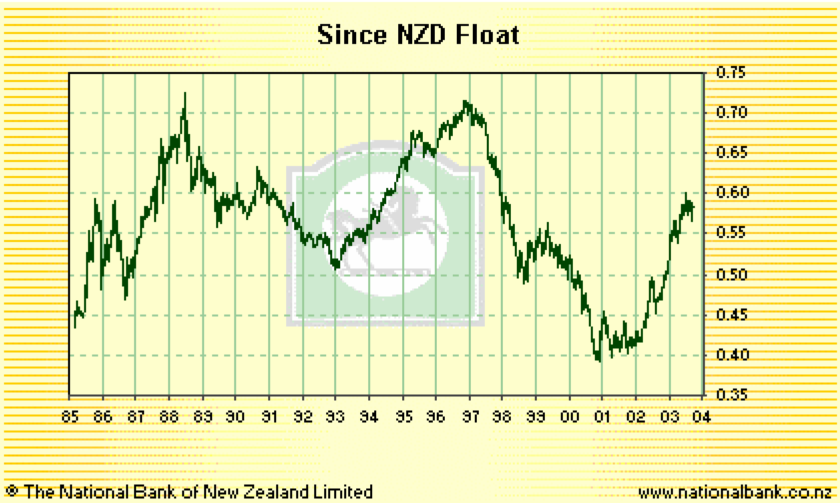
75. Glosen, L.R., R. Jagannathan, and D. Runkle(1993) On the relation between the expected value and the volatility of the normal excess return on stocks. *Journal of Finance,* 48, 1779-1801

9. Appendix

Appendix 1

Performance of the New Zealand Exchange Rate

Since Floated



Note: Data source, National bank of New Zealand Limited website.

Appendix 2

ARCH LM test at lag 1 on NZFX return series

ARCH Test:

F-statistic	55.92812	Probability		0
Obs*R-squared	55.08396	Probability		0
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.00E-05	1.52E-06	19.78538	0
RESID^2(-1)	0.125139	0.016733	7.47851	0
R-squared	0.015653	Mean dependent var		3.43E-05
Adjusted R-squared	0.015373	S.D. dependent var		8.40E-05
S.E. of regression	8.33E-05	Akaike info criterion		-15.9474
Sum squared resid	2.44E-05	Schwarz criterion		-15.9439
Log likelihood	28061.47	F-statistic		55.92812
Durbin-Watson stat	2.021329	Prob(F-statistic)		0

Sample range: January 1st, 1990 to May 31st, 2003

Source: Author

Appendix 3

Correlogram of ACF and PACF on Return of NZFX at lag 36

Correlogram of Residuals Squared

Date: 11/12/03 Time: 10:55
Sample: 1/02/1990 5/30/2003
Included observations: 3499

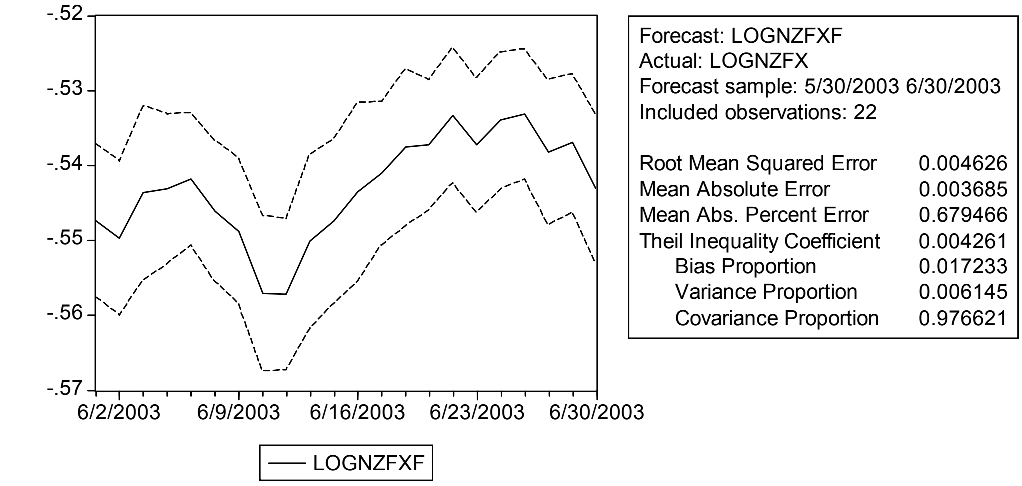
Lag	AC	PAC	Q-Stat	Prob
1	0.125	0.125	54.706	0.000
2	0.101	0.087	90.452	0.000
3	0.147	0.127	166.07	0.000
4	0.093	0.057	196.46	0.000
5	0.075	0.038	215.95	0.000
6	0.059	0.020	228.24	0.000
7	0.107	0.076	268.63	0.000
8	0.061	0.021	281.80	0.000
9	0.092	0.059	311.59	0.000
10	0.037	-0.011	316.44	0.000
11	0.072	0.039	334.78	0.000
12	0.057	0.016	346.31	0.000
13	0.072	0.042	364.33	0.000
14	0.079	0.039	386.46	0.000
15	0.074	0.036	405.62	0.000
16	0.062	0.014	419.11	0.000
17	0.045	0.004	426.16	0.000
18	0.067	0.025	442.00	0.000
19	0.081	0.046	464.94	0.000
20	0.055	0.011	475.68	0.000
21	0.058	0.016	487.59	0.000
22	0.066	0.019	502.85	0.000
23	0.026	-0.018	505.25	0.000
24	0.061	0.027	518.31	0.000
25	0.039	-0.001	523.69	0.000
26	0.059	0.026	535.95	0.000
27	0.041	0.000	541.99	0.000
28	0.056	0.020	553.08	0.000
29	0.076	0.037	573.33	0.000
30	0.080	0.044	595.81	0.000
31	0.070	0.024	613.26	0.000
32	0.043	-0.004	619.65	0.000
33	0.049	-0.004	628.07	0.000

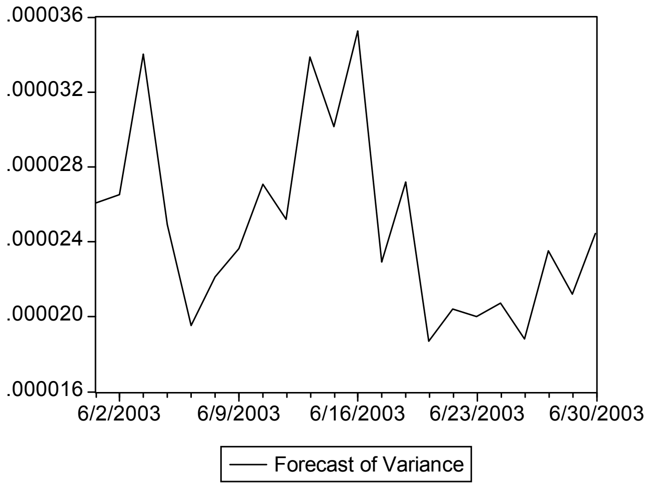
Sample range: January 1st, 1990 to May 31st, 2003

Source: Author

Appendix 4

Forecast by the ARCH(5) model



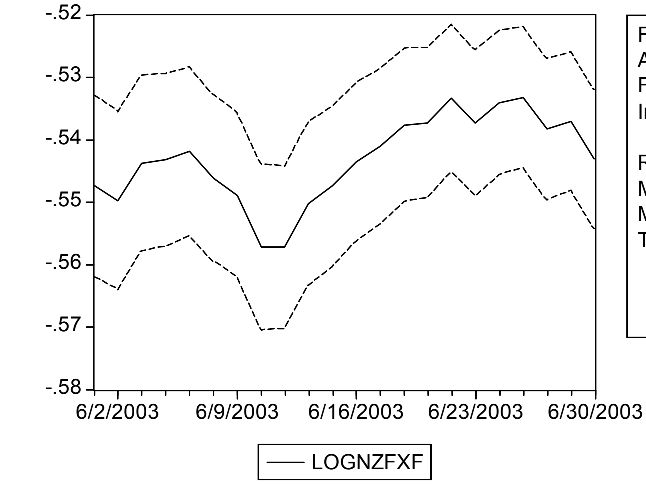


Forecast Period: June 1st, 2003 to June 30th, 2003

Source: Author

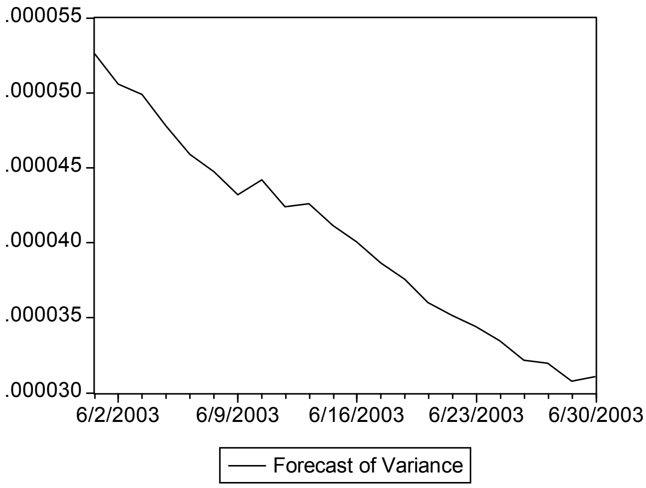
Appendix 5

Forecast by the GARCH(1,1) model



Forecast: LOGNZFXF
Actual: LOGNZFX
Forecast sample: 5/30/2003 6/30/2003
Included observations: 22

Root Mean Squared Error	0.004635
Mean Absolute Error	0.003702
Mean Abs. Percent Error	0.682736
Theil Inequality Coefficient	0.004269
Bias Proportion	0.020948
Variance Proportion	0.006122
Covariance Proportion	0.972929

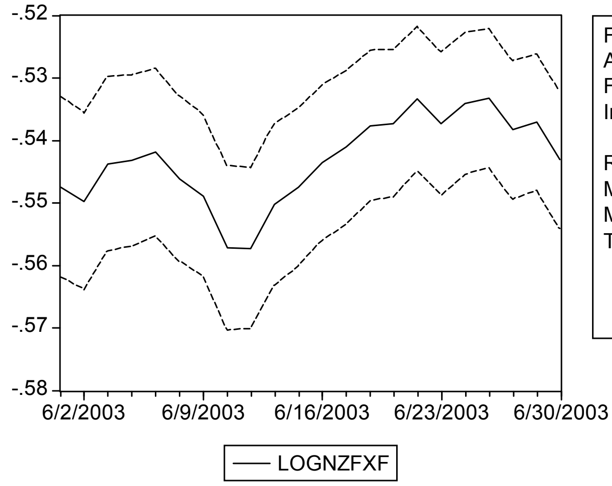


Forecast Period: June 1st, 2003 to June 30th, 2003

Source: Author

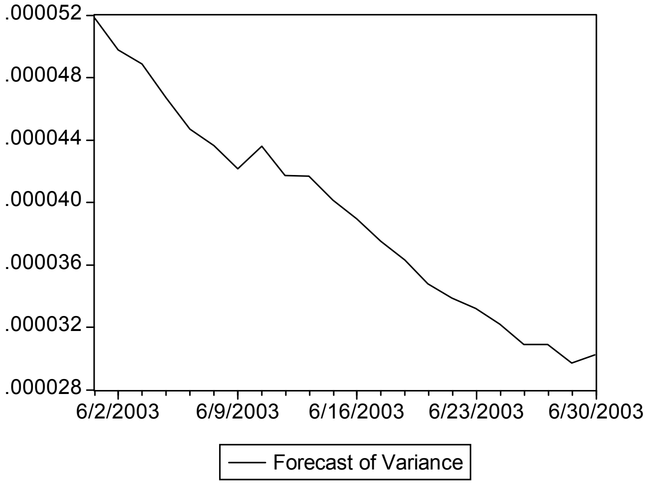
Appendix 6

Forecast by the TARCH model Forecast



Forecast: LOGNZFXF
Actual: LOGNZFX
Forecast sample: 5/30/2003 6/30/2003
Included observations: 22

Root Mean Squared Error	0.004638
Mean Absolute Error	0.003708
Mean Abs. Percent Error	0.683786
Theil Inequality Coefficient	0.004272
Bias Proportion	0.022213
Variance Proportion	0.006114
Covariance Proportion	0.971673

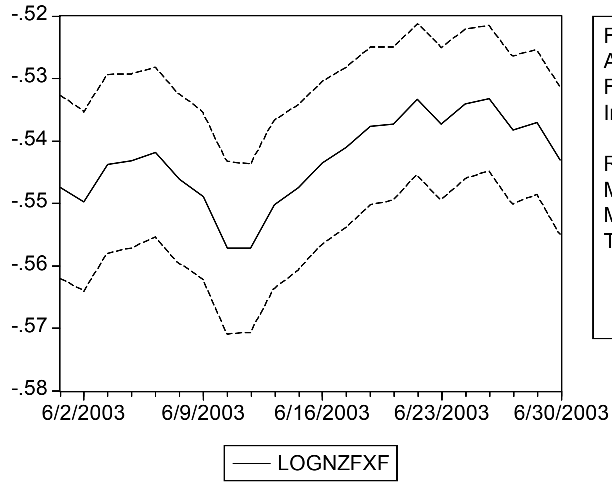


Forecast Period: June 1st, 2003 to June 30th, 2003

Source: Author

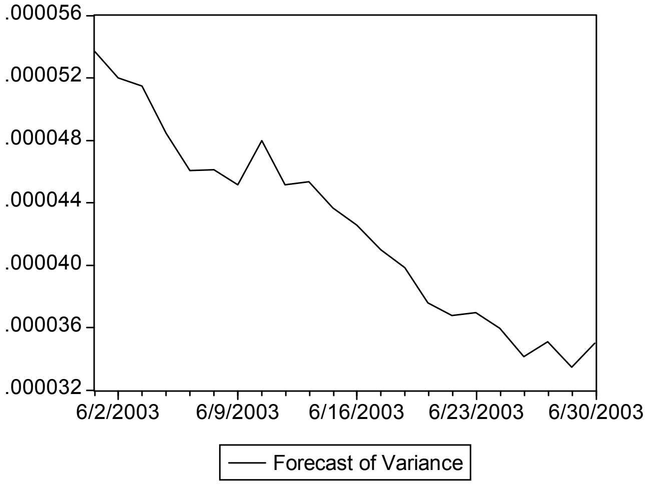
Appendix7

Forecast by the EGARCH Model



Forecast: LOGNZFXF
Actual: LOGNZFX
Forecast sample: 5/30/2003 6/30/2003
Included observations: 22

Root Mean Squared Error	0.004635
Mean Absolute Error	0.003703
Mean Abs. Percent Error	0.682915
Theil Inequality Coefficient	0.004270
Bias Proportion	0.021161
Variance Proportion	0.006121
Covariance Proportion	0.972718

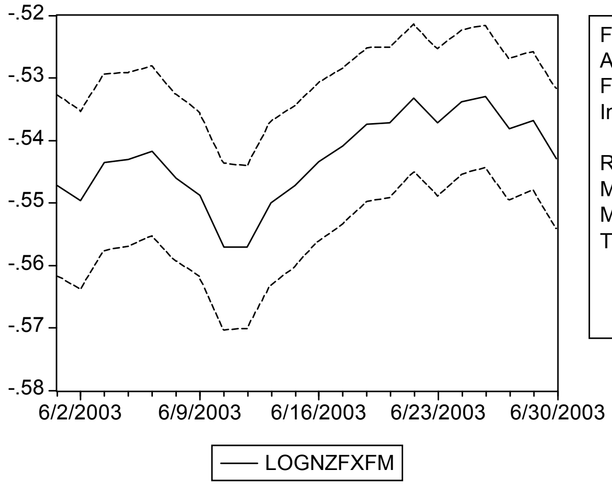


Forecast Period: June 1st, 2003 to June 30th, 2003

Source: Author

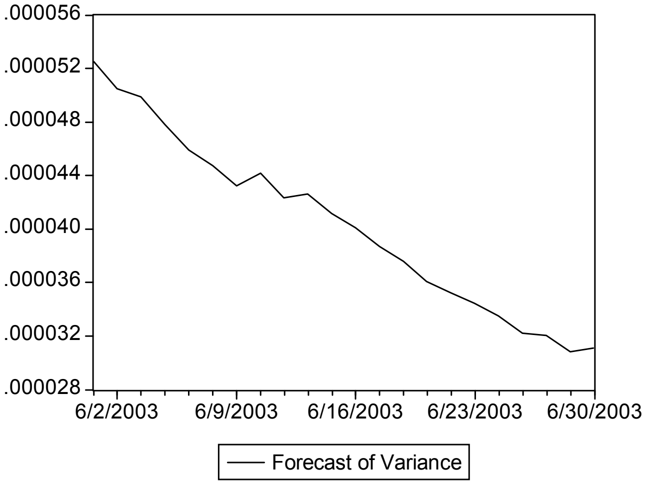
Appendix 8

Forecast by the GARCH-M model



Forecast: LOGNZFXFM
Actual: LOGNZFX
Forecast sample: 5/30/2003 6/30/2003
Included observations: 22

Root Mean Squared Error	0.004617
Mean Absolute Error	0.003665
Mean Abs. Percent Error	0.675695
Theil Inequality Coefficient	0.004253
Bias Proportion	0.013379
Variance Proportion	0.006169
Covariance Proportion	0.980452



Forecast Period: June 1st, 2003 to June 30th, 2003

Source: Author