Long Memory Currency Index Over Exchange Traded Funds: A Case Of CYB Currency Index

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Abstract

This paper investigates the long memory for the closing prices in currency indexof exchange traded funds. ARFIMA and FIEGARCH models for Renminbi (CYB); daily prices in exchange traded funds have been studied and tested in this study in order to find out the best fitted model for Renminbi currency index.Finally the empirical results of this study showfor CYB currencyindex exchange traded funds.TheARFIMA (2, d, 3) and FIEGARCH (2, d, 3) were found to be the best modelsduring sevenyears'(2008-2014).The reason for doing this study was in order to find out the effects on CYB index during the period when recession struck (2008); as most economies came out of it until 2014; thus it was interesting to study the effectiveness of CYB index during the period of (2008-2014) for exchange traded funds; which is one of the finest currency index belonging to China which is again one of the fastest developing and growing economy.

Keywords: ARFIMA, FIEGARCH, long memory, exchange traded funds.

Introduction

Exchange traded fund's (ETF's) can be defined as a security tracking an index or a commodity, but trades similar to that of a stock on an exchange. ETF's experience changes in price throughout the day while they are bought or sold. ETF's can be considered as important and beneficial because we get the opportunity to see the diversification of an index and to sell it at short and purchase small shares on a little margin. The other benefits of ETF's are as they are traded on an intraday basis thus for an investor it becomes very easy and safe to carry on the trade on an intraday basis which is not the similar case with mutual funds or other stocks.

This research evaluates7 years data (2008-2014) of Renminbi (CYB) currency index using ARFIMA and FIEGARCH model in order to find out the best suited model for CYB index. The period of (2008-2014) was chosen for this study due to the reason as recession struck the global market and economies in the start of year 2008 and until the end of 2014, economies have almost recovered during these7 years. Thus we choose the data for the given time frame.Also it was very interesting to find out how did CYB index reacted to the up's and down of the recession period and after it ended. It will give us a glimpse of China's CYB index behavior in order to study more precisely for

exchange traded funds as it is becoming very important these days to study developing economies currency index for tracing their future developments.

Although past literature has studied over various issues about the currency exchange traded funds in the past however we were not able to find a similar research done over CYB index in order to figure out the best fitted model for this specific currency index as per best of our knowledge.

This paper is been divided into 4 sections. First section consists of a brief introduction followed by literature review in section two, section three consists of the methodology being used for this study and finally section four consists of conclusions, limitations of the research and recommendations for the future study.

Literature review

Previousliterature has discussed about ARFIMA FIEGARCH model in the researches carried out over mutual funds, ETF's and other instruments of finance which are used nowadays in different financial markets of the world. This section will discuss the previous research done implementing both the models and also clarifies the importance and orientation of the models in different studies of the past.

Long memory: Long range dependency or long range persistence is defined as a phenomenon that arises during the analysis of the time series data. It can be related to the rate of decay of statistical dependence taking into consideration as this decay more slowly than an exponential decay. Models that are used for the long memory are ARFIMA, FIEGARCH etc. out of the stochastic models.

ARFIMA model: (Autoregressive fractionally integrated moving average model) this model belongs to the time series and it generalizes ARIMA (autoregressive integrated moving average model) as it allows non integer values of the differencing parameter. This model is basically used and is useful for the long memory in case of modelling the data with time series. Here by long memory we mean where the deviations from the long-run mean decay at a slower pace than an exponential decay.

In one of the previous study related to ARFIMA GARCH model (Baillie and Chung 1996)it was found that existence of long memory in CPI inflation of all countries which were used in the research accept Japan which was found to be stationary.

(Bhardwaj and Swanson 2006) worked over a study for finding out the usefulness of ARFIMA model and their study concluded that ARFIMA models may have reasonable approximations to the unknown data generation processes (DGPs). As the models often significantly outperform a fair and wide class of the benchmark non-ARFIMA models; which includes AR, ARMA, ARIMA, random walk, GARCH, and related models. Also the study stated that ARFIMA models mostly and very often outperform simpler linear models at a longer prediction horizons holding up when the alternatives which are being considered may also include various types of threshold, and related non-linear models.

Another study studying the importance, usefulness of ARFIMA model for long memory. Author (Baillie 1996) found that using only ARFIMA model cannotbe appropriate for long memory process; if the ARFIMA model is combined with models like FIEGARCH the results found for long memory are more appropriate and useful.

(Cheung 1993) studied about long memory for foreign exchange rates using ARFIMA model by estimating it with maximum likelihood method and found that there was a presence of long memory in exchange rate data in the conclusion of the study the author mentioned that the impulse-response functions and the forecasts which are based on these estimated ARFIMA models

are finally evaluated to gain a perfect insight of the long-memory characteristics of the given exchange rates.

FIEGARCH model:(Fractional integrated general autoregressive conditional heteroskedasticity model) it was proposed by (Baillie and Chung 1996). Fractionally integrated garch (FIGARCH model) is proposed in order to determine the long memory in return volatility.

A previous research done over long memory in stock market volatility studies FIEGARCH model and concludes that in the final results of FIEGARCH model the results were found to be consistent and the use of FIEGARCH model with news impact in mean thus authors contributed with aggregate time series evidence complementing the cross-sectional findings on the sign of the volatility-return relation using FIEGARCH model.

(Cotter and Stevenson 2008) examined long memory for alternative risk measures, observed absolute and squared returns in their study and compared the findings for a market equity index using two long memory volatility models, fractionally integrated garch (FIGARCH) and fractionally integrated exponential garch (FIEGARCH) and found the existence of long memory, also the models were found to be a good fit for the data used in the research.

(Ruiz and Veiga 2008)studied about modelling long-memory volatilities with leverage effect by comparing FIEGARCH and LMSV model and finally the results showed that both models seem to be fitted easily with the data although LMSV model was found to be a bit easy if compared than FIEGARCH model.

(Perez and Zaffaroni 2008)studied about the finite-sample properties of maximum likelihood and whittle estimators in EGARCH and FIEGARCH models and found out that FIEGARCH model was very well fitted and the results showed that maximum likelihood is more efficient but bivariate whittle sometimes performs comparably. Thus this study shows the use of FIEGARCH model in a successful and evident way.

ARFIMA FIEGARCH model: (Teyssiere, Farge, and Austerlitz 1996) in his book used ARFIMA FIGARCH and ARFIMA FIEGARCH models in order to determine the case of double long memory.

Similarly in order to test long memory and leverage effect in daily exchange rate of euro foreign exchange market, study of (Huang, Zhao, and Hou 2009) used ARFIMA-FIEGARCH model to the return series, using daily exchange rate of EUR/USD, EUR/JPY and EUR/GPB, Where ARFIMA FIEGARCH model was found properly fitted for EUR/USD data.

Study of (De Melo Mendes, Regina, and Lopes 2008)also studied about the long range dependence in copula models and tested ARFIMA FIEGARCH model for the given data finally concluding a presence of long memory in the copula.

Thus the above literature supports the fact that the use of ARFIMA FIEGARCH model for testing long memory in time series data is appropriate. Also we can determine easily that weather the model is best fitted for the used data or not. In the present study we apply ARFIMA FIEGARCH model in order to test the changes occurring in CYB currency index, also to find out if there was an existence of long memory in the time series data used for the given study. This study uses 7 years data (2008-2014) to test the models. The time period used in the study becomes crucial because it was the start of recession thus it seem to be interesting how did CYB behaved in the given time frame.

The next section of this study discusses about the data, data source and the methodology undertaken in this specific research.

Research methodology:

Data:

This study investigates the presence of long memory in the currency index of CYB (renminbi) for the span of 7 years (2008-2014). Data was obtained from the website of Yahoo Finance; we used ox metrics software to run the regression and models. The models ARFIMA FIEGARCH areused in order to find out the presence of long memory in CYB currency index ETF.

Methodology

We have used ARFIMA and FIEGARCH model for the analysis of our data. This methodology was adapted because of the fact as among the given models ARFIMA FIEGARCH is the best suited for the long memory relationships in the variables. In this section the general equations of the models used have been discussed with the steps involved during the undertaken tests.

ARFIMA Model : (Granger 1980) and (Hosking 1981) proposed an ARFIMA model and proposed the method to fit long-memory data. ARFIMA(p,d, q) is written as follow:

$$\Phi(L)(1-L)d\ (Xt - \mu)=\theta(L)\varepsilon t \qquad (1)$$

ARFIMA(p,d,q) is written as follow:

$\varphi(L)\Delta dyt = \delta + \theta(L)ut$ with $\varphi(L) = (1 - \varphi 1L - \ldots - Lp)$ and $\theta(L) = (1 - \theta 1L - \ldots - \theta qLq)$ (2)

where: δ = a constant term;
$\theta(L)$ = the MA operator at order q
ut = an error term
$\varphi(L)$ = the AR operator at order p
Δdyt = the differencing operator at order d of time series data yt.

ARFIMA model is basically a time series model that generalizes ARIMA (autoregressive integrated moving average) model by allowing the non-integer values of the differencing parameter.
These models are useful in modeling time series with long memory - that is, in which deviations from the long-run mean decay more slowly than an exponential decay. A general multiplicative seasonal ARIMA model for time series Zt is as follows:

$$\varphi(L)\Phi(Ls)(1-L)d(1- Ls)DZt = \theta(L)\rho(Ls)\alpha t \qquad (3)$$

Where:
L = a backshift or lag operator (Bzt - Zt-1);
S = seasonal period;
$\varphi(L) = (1 - \varphi 1L - \ldots - Lp)$ is the non-seasonal AR operator;
$\Phi(Ls) = (1 - \Phi 1Ls - \ldots - \Phi sLs)$ is the seasonal AR operator;
$\theta(L) = (1 - \theta 1L - \ldots - \theta qLq)$ is the non-seasonal MA operator;
$\rho(L) = (1 - \rho 1Ls - \ldots - \theta 0LQs)$ is the seasonal MA operator;
(1 - L)d(1 - Ls) = non-seasonal differencing of order d and seasonal differencing of order D.

The process is called stationary when the value of ARFIMA model is $-0.5<d<0.5$. This happens where the effect of shocks to εt decays at a gradual rate to zero.

- The process is said to have a short memory if d=0. This is where the effect of shock decays geometrically.
- A unit root process is undertaken when value of d=1.

- A long memory process or the so-called positive dependence among remote observations exists when 0<d<0.5. Also, there is a presence of intermediate memory or anti-persistence when -0.5<d<0 (Baillie et al., 1996).
- The process is non-stationary if d≧0.5 (Galbraith & Zinde-Walsh, 2001). While it is stationary but noninvertible process if d≦-0.5, making the time series impossible to model by any autoregressive process.

FIEGARCH Model:(Baillie 1996) proposed fractionally integrated GARCH (FIGARCH) model to determine long memory in return volatility. The FIGARCH (p, d, q) process is as follows

$$[\Phi(L)(1 - L)d]\varepsilon 2t = \omega + [1 - \beta(L)](\varepsilon^2 t - \sigma^2 t) \qquad (4)$$

Where $vt = u^2t - \sigma^2t$, t 0<d<1, Φ (L) = $\sum_{i=1}^{n-1} \varphi_i L^i$ is of order m-1, and all the roots of Φ (L) and [1 - β (L)] lie outside the unit circle.

The FIGARCH model is derived from standard GARCH model with fractional different operator (1-L) d. The FIGARCH (p,d,q) model is reduced to the standard GARCH when d=0 and becomes IGARCH model when d=1.

It is known that for 0<d≤1 the FIGARCH (p,d,q) process has an undefined unconditional variance. However, the process does possess cumulative impulse response weights with a finite sum. This property makes the FIGARCH model different from other possible forms of long memory ARCH models.Thus these models were used in this study to find out the presence of long memory for CYB currency index.

The Database information including the sample size and period of emerging markets currency is given in table 1.

Table.1 Sample Size and Period of Emerging Markets Currency

Currency	Start of Data	Obs	Mean	Std Dev.	Skew	Kurtosis	J-Bera	Q.10
Renmimbi (CYB)	3/15/2008	1259	0.00056371	0.10767	-1.3997	18.098	16894	68.981

Table 1 show that the average return from CYB is 0.00056371 and the standard deviation of CYB index is 0.10767. Skewness result was found to be -1.3997; which means thatskewness slope is moving to the left because the given value -1.3997 < 0 and on the other hand we can say that it is not a normal curve. Looking at the kurtosis the resulted value wasa positive value (18.098), and it tends to the pointed curve because the value is greater than 0, or 18.098> 0. The value of the result of J.Bera test was 16984; thus seeing the facts and figures we can therefore accept the data or the error term distributed normally. The result of Q statistic is higher than chi square lag {Q < chsq(lag)} so we can conclude that the outcome value should not be significant and we must accept the null hypothesis of presence of no serial correlation in the data of CYB for the given period of time.

Table 2 depicts the ARFIMA model results and depicts the best model considered for the CYB current index data taken for the period of 7 years.

Table.2 ARFIMA model

ETFs	Model	d-coeff	AIC value
CYB	(2,0)	-0.2510(0.000)	-1.62882191

Interpretation:-According to the results given in above table value of d-coefficient is (-.2510) which is greater than -0.5 so the process is considered as a non-stationary process.

Table 3 depicts the results of ARFIMA FIEGARCH model for the CYB currency index.

Table.3 ARFIMA FIEGARCH

ETF's	d-coefficient	ARCH	d-coefficient	AIC value
CYB	0.092218(0.1173)	(1,0)	0.653298 (0.0000)	-2.186357

Interpretation: According to the results in table 3 value of d-coefficient is 0. 653298 which means d is the long memory parameter with a range of 0<d<1 that allows for stronger volatility persistence.Thus looking at the result of ARFIMA and ARFIMA FIEGARCH models for the ETF of CYB we conclude that the process is found to be non-stationary and has a long memory parameter.

Conclusion: From the above interpretations of the data by using ARFIMA and FIEGARCH model it is clear by looking at the value of d-coefficient in ARFIMA model that the process is non stationary; also ARFIMA FIEGARCH model value of d-coefficient shows that it allows for stronger volatility persistence and has a long memory parameter. Thus these models are fitted perfectly for the given data of CYB ETF.

Limitations of the study: This study is a short study done over a single ETF of CYB to study the specific currency index of renminbi which evaluates the current position of the ETF starting from the period of recession. Thus the test results of this study cannot be the same for other currency indexes because every ETF changes multiple times in a day thus the changes are very frequent.

Recommendations for the future research: for the future research researchers can make the comparison between different currency indexes using the same model or also can compare by using two different models like ARFIMA FIEGARCH and ARFIMA HYGARCH. ETF's are known for changing very frequently thus it is a very interesting topic to find out and compare ETF's of different countries to see the effect they are causing by the use of different models.

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