Volatility Spillover Between the UK Exchange Market and Stock Market by Wavelet Analysis

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1 Introduction

1.1 The Literature about Volatility Spillover effect

In modern financial market, volatility is a key variable in asset pricing, risk management. Ross [11] claims not only the price of asset contains information, but also the volatility contains useful information on the market. Volatility of one specific financial market influences the volatility of others, which is called the volatility spillover effect. With the trend that financial markets have been more and more closely connected, the volatility spillover will be more and more significant. There are many volatility spillover researches around the stock market, oil price, bond market, exchange market, derivative market , and further more some researchers also investigate volatility spillover effect between different countries' markets.

Jeff Fleming [6] proved the volatility linkages between stock market, bond market, money market are indeed strong due to common information and information spillover by cross-market hedging.

Heni Boubaker [2] studied the volatility spillover between oil price and BRICS stock market by wavelet transform and ARMA-GARCH model and found that oil price and BRICS stock markets are driven indirectly by other prices.

Kanas [8] used EGARCH filter to analyze daily volatility of stock index and exchange rate within in 6 different developed countries and found significant volatility spillover from stock market to exchange market in 5 countries and this effect has increased since October 1987 crash, but the volatility spillover effect from exchange rate to stock is insignificant in all 5 countries.

Panda [10] applied GARCH and EGARCH model to compare asymmetrically the volatility spillover effect between Indian stock market and Indian foreign exchange in two different time periods. one is before the financial crisis, the other one after, and concluded eventually a fact the volatility spillover effect is more significant after the financial crisis.

Exchange rate and stock index both are important indicators in macro-economy, the volatility relationship between them is complex. It is meaningful to investigate the volatility spillover of them. Previous researches mostly focus on the daily data, for volatility research the daily data will obviously lose lots of useful information, and make the volatility spillover effect hard to find. What's more, with the advancement of IT technology, the high-frequency trade has deeply influenced the linkage of markets.

Two classical explanations on the stock market and exchange market relation is the cash-flow view and monetary approach. The cash-flow view is proposed by Dornbusch and Rudiger [5] who claim that the varying of exchange rate will influence the competitive strength of the domestic companies in the international market, and even affect the cash flow of the companies, which will have impacts on stock price. This model illustrates the influence from exchange market to stock market.

The monetary approach is proposed by Branson and Frankel[7] [3] who focus on the influence from stock market to to the exchange market. The main idea is if the stock price rises, the stock market will attract the foreign investors to put money in, the increasing demand of domestic asset portfolio will lead to a huge demand for the domestic currency, so the exchange rate will rise.

The last model has been observed by many researchers, such as Angelos Kanas[9] who finds that volatility from domestic stock return is significant determinant of the volatility of the exchange rate market in the three industrialized countries (the US,the UK and Japan).

Both models explain how one market put influence on another in a specific way. Overall the previous researches find the volatility spillover from stock market to currency market is significant, the opposite way is not significant and hard to find.

In this study, we will use wavelet transform to analyze the volatility spillover between FTSE100 and USD-GBP in past half a year by using the 30-min close price data. Then using MODWT to decompose the data and get wavelet coefficients to analyze the correlation between wavelet coefficients and finally investigate the lead-lag relation between the two time series. This essay will introduce the measures of volatility, wavelet transform idea and how to realize that, after the theory part, there are empirical applications of MODWT on a artificial signal and real data.

1.2 The Measures of Volatility

There are three kinds of volatility measures in general.

Historical volatility is the commonest volatility for the security market. It uses the standard deviation of the daily return in a month or a year to measure the volatility of market monthly and yearly. There are many traditional time-series methods such as GARCH, ARCH to estimate and predict it.

Implied volatility refers to the market's assessment of future volatility, which is calculated by price of option and is usually used in derivative market. According to the Black-Scholes model, If the price of a option is known, the volatility can be calculated by other 4 known parameters which are the underlying stock price, the strike price, the time to expiration and the interest rate.

Realized volatility is designed by Torben G. Andersen [1] , which is created to get the volatility in high-frequency intraday returns and make it possible to apply the traditional time-series method in high-frequency data. The realized volatility is also be proved to be unbiased estimator for the daily volatility result by Torben G. Andersen [1]. One common use of realized volatility is to get the volatility of a particular day by summing the squared intraday returns. The calculation process is shown as follows.

To calculate the realized volatility, we log the stocks price p_t and calculate the first-order difference between them.

$$r_t = \log(p_t) - \log(p_{t-1}) \tag{1}$$

Then summing the past N squared return to get realized volatility variance

$$RV_t = \sum_{t=1}^{N} r_t^2 \tag{2}$$

The realized volatility is the square root of volatility variance

$$RV_t = \sqrt{RV_t} \tag{3}$$

In this study, the calculation is similar to realized volatility calculation process. Firstly log the return of index and exchange rate and calculate the first-order difference of the log return.

$$r_s = \log(S_t) - \log(S_{t-1}) \tag{4}$$

$$r_e = \log(e_t) - \log(e_{t-1}) \tag{5}$$

Where S_t is the index at time t,S_{t-1} is the index at time $t-1$, and e_t represents the exchange rate at t.

After the calculation, We now get two time series contain r_s and r_e,which represent the change from two next close price. This method will be applied in the empirical analysis to represent the volatility of the data.

2 Theory Method

2.1 Continuous Wavelet Transform

Generally the wavelet transform can be considered as two categories, one is continuous wavelet transform, the other one is discrete wavelet transform. The first topic is what is wavelet and how it generates. Wavelet is a French word which means small wavelet, because it only exists in a finite interval not like the sine or cose functions used in Fourier transform which has infinite interval, so the wavelet is also called "small wave".

Consider two conditions:

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \tag{6}$$

$$\int_{-\infty}^{+\infty} \psi^2(t)dt = 1 \tag{7}$$

If a function ψ (t) satisfies these conditions, we can call it a wavelet mother function[4]. Based the two conditions, there must exist a interval [-T,T] to make

$$\int_{-T}^{T} \psi^2(t)dt > 1 - \varepsilon \tag{8}$$

If ε is close to zero, the value of integral squared mother function is not equal to zero in the limited interval[-T,T]. And from the second condition we will see values of mother wavelet function fluctuate near zero just like a small wave.

Here are two common wavelet mother functions to show what a wavelet looks like. The wavelet mother function depends t, the horizontal axis is the time t,the vertical axis is mother function value.

This is the Morlet wavelet mother function formula:

$$\psi_\sigma(t) = c_\sigma \pi^{-\frac{1}{4}} e^{-\frac{1}{2}t^2}(e^{i\sigma t} - k_\sigma) \tag{9}$$

$$k_\sigma = e^{-\frac{1}{2}\sigma^2} \tag{10}$$

$$C_\sigma = (1 + e^{-\sigma^2} - 2e^{-\frac{3}{4}\sigma^2})^{-\frac{1}{2}} \tag{11}$$

In this formula, σ is a positive constant and is usually defined greater than 5. ψ is the Morlet mother function and generates different values by different t. The following picture is the shape of Morlet wavelet.

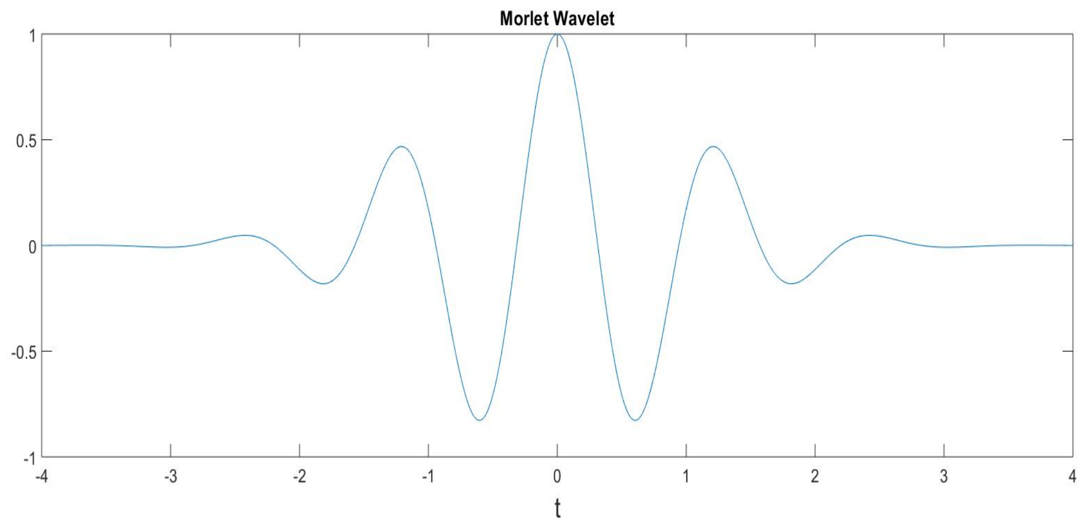

Figure 1: Morlet Wavelet Picture

This is the Haar wavelet transform formula, Haar wavelet is considered as the simplest wavelet transform. It is easy to notice the formula satisfied the wavelet mother function condition (6) and (7):

$$\psi(t) = \begin{cases} 1, & 0 \leq x < \dfrac{1}{2}, \\ -1, & \dfrac{1}{2} \leq x < 1, \\ 0, & otherwise \end{cases} \tag{12}$$

So the wavelet function is defined to be concussive and decay to zero swiftly.The mother function shifts and stretches by giving two different parameters s and τ to form the wavelet function family.

$$\psi_{s,\tau}(t) = |s|^{-\frac{1}{2}} \psi(\frac{t-\tau}{s}) \tag{13}$$

$\psi_{s,\tau}(t)$ is the children function which suffered from compression and shift, $\psi(t)$ is the wavelet mother function form. Where s is a positive number called scale factor (dilation factor) that controls scale and τ is named translation parameter which moves the wavelet to different position in time zone. $\psi(\frac{t-\tau}{s})$ is used to realize the function of compression and shift.

The basic idea of wavelet transform is using a series of waveform curves to capture the features of original signal, which always make original signal can be observed more implied features.

$$C_{s,\tau} = \int_{-\infty}^{\infty} f(t)\psi_{s,\tau}(t)dt \tag{14}$$

$f(t)$ is the original time series data, $\psi_{s,\tau}$,is the wavelet children function, and $C_{s,\tau}$ are the wavelet coefficients. The coefficients show the result of the wavelet transform. Varying the scale factor and shifting the position factor to get the first wavelet coefficient $C_{s,\tau}$ and continue to move the translation parameter until cover the whole signal. Then changing the scale factor to the next scale to continue transform until all scales have been processed. That is the how continuous wavelet transform works.

It is obvious that if we calculate wavelet coefficients at every scale factor and translation parameter, we will get a lot of redundant and useless data. Two closed scale factors and translation parameters are unnecessary, because the information are almost same with a small change on translation parameter. Due to the shortcoming of the continuous wavelet transform, it is not widely used in research. So people use discrete wavelet transform to replace the continuous wavelet transform but the discrete wavelet transform share the basic idea with the continuous one.

2.2 Discrete Wavelet Transform

As for the Discrete Wavelet Transform (DWT), the basic theory is same with the continuous one. The wavelet related coefficient s and τ will be sampled discretely to make the wavelet transform discrete. The discrete method as follows.

Scale parameter s is sampled discretely by j levels, each s_0^j will be s_0 with power of j, which will be explained clearly in MODWT chapter.

$$s = s_0^0, s_0^1.....s_0^j \tag{15}$$

Now the wavelet function (13) can be written in this form.

$$\psi_{s,\tau}(t) = {s_0}^{-\frac{j}{2}}\psi[s_0^{-j}(t-\tau)], j = 0, 1, 2... \tag{16}$$

To avoid to miss the leading information, Translation parameter should be sampled determined by the j level scale factor s_0^j, $\Delta\tau$ will be the smallest unit of moving. So translation parameter τ is sampled discretely by

$$\Delta\tau = s_0^j\tau_0 \tag{17}$$

The wavelet function (13) now can be written as:

$$\psi_{s,k}(t) = {s_0}^{-\frac{j}{2}}\psi[s_0^{-j}(t - ks_0^j\tau_0)], j = 0, 1, 2...; k \in Z \tag{18}$$

The continuous formula can be changed in this form, where k is an integer which means how many $\Delta\tau$ has been moved. And the $\psi_{s,\tau}(t)$ will be replaced by $\psi_{s,k}(t)$. Normally,For the discrete condition the function choose

$$s_0 = 2, \tau_0 = 1 \tag{19}$$

We can get

$$\psi_{j,k}(t) = 2^{-\frac{j}{2}}\psi[2^{-\frac{j}{2}} - k], j, k \in Z \tag{20}$$

Now we get the wavelet mother function in the discrete form. Compared with the continuous wavelet transform, this one will lead to less wavelet coefficients so as to save the time and reduce the redundancy.

Now considering the final level of the signal in wavelet transform, there is another function expression as follows,

$$\varphi_{j,k}(t) = 2^{-\frac{j}{2}}\varphi[2^{-\frac{j}{2}} - k], j, k \in Z \tag{21}$$

This function is called the wavelet father function(scale function) which share the similar form of the mother function are used to capture the low-frequency part of the signal, the $\varphi_{j,k}(t)$ is demanded to be orthogonal with mother function $\psi_{j,k}(t)$.

$$X_t = \sum_k s_{J_0,k}\varphi_{J_0,k}(t) + \sum_{j>J_0}\sum_k d_{j,k}\psi_{j,k}(t), j = J_0, ..., J \tag{22}$$

Where X_t means the given discrete data, the discrete wavelet transform, J_0 is the base level so to be transformed by scale function φ. Other levels $j > J_0$ will be transformed by mother wavelet ψ, the k means the how many times the wavelet will be moved.

For discrete wavelet transform, it inputs a vector of discrete data, the way to calculate the wavelet coefficient is not like the continuous one. In actual algorithm people often define a series of band-pass filters to process the input discrete data, the low-pass filter will replace the father wavelet (scale wavelet) and high-pass filter will replace the mother wavelet. For different wavelet function, people design different filters and algorithms to realize the function. For example,the first-level high-pass filter of Haar wavelet is defined as,

$$h(n) = \begin{cases} \dfrac{1}{\sqrt{2}}, & if \;\; n = 0, 1 \\ 0, & otherwise \end{cases} \tag{23}$$

$$w_{j,t} = \sum_{l=0}^{L-1} h_{j,l}X(t-l) \tag{24}$$

$$v_{j,t} = \sum_{l=0}^{L-1} g_{j,l}X(t-l) \tag{25}$$

Where $h_{j,l}$ is the high-pass filter, $g_{j,l}$ is the low-pass filter, j is the scale factor of the wavelet transform, t is translation parameter of the wavelet, $X(t-l)$ is the data need to be transformed. The wavelet detail coefficient is $w_{j,t}$, the wavelet scale coefficient is $v_{j,t}$. In general, we use d_j to represent the series of j-level the detail coefficients, s_0 to represent the series of scale coefficients.

2.3 Wavelet Transform Properties

To some extent, the wavelet transform is designed to overcome the drawbacks of Short-time Fourier transform, so compared with the Fourier transform:

1.Wavelet transform use wavelet function $\psi_{s,\tau}(t)$ to capture the signal and wavelets are localized in both time and scale.

2.The wavelet transform's multiresolution properties can capture the details and the trend well at the same time.

3.Another advantage of wavelet is that it can make people investigate the relationship between various variables at various time scales possible, people can not only focus on relationship on just one time scale. That is why wavelet transform is called "The Mathematical Microscope".

4. Fourier transform transfers the time zone signal to frequency zone, however, in Fourier transform the whole-duration frequency will be shown in the frequency result. Some frequency signal may only exist in the beginning of the duration which has little influence on the later signal but it also shows in the whole-duration transform result, so the Fourier transform can only be used on stationary time series data. On the other hand, the real financial data usually is non-stationary and the information of time zone is needed. Wavelet analysis will give us the frequency signal in different time zone, which make it a powerful tool to find the property of the volatility in multiresolution.

2.4 MODWT

Maximal Overlap Discrete Wavelet Transform (MODWT) is a kind of discrete wavelet transform(DWT).MODWT has several names in different literature, such as, "stationary DWT", "time-invariant DWT", "translation-invariant DWT". the filters of MODWT is formed as below:

$$\tilde{g}_l = \frac{g_l}{\sqrt{2}} \tag{26}$$

$$\tilde{h}_l = \frac{h_l}{\sqrt{2}} \tag{27}$$

$$\tilde{w}_{j,t} = \frac{1}{2^{\frac{j}{2}}} \sum_{l=0}^{L-1} \tilde{h}_{j,l} X_{t-l} \tag{28}$$

$$\tilde{v}_{j,t} = \frac{1}{2^{\frac{j}{2}}} \sum_{l=0}^{L-1} \tilde{g}_{j,l} X_{t-l} \tag{29}$$

Where $\tilde{g}_l$ is new form of low-pass filter, $\tilde{h}_l$ is the new form of high-pass filter, j is the scale factor of the wavelet transform, t is translation parameter of the wavelet, X_{t-l} is the data need to be transformed. The wavelet detail coefficient is $\tilde{w}_{j,t}$, the wavelet scale coefficient is $\tilde{v}_{j,t}$.

For the MODWT, it keeps the basic features of DWT and gives up the orthogonality property to obtain some features so as to apply on financial data.

1.The multiresolution of DWT is different from the MODWT, MODWT has the ability to form a multiresolution analysis(MRA) which is shift invariant, so any shift in the original time series will have a corresponding shift on MODWT and scaling coefficient and details.

2.There is no restriction on sample size.

MODWT is often used on financial data to study variance of time-series. The follow chart shows how to process the signal by MODWT transformation.

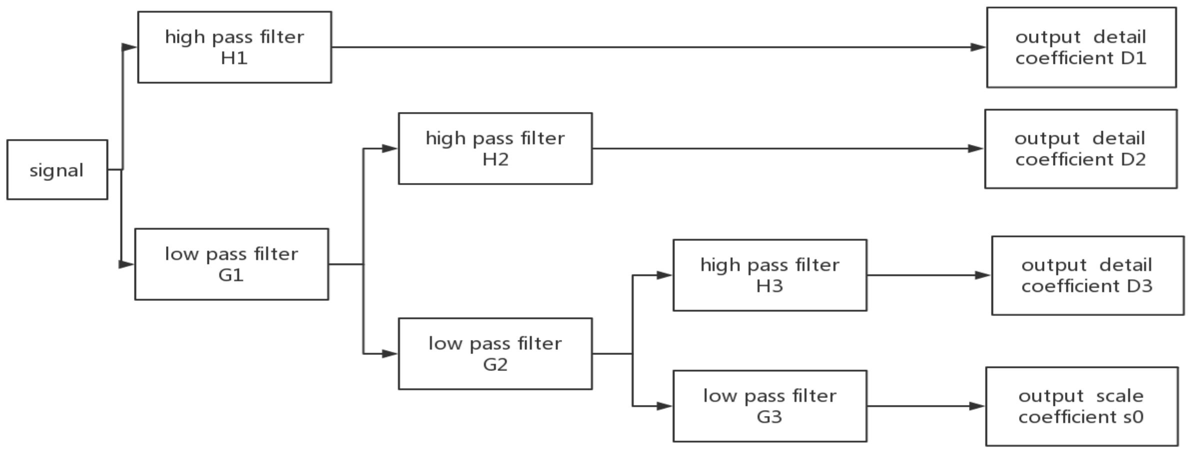

Figure 2: The process of how MODWT works

The MODWT can transform the original data points into wavelet coefficients. By passing high-pass filter and low-pass filter, the original signal will be extracted the high-freq component firstly. After the high-freq component pass the filter, we will get a series of level 1/scale 2 wavelet detail coefficient D1. Secondly, the rest signal will be decomposed further in a larger scale level2/ scale 4, apart from the former level 1, this filter has a larger scale. It can focus on larger scale features but ignore the detailed features. Next the signal will be decomposed further until we get the largest scale or the set decomposed level and get the scale coefficients.

As we told before s_0 is normally set to 2 in DWT, so MODWT will get at most $\log_2 N$ level wavelet coefficients in default. For each j level, the scale will be 2^j. That's the reason why

$$s = s_0^0, s_0^1 .....s_0^j \tag{30}$$

So for level 1 the scale is 1-2, and for level 2 the scale is 2-4, then for level 3 the scale is 4-8, then for level 4, the scale will be 8-16,...

Such decomposition mechanism can tells us the averages of a time series change from one interval to another over various scales, which can make us study the time series data in different scales simultaneously. That is why wavelet transform can do multirescale analysis.

After several former processes, the original signal will be decomposed into several detail coefficients $d1, d2, d3...$ and the coarser coefficients $s0$.

3 Empirical Application

3.1 Artificial Signal using MODWT

To verify the MODWT method and show how it works, setting a artificial signal with 5 kinds of different volatility. Because in general situation, people assume the stock price follow GBM(Geometric Brownian Motion), simulating GBM processes as follows:

$$dS = \mu S dt + \sigma S dx \tag{31}$$

$$dS = 0.001 S dt + 0.02 S dx, t \in (0, 100) \quad dS = 0.001 S dt + 0.05 S dx, t \in (100, 200)$$

$$dS = 0.001Sdt + 0.03Sdx, t \in (200, 300) \quad dS = 0.001Sdt + 0.01Sdx, t \in (300, 400)$$
$$dS = 0.001Sdt + 0.04Sdx, t \in (400, 500)$$

For the five formulas, S is the share price, μ is the drift term of the process, σ is the volatility term of the process.

For the signal, the whole time period has been cut into five parts, each period is simulated by 100 steps, we can get a simulated stock price path, then draw them as follows.

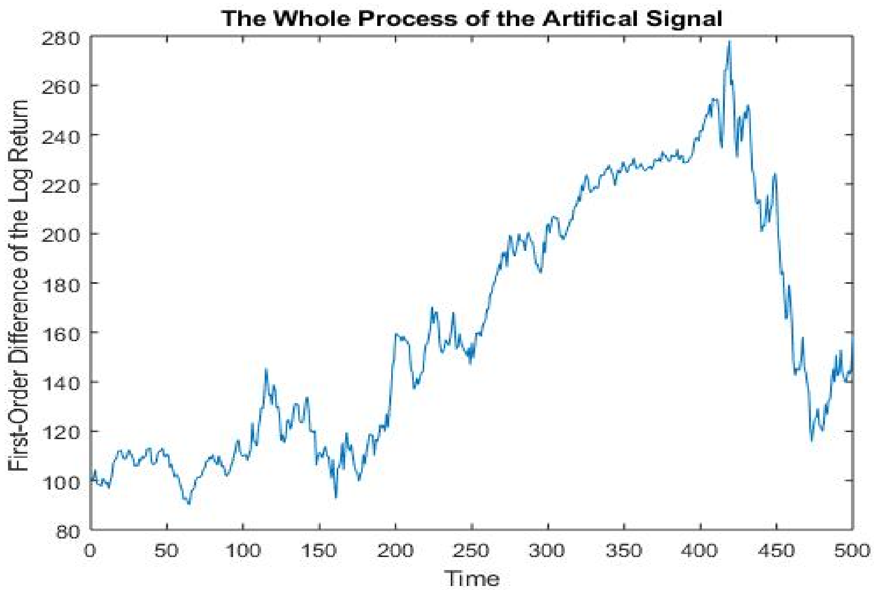

Figure 3: The Whole Process of the Artificial Signal

Next we just shift the whole signal 16 units of time afterwards to create another time series data then calculate the first-order difference of the log return as the volatility. Comparing the lagged signal with the original signal.

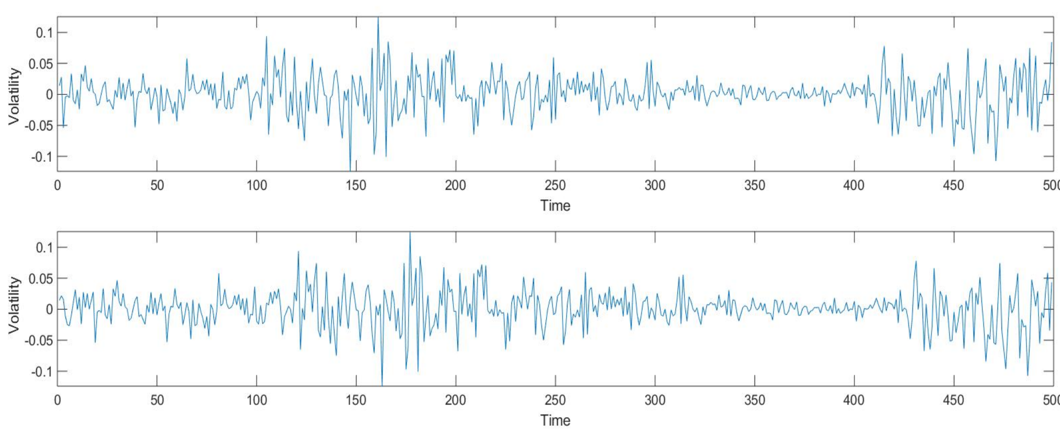

Figure 4: The Volatility Compare of the Original Signal and the Lagged One

Then using the inner function modwt in Matlab, the two signal will be decomposed into 8 levels $((\log_2 500 = 8))$ level by default. 7 detail coefficient $d1, d2, d3, d4, d5, d6, d7$ and 1 coarse coefficient $s0$

Plot the MODWT decomposition result of artificial signal volatility.

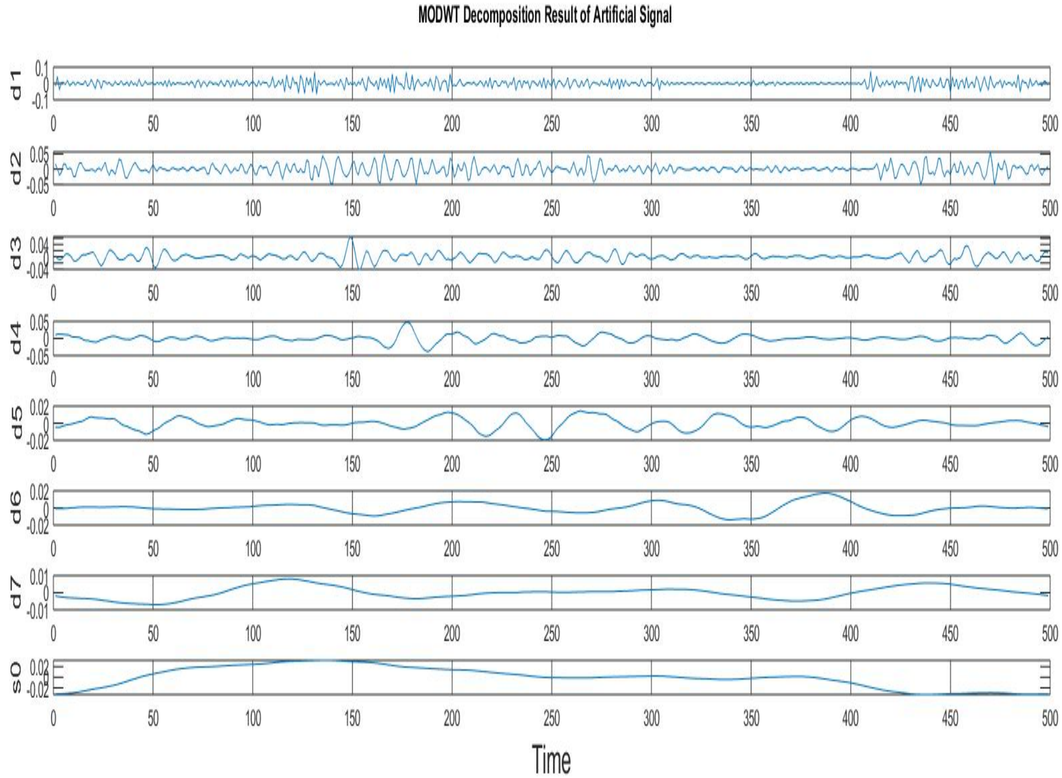

Figure 5: MODWT Decomposition of the Artificial Result

Comparing different level detail coefficients, the volatility will show different features on various scales. That is key part we use the wavelet transform method.

Based on MODWT decomposition results of the two signals, we can use the specific inner function modwtxcorr() to find the cross-correlation relationship, the function modwtxcorr() is designed to process the decomposition result of MODWT to s.The similarity of two sequences will be measured.

$$\rho_{x,y}(\tau_j) = \frac{\mathrm{cov}(\bar{w}^{(x)}_{j,t}, \bar{w}^{(y)}_{j,t+lag-term})}{(\mathrm{var}(\bar{w}^{(x)}_{j,t}) * \mathrm{var}(\bar{w}^{(y)}_{j,t+lag-term}))^{\frac{1}{2}}} \tag{32}$$

where $\bar{w}^{(x)}_{j,t}$ is the vector of detail coefficients with level j which is the decomposition result of time series X. $\bar{w}^{(y)}_{j,t+lag-term}$ is the vector of detail coefficients level j which is the decomposition result of time series Y. The lag-term is set to get the vector $\bar{w}^{(y)}_{j,t+lag-term}$ lag by lag-term units, which starts from lag 0 unit,when $\bar{w}^{(y)}_{j,t+lag-term}$ is lag the proper term, $\bar{w}^{(y)}_{j,t+lag-term}$ and $\bar{w}^{(x)}_{j,t}$ will be highly correlated, $\rho_{x,y}$ will get the maximum.

We can plot the correlation of the wavelet coefficients by scale.

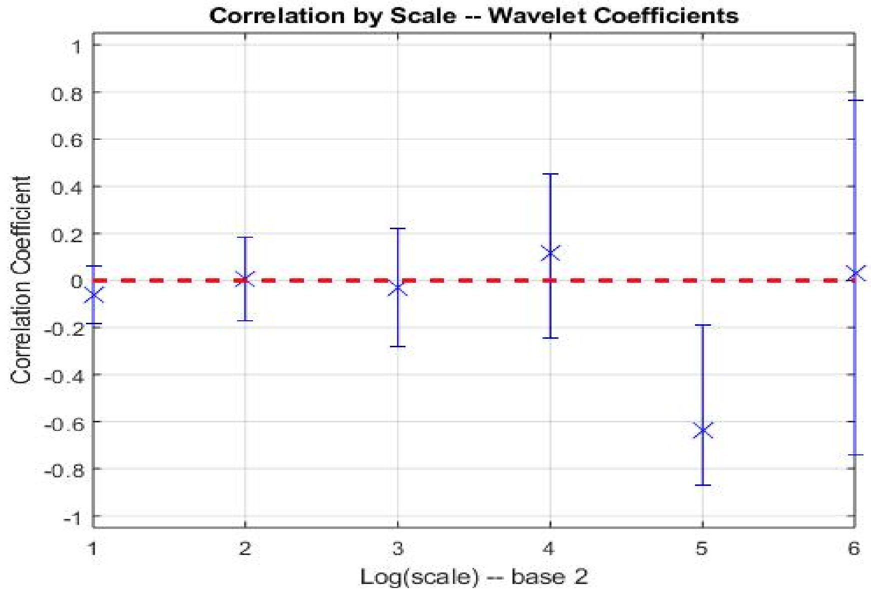

Figure 6: Wavelet Cross-Correlation by Scale lag 16 units

In the this picture,we can find the level 5 get the maximum. Due to the lag term we set is 16 units($\log_2 16 = 4$), so the lead-lag relation will be capture by level 5 scale, it captures the features in (16,32).

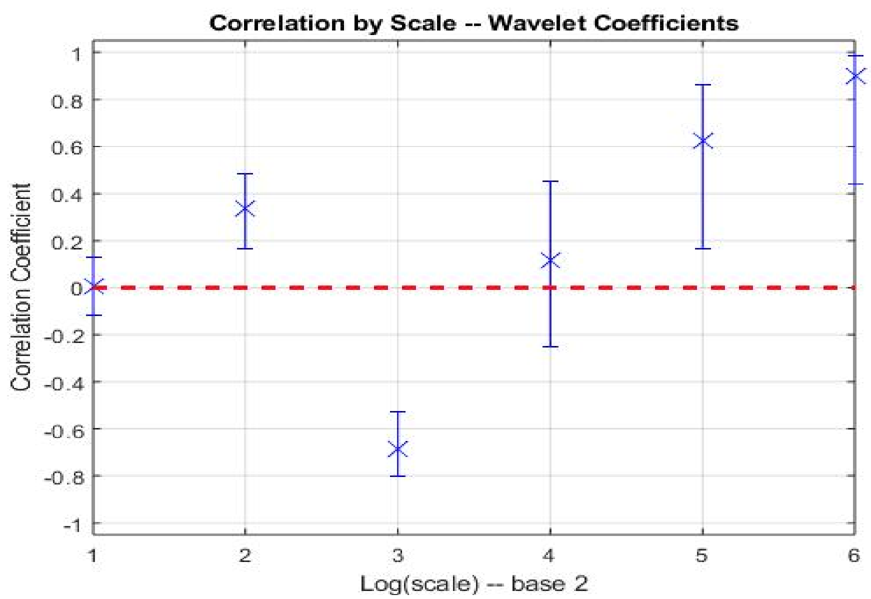

Figure 7: Wavelet Cross-Correlation by Scale with lag 4 time units

If we change the lag term to 4 time units, we can the level 3 wavelet coefficient is significant, which captures the features in (4,8) scale. As for the level 5 and level 6, the correlation are very high, because at that scale (16,32),(32,64) the coefficients will cover larger scale information, the only 4 units time lag can be ignored, so the two time series data are almost same in the large scale.

3.2 Data description and Pre-process

In this section, the analysis will be based on real data, the wavelet analysis will be applied in two time series data.We get two financial data from Bloomberg Teriminal. One is FTSE100 index and the other is USD-GBP exchange rate. Both data is 30-minute close price and from 5/4/2018 to 22/1/2019.

Due to difference of the trading time of the two markets and the gap between former trading day's close price and next trading day's open price, the two groups of data should be pre-processed, otherwise the two data will not match and lead to volatility increasing abnormally.

To solve the problems, firstly we only collect the data when the both markets are open, and for each gap we just times a number to adjust the afterward data to make sure the price along all days is continuous.

So adjusting all data in the two time series, the next picture shows the them.

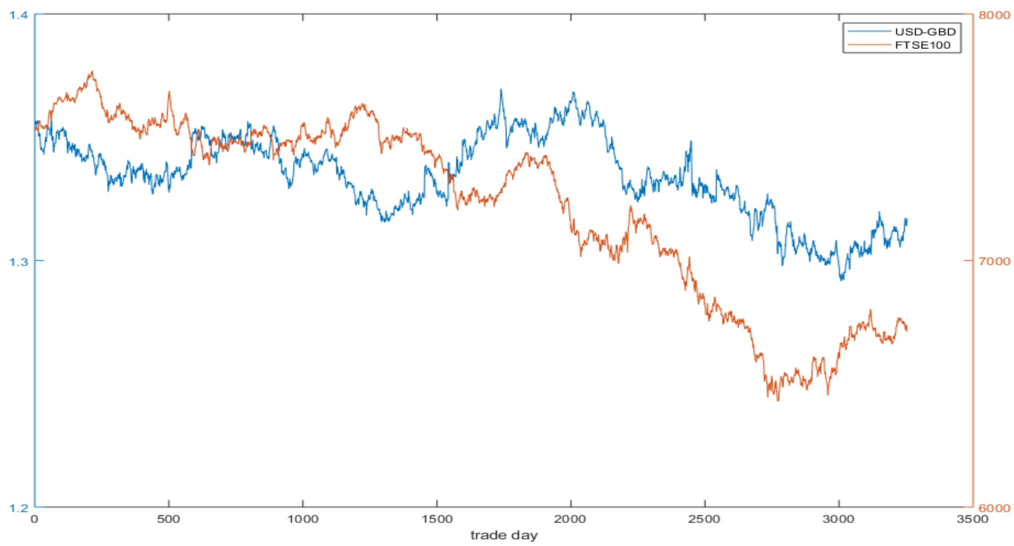

Figure 8: Adjusted Data by multiplier method

3.3 MODWT decomposition of high-frequency data

Now,it is time to analyze the correlation between the two time series. Calculating the volatility of two time series and plot it.

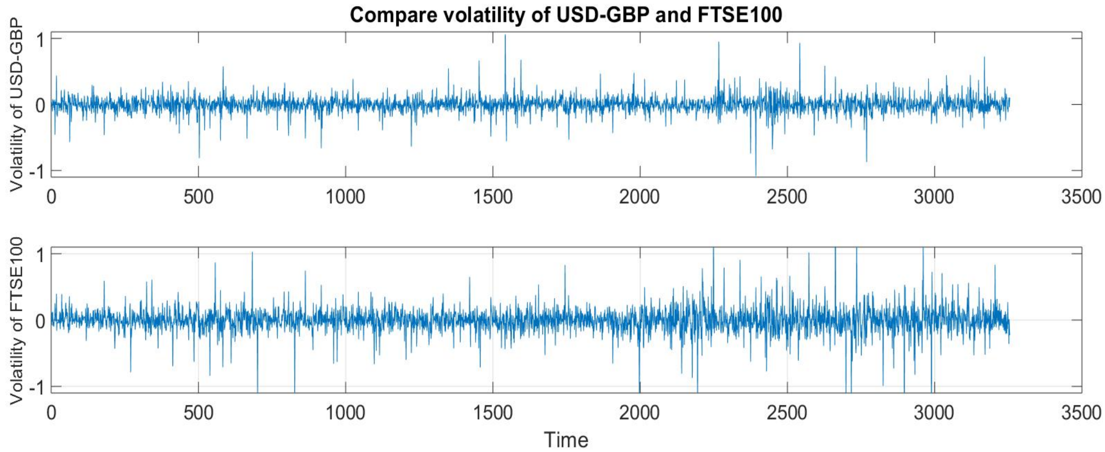

Figure 9: The Volatility of the Two time series

Using the MODWT to process the two time series data and get the wavelet correlation coefficients.

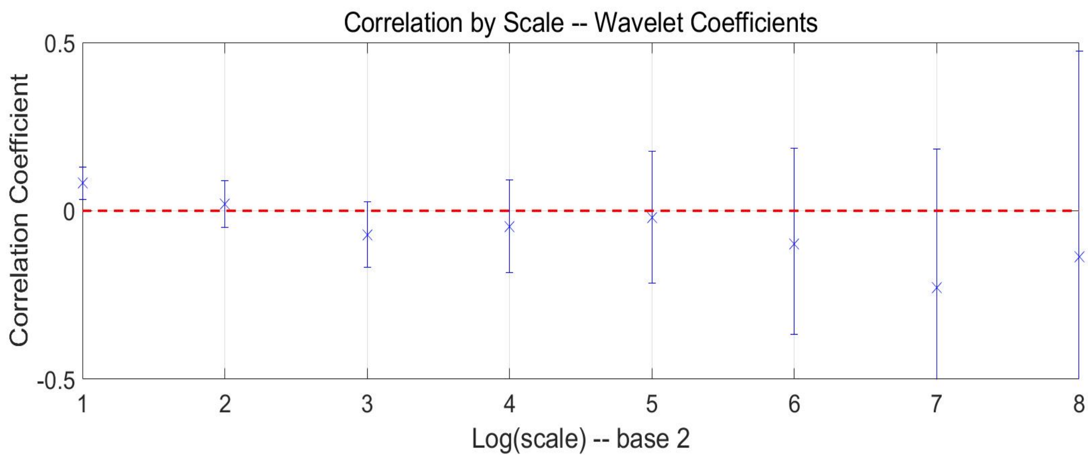

Figure 10: Correlation by Scale-Wavelet Coefficients

Because we choose 30-min closing price data.One trading day has 8 hours trading time. scale 1 means the details existing in 0.5-1 hour, scale 2 means 1-2 hours, scale 3 means 2-4 hours, scale 4 means 4-8 hours(one trade day), scale 5 means 8-16 hours(two trade days), scale 6 means 16-32 hours (weekly features), scale 7 means 32-64 hours (half a month).

From this picture, we can observe that in small scale the lead-lag relation is not significant. Until in the large scale 7 can see the exchange rate has lag relationship with index, but at that time the standard error is also increasing, which means we may not trust the correlation coefficient

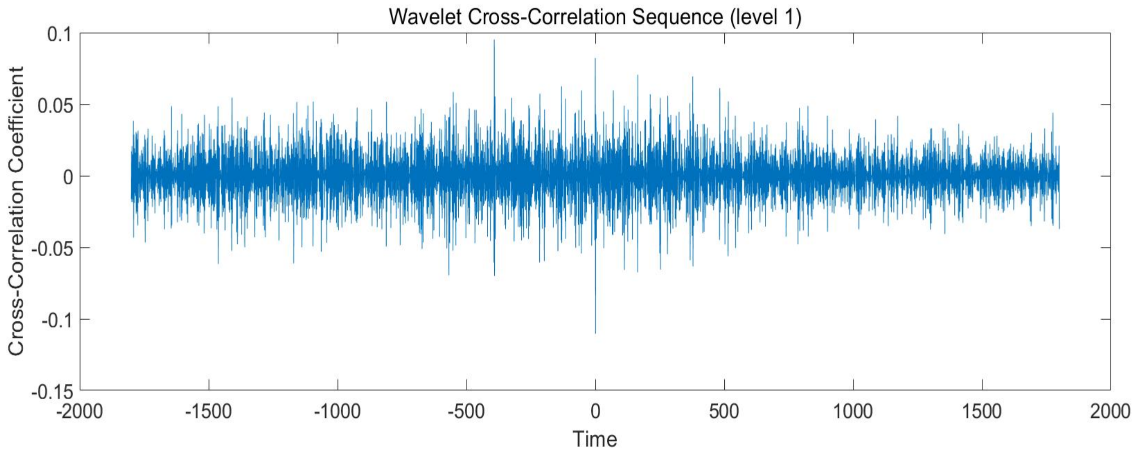

Figure 11: Correlation by Scale-Wavelet Coefficients level 1

This picture is level 1 correlation coefficient picture with different lag term, the cross-correlation coefficient is always almost less than 0.05 with any lag term. It means there is almost no cross-correlation in the two time series in 0.5-1hour scale. The similar things can also be observed in the level 2 scale until scale 6. But for the larger scale, such data may not be reliable because o f the huge stand error.

4 Conclusion

4.1 Volatility Spillover Effect

For short time scale from 30min-60min to two-day scale data, the Figure 11 shows most cross-correlations with different lag-term coefficients are less than 0.05. The lead-lag relation is not significant, so the volatility spillover effect is not significant in this scale.

For short time scale from 30min-60min (scale 1) to two-day (scale 5), the lead-lag relationship is not significant and the figures are similar to the Figure 11, so the volatility spillover effect is not significant in these scale levels.

For a longer time scale such weekly scale and half-month scale the lead-lag relation is significant about 0.2, but the standard error is also rise up,which cause the result can not be trusted. There are 2 possible reasons for that one is the decomposition of the MODWT, because after 5 level decomposition, the signal is very smooth and the details has been removed a lot.So at that time, analyzing the volatility at weekly scale is pointless, actually when people need to analyze the volatility at this scale, Then will choose the daily data not 30-minute data.

The other reason is the data type. In modern financial system, when some news happened, the market is very efficient and can react soon, the data type we choose is 30-min close price may be not high-frequency enough for this short-time volatility, the higher frequency data may be better for the topic.

Overall, in this study we study the volatility spillover effect between USD-GBP and FTSE100 based on 30-minute close price. The study shows that at small scale (30minute-60minute to one day-two day scale), the volatility spillover effect is not significant.

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