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Time-of-Day Pattern and Long Memory Volatility in High Frequency Foreign Exchange Rates across Trading Time Zones*

거래시간대에 따른 고빈도 환율의 일중 시간패턴과 장기기억 변동성*

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By using the 1-hour EUR/USD, JPY/EUR and JPY/USD high frequency exchange rates, this paper presents two important features of the high frequency exchange rates across different trading time zones in FX markets: time-of-day pattern and long memory volatility. First, this paper finds statistical evidence of the time-of-day pattern in the 4-hour period returns of the high frequency exchange rates across the time zones through the significant tendency for the currency to depreciate (appreciate) during domestic (foreign) trading hours across the time zones. Then, this paper employs the FIGARCH model and the Local Whittle method to estimate the long memory volatility of the 4-hour period returns and shows that the long memory volatilities of the 4-hour period returns appear to be different across the time zones and only market specific. Also, this study presents that the time-of-pattern and the long memory volatility in the 4-hour period returns across the time zones could be explained quite well by the theories of the asymmetric information and the liquidity effect in FX markets.

Key words: High frequency foreign exchange rates, Time-of-day pattern, Long memory volatility, FIGARCH model, Local Whittle method

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Ⅰ. Introduction

This paper considers empirical evidence on important features in the mean process and the volatility process of high frequency exchange rates, time-of-day pattern and long memory volatility, across different trading time zones in FX markets. Since the two features are in their own right importance in explaining the high frequency exchange rate dynamics, they could have significant implications for the overall understanding of FX markets. Also, this paper attempts to provide some explanations for theoretical reasons why the two features, the time-of-day pattern and the long memory volatility exist in FX markets.

Even though there has been an extensive literature on the time-of-the day pattern and the long memory volatility in the high frequency exchange returns, most of the attention in the previous studies has been devoted to either the time-of-the day pattern or the long memory volatility in the exchange returns separately. So far the literature to date has nothing to say about both the time-of-the day patterns and the long memory volatility in the high frequency exchange returns. Thus, this paper could add to this literature by investigating the two features of the time-of-day pattern and the long memory volatility in the exchange returns of the high frequency exchange rates across different time zones in FX markets together.

The time-of- day pattern in the high frequency exchange returns have been presented by several papers including Cornett et al. (1995), Ranaldo (2009) and Breedon and Ranaldo (2013). They have found that home currencies depreciate systematically during domestic working hours and appreciate during the working hours of the foreign counterpart country. In particular, Cornett et al. (1995) have investigated the hourly exchange rate data for the

US trading hours of FX futures and found that a significant tendency for the foreign currency to rise during the US trading hours, with the majority of that rise occurring in the first and last 2 hours of trading while the foreign currency had a significant tendency to fall outside the US trading hours. Thus, the exchange returns generally appear to follow market specific and cyclical patterns during the day across the times zones whereby local currencies tend to depreciate during their own trading hours and appreciate outside them.

There have been two main explanations for the time-of-day pattern in the exchange returns; liquidity effect(Ranaldo, 2009; Breedon and Vitale, 2010; Breedon and Ranaldo, 2013) and asymmetric information effect(Andersen et al., 2002; Bauwens et al., 2005; Evans and Lyons, 2008; Rime et al., 2010). The liquidity effect refers to imbalances in the inventories of liquidity suppliers that are caused by systematic excess demand or supply at specific intraday times, and the asymmetric information effect refers to the possibility that traders may profit from superior information because of their networking, trading location and the time zone in which that operate.

Some papers have argued that the liquidity effect is more important and could come from various sources such as interventions, transaction data, institutional flows and order flows(Fatum and Hutchinson, 2003; Froot and Ramadorai, 2005; Ranaldo, 2009; Breedon and Vitale, 2010; Breedon and Ranaldo, 2013). They have presented that coupled with the "domestic currency bias" in which traders located in one specific country tend to hold assets denominated in the reference currency of that country so that the domestic currency prevails over foreign currencies, the geographic segmentation creates sell price(buy-price) pressure on the domestic currency during domestic(foreign) trading hours. In particular, Breedon and Ranaldo (2013) have showed that the time of day patterns in exchange returns can be caused by the regular patterns in order flow by using hourly high frequency exchange rate data from 1997 to 2007 and argued that the time of day pattern could give strong evidence for the liquidity effect since it can be observed in a large sample and seems a clear case of a deterministic trading pattern that cannot be related to private information.

Also, there has been widespread evidence that foreign exchange rates tend to exhibit “highly persistent volatility clustering” in which large changes tend to be followed by the period of tranquility alternate with great volatility(Engle, et al., 1990). This phenomenon has been originally noted by Mandelbrot (1963) and Fama (1965). The occurrence of the volatility clustering lies either in the asymmetric information and the liquidity effect or in the arrival process of news or in market dynamics in respond to the news(Baillie and Bollerslev, 1990; Engle et al., 1990). According to the theories of the asymmetric information and the liquidity effect, traders in FX markets with heterogeneous priors and private information may take some time of trading after shocks to have expectation differences resolved. Thus, the pattern of the concentrated trading volume and price variability can be generated because of the interaction between strategic informed traders and strategic liquidity traders(Admati and Pfleiderer, 1988) and the informed traders act strategically to take advantage of their superior set of private information(Foster and Viswanathan, 1988). Alternatively, the exchange returns may exhibit the ARCH behavior even if the market perfectly and instantaneously adjusts to the news if information comes in clusters.

Since Engle et al. (1990), many empirical studies have concerned with volatility spillover on international FX markets. Initially, Engle et al. (1990) have proposed two hypotheses, heat wave hypothesis in which the volatility has only country specific autocorrelations and meteor shower hypothesis which there exits intraday volatility spillover from one market to the next in order to explain the causes of the volatility clustering. They have presented that empirical evidence is generally against the null hypothesis of the heat wave so that the news in one market impacts on the time path of per hour volatility in other markets and that the exchange market dynamics exhibits volatility persistence possibly due to private information or heterogeneous belief of traders.

And, Baillie and Bollerslev (1990) have presented the volatility clustering in the high frequency exchange returns by using the hourly exchange rates and explained that the volatility clustering of the high frequency exchange returns appear to be some heat wave or market specific new characteristics due to the presence of the seasonal ARCH terms. And more studies including the papers of Engle et al. (2012), Bubak et al. (2011) and Melvin and Melvin (2003) have examined the volatility transmissions between international markets by using high frequency return data and GARCH type model which lead to an improved inference about the volatility spillover across markets and presented that there exist both the heat wave effect and the meteor shower effect in the FX markets.

In particular, the paper of Baillie (1996) has presented that the volatility process of foreign exchange returns exhibits the long memory property with quite persistent and hyperbolic decaying autocorrelations. The long memory volatility has been presented in their squared returns(Ding et al., 1993; Granger and Ding, 1996), power transformations of absolute returns(Lobato and Savin, 1998), conditional variance(Baillie et al., 1996) and other measures of volatility like realized volatility(Ebens, 1999; Andersen et al., 2002). Following Ding et al. (1993) and Dacorogna et al. (1993), several long memory models have been developed to represent the long memory volatility in the exchange rate data.

Among them are the Long Memory Stochastic Volatility(LMSV) models of Breidt et al. (1998) and Harvey (1998), and the Fractionally Integrated Generalized AutoRegression Conditional Heteroskedasticity(FIGARCH) models of Baillie et al. (1996).

Several papers have also explored the aspects of the long memory, persistent volatility that has become a well-documented feature of the high frequency exchange returns; see e.g. Dacorogna et al. (1993), Andersen and Bollerslev (1997; 1998), Baillie et al. (2000), Andersen et al. (2002) and Baillie and Han (2002). Even though these studies have appeared to be useful in describing the long memory volatility in the exchange returns, there could be more interest in explaining the underlying causes of the long memory volatility, whether the long memory property is only market specific(heat wave) or caused by the volatility spillover effects(meteor shower).

Given the previous studies summarized above, this paper uses time series analysis methods for three major high frequency EUR/USD, JPY/EUR and JPY/USD exchange rates, which are the most traded in major FX markets(US, Europe and Japan) across the different time zones in order to examine the linkages among the trading session returns in the time zones. In particular, this paper uses the 1-hour high frequency exchange rates provided by the Olsen & Associates who is a real pioneer in collecting and analyzing the high frequency financial data(e.g. Dacorogna et al., 1993; Olsen et al., 1997).

First, this paper focuses on the significant time-of-day pattern in the 4-hour period returns obtained from the hourly EUR/USD, JPY/EUR and JPY/USD high frequency exchange rates. In particular, this paper presents significant evidence of the time-of-day pattern in the high frequency exchange returns in which domestic(foreign) currencies tend to depreciate(appreciate) during domestic(foreign) working hours across the time zones. This result can support market microstructure theories building on the liquidity effect and the order flow of information by the liquidity based traders in FX markets.

Then, this paper investigates the long memory volatility in the 4-hour returns of the high frequency exchange rates by adopting the parametric FIGARCH model and the semi-parametric Local Whittle estimation method, and finds that the long memory volatility appears to be different across the time zones and only country specific supporting the heat wave hypothesis with some possibility of the meteor shower hypothesis as the cause of the persistent and long memory volatility clustering in the 4-hour returns. And, this paper presents that the pattern of the long memory volatility across the time zones also could be related to the asymmetric information and the liquidity effect.

Thus, the main contributions of this paper are to provide statistical evidence of supporting the time of day pattern and the different long memory volatilities in the exchange returns of the high frequency exchange rates across the time zones in FX markets and to suggest theoretical explanations based on the theories of the asymmetric information and the liquidity effect in FX markets. In these aspects, this paper lies both in the large number of independent studies which enhances the significances of a statistical analysis and in the increased ability to analyze finer details of the behavior of different market participants in the FX markets.

The plan of the rest of this paper is as follows. Section II presents the descriptive statistics of the hourly high frequency exchange returns and explains the significant time-of-day pattern in the 4-hour period returns across the time zones. Section III describes the long memory volatility in the 4-hour period returns of the high frequency exchange rates across different time zones with providing the estimation results from the FIGARCH model and the Local Whittle method, and supports the heat wave hypothesis in which the long memory volatility is only market specific with some possibility of the meteor shower hypothesis in which it is a phenomenon of the high frequency volatility spillover from one market to the next. Then section IV provides a brief conclusion.

II. Descriptive statistics and the time-of-day pattern in high frequency exchange rates

This section is concerned with the descriptive statistics of the high frequency exchange returns and the time-of-day pattern in the mean process of the exchange returns by using the dataset of the 1-hour high frequency EUR/USD, JPY/EUR and JPY/USD spot exchange rate data which are the most traded in the world exchange markets(US, Europe and Japan) in order to give results for a range of different time zones. The high frequency exchange rate data is provided by Olsen & Associates, in which Reuter FXFX quotes are taken at every 1-hour for the complete calendar years of 2012 through 2014 in which the world FX markets have relatively been stable after the global financial crisis caused by the US subprime mortgage crisis in 2008. In particular, this paper uses the mid-quote prices which are the average prices between the representative ask and bid prices quoted in every hour, and the FXFX indicative quotes can be taken as a very good an close proxy for the real quotes(Goodhart et al., 1996). As an over-the-counter(OTC) market that trades across several time zones, the FX market does not have precise trading hours, though it is clear that traders in particular locations tend to operate over fairly fixed trading hours. Thus, this paper takes FX trading hours as the guide and find that the trading hours fit well with distinct changes in trading volume.

It has become fairly standard in this literature to remove atypical data associated with slower trading patterns during weekends and the worldwide holidays like X-MAS and New Year Day(Müller et al., 1990; Bollerslev and Domowitz, 1993). In particular, this definition of the weekend is motivated by the daily FX activity patterns presented in Bollerslev and Domowitz (1993). They have documented that the weekend data with much lower trading activities are excluded since they cannot provide any economic implications. Thus, this paper eliminates the exchange rates during the holidays and the weekends from Friday 21:00 GMT(Greenwich Mean Time) through Sunday 20:00 GMT[1] and uses the eventual sample data which contains 778 trading days with a total of 18,672 observations and each with 24 intervals of 1-hour duration. Thus, the 1-hour high frequency return(y_t) is,

$$y_t = 100*[\ln(S_t)-\ln(S_{t-1})] \tag{1}$$

where S_t is the 1-hour spot foreign exchange rate at time(t).

Following the definitions of trading hours in FX markets proposed by Breedon and Ranaldon (2013), this paper specifies the local trading hours of the three exchange rates across different regions and time zones in Table 1. For the case of the currency pair of EUR/USD, the trading activity begins at 07:00(GMT) in Europe market and ends at 21:00(GMT)(corresponding to 16:00 in local time) in the US market. Even though traders in particular locations and time zones tend to trade over fairly fixed trading hours as in Table 1, the FX markets do not have precise trading hours since the market is the OTC market that trades across different time zones. Thus, this paper investigates

1) Several studies including Andersen and Bollerslev (1997) and Baillie et al. (2000) have used the same definition of the weekends to analyze similar high frequency exchange rates.

the exchange returns over 4-hour periods since these time brackets allow us to observe overlapping and non-overlapping intraday periods in the different trading hours of each region and time zone, and the 4-hour interval is a reasonable length of time for marketable intraday trading(Ranaldo, 1990).[2] In particular, the trading hours from 00:00 to 07:00, from 07:00 to 13:00 and from 15:00 to 21:00 present the time periods in GMT of the main trading activity in Japan, Europe and the US market respectively.[3]

〈Table 1〉 Trading Hours in Major FX Markets

Region	Trading Hours at local time	Trading Hours at Greenwich Mean Time(GMT)	Main Trading Center
Europe	07:00-15:00	07:00-15:00	London
Japan	08:00-15:00	00:00-07:00	Tokyo
United States	08:00-16:00	13:00-21:00	New York

The descriptive statistics of the six non-overlapping 4-hour period returns of the hourly high frequency EUR/USD, JPY/EUR and JPY/USD exchange rates are presented in Table 2. In particular, the mean values of the 4-hour period returns clearly show the time-of-day pattern in the mean process of the exchange returns in which all currencies tend to depreciate during the trading hours of their reference domestic markets and to appreciate during the trading hours of their counterpart foreign market. And, the 4-hour period returns generally have the values of the sample mean ranging from −0.0070 to 0.0068, which are very close to zero and indistinguishable at the standard

2) As pointed by Ranaldo (1990), it is possible to use the shorter time frames like 2-hour or 3hour period for the analysis of the more short-lived patterns, but the main results are found to be almost same as those from the 4-hour period. Also, the main results of this paper are not substantially affected by the precise choice of trading times.

3) This paper considers the daylight saving times in the US and the Europe, but finds that the main results are not changed significantly.

significance level. Similarly, the values of the maximum and the minimum in the high frequency exchange returns are all centered around zero. In particular, the Ljung-Box test statistics for the test of the serial correlations in the level of the 4-hour returns, the Q(50) statistics generally cannot reject the null hypothesis of no serial correlation even with some exceptions, and implies that the high frequency returns do not have any serial correlations. And, there generally exit negative small values of the first order autocorrelations(ρ) which may be attributed to a combination of a small time varying risk premium, bid-ask bounce, and/or non-synchronous trading phenomena(Andersen and Bollerslev, 1997; Goodhart and O'Hara, 1996).

However, the returns appear not to be normally distributed since the values of the sample kurtosis from 6.47 to 28.44 are quite different from the value of 3 for the normal distribution even though the values of the sample skewness are similar to 0 for the normal distribution. In particular, the estimated kurtosis statistics for the high frequency returns are relatively large, which implies the rejection of a Gaussian normal distribution assumption. And, the values of the Ljung-Box test statistics, $Q^2(50)$ calculated from the squared returns of the 4-hour returns are very large ranging from 110 to 1126 indicating the existence of the significant volatility clustering and the highly persistent autocorrelations in the volatility process. Also, the test statistics of the JPY/EUR and the JPY/USD exchange returns are generally found to be the greater than them of the EUR/USD exchange returns indicating the more significant volatility clustering across the time zones.

〈Table 2〉 Descriptive Statistics for the 4-hour Period Returns across Different Time Zones

a) EUR/USD exchange rates

Time(GMT) Time Zone	0-4 JP	4-8 JP/EU	8-12 EU	12-16 EU/US	16-20 US	20-24 US
Mean	0.0009	0.0007	0.0042	-0.0012	-0.0024	-0.0005
Variance	0.0037	0.6052	0.0115	0.0816	0.0103	0.0054
Max	0.5538	0.5538	0.7828	0.7278	0.9850	1.1650
Min	-0.4526	-0.5389	-0.6414	-1.0053	-1.0097	-1.3272
Skewness	0.5222	-0.7745	-0.1699	-0.2131	-0.1876	0.1504
Kurtosis	11.6056	8.9407	6.6669	7.9890	16.8286	17.9264
Q(50)	82.8895	53.7486	39.2484	48.2104	58.5174	55.2502
$Q^2(50)$	312.1936	476.5698	243.5357	144.3317	160.6351	110.4277
$\rho(1)$	0.00327	-0.04503	0.01493	-0.0133	-0.0344	-0.0480

b) JPY/EUR exchange rates

Time(GMT) Time Zone	0-4 JP	4-8 JP/EU	8-12 EU	12-16 EU/US	16-20 US	20-24 US
Mean	00024	0.0007	-0.0023	-0.0010	0.0068	0.0065
Variance	0.0139	0.0161	0.0231	0.0280	0.0163	0.0155
Max	0.7118	1.1825	0.9146	1.3072	1.3072	2.8349
Min	-1.1251	-1.0181	-1.0181	-0.9849	-1.2730	-1.9187
Skewness	-0.3413	-0.0518	-0.1729	0.0248	-0.3477	1.2592
Kurtosis	9.1887	9.7209	6.4797	8.1702	16.2549	17.0198
Q(50)	73.6348	86.1318	90.8711	55.7510	69.2705	62.2058
$Q^2(50)$	845.8295	324.7089	537.4021	665.7804	616.3690	358.0140
$\rho(1)$	-0.0167	0.00561	0.0315	-0.0012	-0.0496	-0.0904

c) JPY/USD exchange rates

Time(GMT) Time Zone	0-4 JP	4-8 JP/EU	8-12 EU	12-16 EU/US	16-20 US	20-24 US
Mean	0.0032	0.0001	0.0018	0.0022	-0.0070	-0.0048
Variance	0.0119	0.0117	0.0117	0.0193	0.0134	0.0097
Max	0.6170	1.3221	0.5713	1.056	1.0895	0.8962
Min	-1.1882	-0.8291	-0.9038	-1.1886	-1.1452	-1.4261
Skewness	-0.6129	0.4022	-0.4605	0.0549	-0.0784	0.1687
Kurtosis	11.5036	15.5930	8.7767	10.8061	20.0793	28.4412
Q(50)	83.9162	120.3255	103.4805	88.0305	76.4366	96.1992
$Q^2(50)$	1126.8834	630.2142	922.7935	290.5111	477.5804	390.4338
$\rho(1)$	-0.0235	0.0456	0.0066	0.0214	-0.0249	0.0017

Note: The Q(50) and $Q^2(50)$ are the Ljung-Box test statistics at 50 degrees of freedom based on the returns and the squared returns. ρ_1 is the first order of autocorrelation of the returns.

Following the methods of Ranaldo (2009) and Breedon and Ranaldo (2013), this paper calculates the annualized values of the mean in which the 4-hour returns of the high frequency exchange rates are multiplied by 260 in order to check the statistical significance of the time-of-day pattern in the means of the exchange returns, and undertakes the two-sample t-test for the acceptance of the null hypothesis of equality in mean. This t-test statistics refers to two tail statistics on the difference between returns over a given 4-hour return mean and average returns over the whole sample. The test results for the mean values of the annualized 4-hour period returns for the three high frequency exchange rates are presented in Table 3.

By providing the statistically significant values at the conventional significance level, the significance tests generally confirm the time-of-day pattern in the mean values of the 4-hour period exchange returns of the high frequency EUR/USD, JPY/EUR and JPY/USD exchange rates. For the returns of the EUR/USD exchange rates, the USD(EUR) depreciate(appreciate) by 0.02% from 16:00 to 20:00 when only the US market is trading, but the USD(EUR) appreciate(depreciate) by 1.09% from 08:00 to 12:00 when only the Europe market is trading. For the returns of the JPY/USD exchange rates, the USD(JPY) depreciate(appreciate) by 1.79% from 16:00 to 24:00 when only the US market is trading, but the USD(JPY) appreciate(depreciate) by 0.83% from 00:00PM to 04:00 when only the Japanese market is trading. However, for the returns of the JPY/EUR exchange rates, the EUR(JPY) appreciate(depreciate) by 0.61% from 00:00 to 04:00 when only the Japanese market is trading, but it is not so clear whether the EUR(JPY) may depreciate(appreciate) from 08:00 to 12:00 even when only the Europe market is trading since the annualized mean is found to be statistically insignificant.

〈Table 3〉 Two Sample T-test for Mean Values of the Annualized Returns across Time Zones

Time(GMT) Time Zone	0-4 JP	4-8 JP/EU	8-12 EU	12-16 EU/US	16-20 US	20-24 US
EUR/USD	0.2444	0.1924*	1.0920***	-0.3042*	-0.0214**	-0.1170
JPY/EUR	0.6136***	0.1820***	-0.6058	-0.2548***	1.7576***	1.6770***
JPY/USD	0.8320**	0.0135	0.4654	0.5720	-1.7940**	-1.1622**

Note: (*),(**), and(***) represents the significance level at 1%, 5% and 10%.

It is interesting to note that the trading influence from the other time zone except the two counter-parties can exist in the case of JPY/EUR exchange rate. For instance, the currency trading of the Euro and Japanese Yen in the US trading hours(16:00-20:00/20:00-24:00) appears to depreciate the JPY against the EUR by 1.76% and 1.68% significantly. Also, the trading activities during the trading hours in which the two involved markets are trading together appear to influence the returns of the EUR/USD and the JPY/EUR exchange rates implying that two markets can be closely related in the information transmission, but the effects seems to be mixed even though they are statistically significant.

These results are quite in consistent with the papers of Ranaldo (2009), Breedon and Ranaldo (2013) and Jiang (2016) who have provided some evidence of the time-of-day pattern in exchange returns by using a comprehensive high frequency exchange rates and presented that the pattern is statistically and economically persistent and significant. In particular, Breedon and Ranaldo (2013) and Ranaldo (2009) have supported the liquidity effect based on the microstructure and behavioral aspects of FX markets. They have found that the time-of-day pattern is strongly reflected in the liquidity effect by the order flow of traders in the exchange markets for portfolio management in which FX traders tend to be net buyers of foreign exchange in their own trading hours making trading profits without any informational advantage by intermediating between different trading time zones. Thus, they have suggested the importance of the liquidity effect and the order flow in driving the exchange returns through a mechanism not driven by asymmetric information.

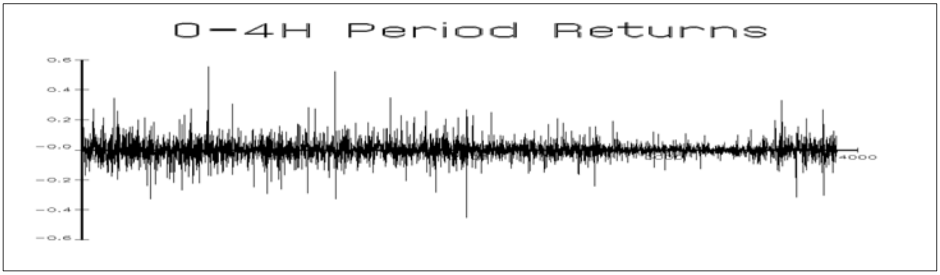
III. Long memory volatility across time zones in high frequency exchange rates

This section investigates the long memory volatility feature of the 4-hour period returns of the high frequency EUR/USD, JPY/EUR and JPY/USD exchange rates across the different time zones. Figures 1(a) through(c) present the realizations of the 0-4 hour period returns of the high frequency EUR/USD, JPY/EUR and JPY/USD exchange rates. The 0-4 hour period returns are all centered on zero but there exists persistent volatility clustering in the all series. The extremely persistent volatility clustering and turbulence across the markets can induce a heavy tailed and undefined variance of unconditional returns phenomenon(Koedijk et al., 1990). In particular, the volatility clustering appears to be more significant in the JPY/EUR and the JPY/USD exchange returns than in the EUR/USD exchange returns.[4] These findings are quite consistent with the descriptive statistics in Table 2.

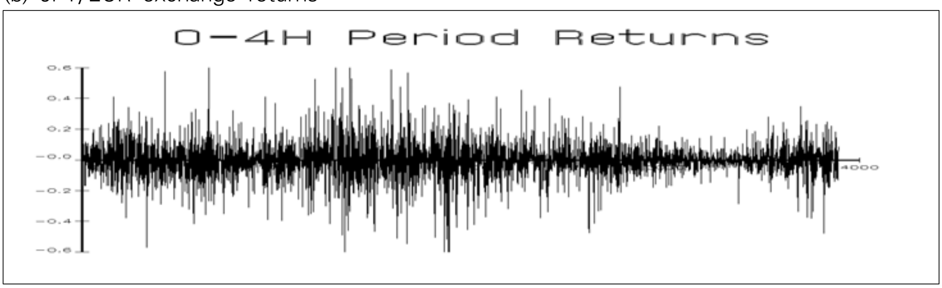
4) Similar graphs can be available for the other periods of the three exchange returns, but they are not reported for the reason of conserving space.

〈Figure 1〉 4-hour Period Returns of High Frequency Exchange Rates

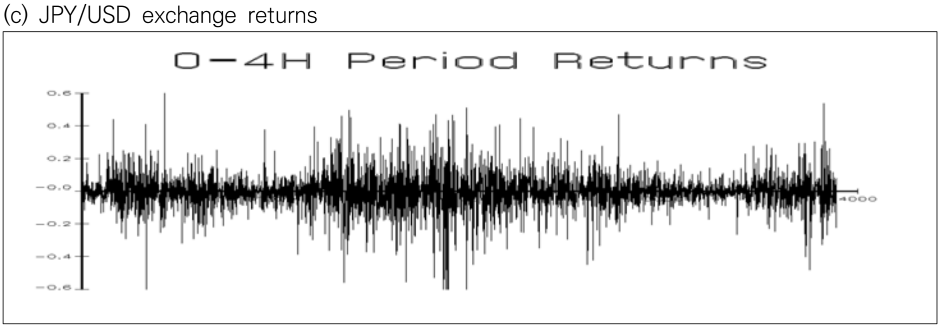
(a) EUR/USD exchange returns



(b) JPY/EUR exchange returns



(c) JPY/USD exchange returns



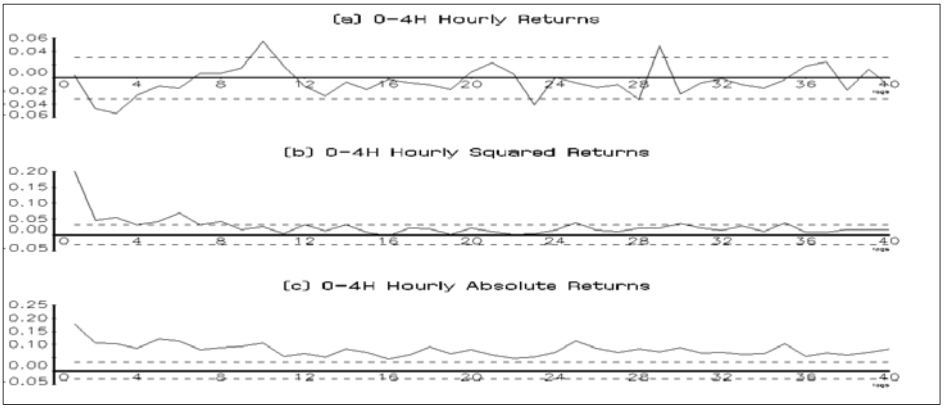
And, these finding can be confirmed by Figures 2(a) through(c) which plot the correlograms of the first 4-hour period(0-4h) returns of the high frequency EUR/USD, JPY/EUR and JPY/USD exchange rates.[5] The first order autocorrelation and the higher order autocorrelations of the raw returns are inside the dotted

5) The correlograms for the other periods of the 4-period returns are not reported for the reason of conserving space, but they appear to be quite similar.

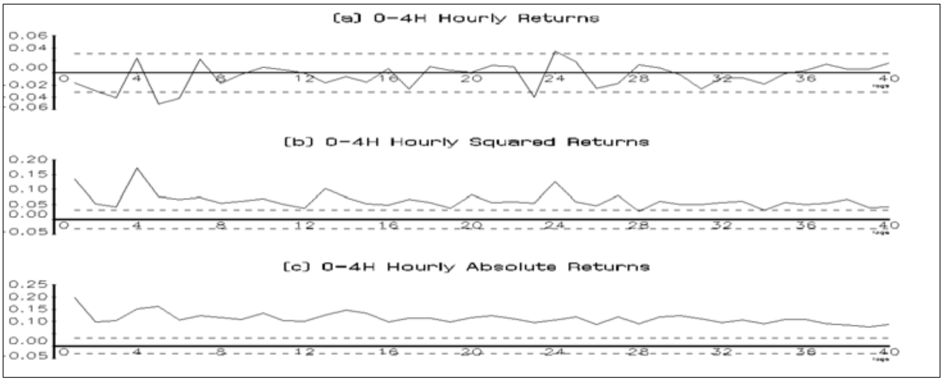
lines which represent the 95% confidence level for the acceptance of no serial correlations indicating that the raw returns are statistically insignificant and not serially correlated. However, the autocorrelations of the squared returns and the absolute returns present very large and statistically significant autocorrelations and they appear to decay very slowly at the hyperbolic rate, which is the typical feature of the persistent volatility clustering and the long memory property.

〈Figure 2〉 Correlograms for 4-hour(0-4H) Period Returns

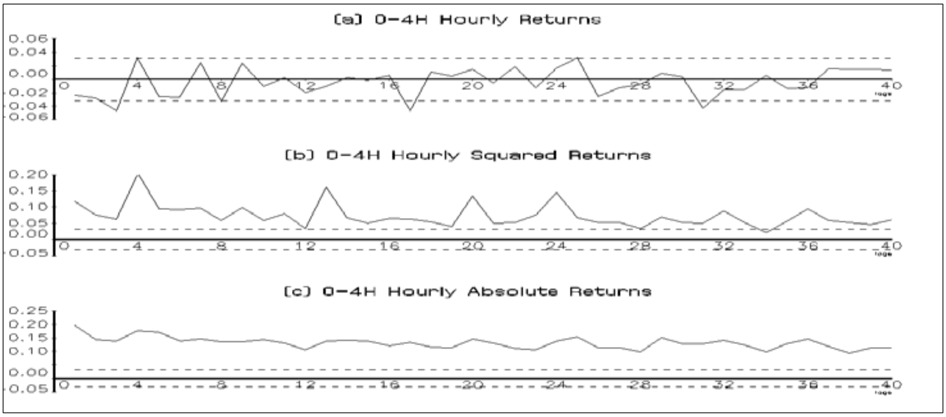
(a) EUR/USD exchange rates



(b) JPY/EUR exchange rates



(c) JPY/USD exchange rates



The long memory volatility feature of the high frequency exchange returns is very significant in the autocorrelations of the squared and absolute returns of all the three high frequency returns and is more apparent in the autocorrelation functions of the absolute returns(Granger and Ding, 1996). The long memory volatility in the 4-hour period returns of the high frequency exchange rates can be also found across different period returns and time zones. In particular, the highly persistent autocorrelations in the absolute returns appear to be more significant in the JPY/EUR and the JPY/USD exchange returns than in the EUR/USD exchange returns as presented by Figures 1 and the descriptive statistics in Table 2. Thus, this section investigates the long memory volatility across the time zones, and explains the relations of the long memory volatility across different markets and time zones: whether the long memory volatility is only market specific(heat wave) or the volatility spillover from one market to the next(meteor shower) as the cause of the persistent long memory volatility.

For the analysis of the long memory volatility in the 4-hour period returns of the high frequency exchange rates over different time zones, this paper adopts the parametric ARMA(m,n)-FIGARCH(p,d,q) model which is consistent with the basic stylized properties above. The model specification is the following;

$$y_t = \mu + \varphi(L)y_{t-1} + \theta(L)\varepsilon_t \tag{2}$$

$$\varepsilon_t = z_t\sigma_t \tag{3}$$

$$[1-\beta(L)]\sigma_t^2 = \omega + [1-\beta(L) - \phi(L)(1-L)^d]\varepsilon_t^2 \tag{4}$$

where y_t is the 4-hour period returns, μ and ω are scalars, φ(L), θ(L), β(L) and Φ(L) are polynomials in the lag operator, and(d) is the long memory parameter.

The parameter(d) characterizes the long memory feature of the very slow and hyperbolical decline in the volatility process because the autocorrelations can be decaying very slowly and hyperbolically. When 0 〈 d 〈 1, the FIGARCH model can represent a long memory behavior and can be strictly stationary and ergodic(Baillie et al., 1996; Baillie and Morana, 2009). But, the FIGARCH model can be different from other possible forms of the long memory ARCH models of Karanassos et al. (2004) due to the finite sum to its cumulative impulse response weights. When d = 0 and p = q = 1, the model becomes the GARCH(1,1) model; and when d = p = q = 1, the model would be the IGARCH(1,1) model.

The FIGARCH process is quite useful because when 0 〈 d 〈 1, the process is so flexible enough to represent middle ranges of persistence which shows the slowly and hyperbolically decline in the autocorrelations of the squared returns. And, the associated impulse response weights also can present highly persistent hyperbolic declines. The impulse response weights of the FIGARCH process can be specified as, $\sigma^2_t=\omega/(1-\beta)+\lambda(L)\varepsilon^2_t$, where for lags k, $\lambda k \approx k^{d-1}$, which is basically the long memory feature or Hurst effect of the hyperbolic declines(Granger and Joyeux, 1980; Hosking, 1981). Since the FIGARCH process is strictly stationary and ergodic when 0 〈 d 〈 1, any shocks can not have any permanent effect. See Baillie (1996) and Baillie et al. (1996) for the further theoretical details for the long memory process and the FIGARCH model.

The ARMA-FIGARCH model in equations(2) through(4) are estimated by using non-linear optimization procedures to maximize the Gaussian log likelihood function:

$$\ln(L;\Theta) = -(\frac{T}{2})\ln(2\pi) - (\frac{1}{2})\sum_{t=1}^{T}[\ln(\sigma_t^2) + \varepsilon_t^2\sigma_t^{-2}] \tag{5}$$

where Θ is a vector containing the unknown parameters to be estimated.

However, it has long been presented that most asset returns are not well specified by assuming that z_t in equation(3) is normally distributed(McFarland et al., 1982). And, the inference is based on the QMLE(Quasi Maximum Likelihood Estimation) method of Bollerslev and Wooldridge (1992), which is valid even when z_t is non-Gaussian. Denoting the vector of parameter estimates obtained from maximizing(5) using a sample of T observations on equations(2),(3) and(4) with z_t being non-normal by the limiting distribution of $\hat{\Theta}_T$ is

$$T^{1/2}(\Theta_T - \Theta_0) \rightarrow N[0, A(\Theta_0)^{-1}B(\Theta_0)A(\Theta_0)^{-1}], \tag{6}$$

where A(.) and B(.) represent the Hessian and outer product gradient.

Equation(6) is used to calculate the robust standard errors that are reported in the subsequent results with the Hessian and outer product gradient matrices being evaluated at the point.

As presented by Baillie et al. (1996), the orders of the ARMA and the FIGARCH polynomials in the lag operator are arbitrary chosen to provide an adequate representation of the autocorrelation structure in the 4-hour period returns of the high frequency exchange rates. After conducting several experimentations, this paper finds the most appropriate specifications for the 4-hour period returns by using LR test statistics. The exact parametric specification of the model which best represents the degree of autocorrelation in the conditional mean and the conditional variance process of the 4-hour period returns is found to be the Martingale-FIGARCH(1, d, 1) model for the 4-hour period returns of the high frequency EUR/USD, JPY/EUR and the JPY/USD exchange rates.

Table 4 presents the estimation results of the Martingale-FIGARCH(1, d, 1) model for the 4-hour period returns of the high frequency exchange rates. In particular, the estimated values of the $Q^2(50)$ from 13.09 to 74.80 in Table 4 are generally found to be small enough to accept the null hypothesis of no autocorrelations in the volatility process and they present that the FIGARCH model specified for the 4-hour period returns performs very well in capturing the autocorrelations in the volatility process of the all return series. Since there is no statistical evidence of additional autocorrelation in the standardized residuals or squared standardized residuals in each case, the chosen model specification provides an adequate fit for the 4-hour period returns[6]. Thus, the FIGARCH model appears to be appropriate in representing the long memory volatility of the 4-hour period returns.

And, the estimated long memory parameters(d) in the volatility process of

6) A sequence of diagnostic portmanteau tests on the standardized residuals and squared standardized residuals could not find any more need to further complicate the model following Diebold(1988). Their results are not reported to save the space but they could be available by the request to the author.

the 4-hour period returns range from 0.23 to 0.43 for EUR/USD returns, 0.33 to 0.45 for JPY/EUR returns and 0.27 to 0.38 for JPY/USD returns and they are all statistically significant at the conventional level indicating the existence of the persistent long memory volatility clustering across the different time zones. And the long memory parameters in the 4-hour period returns of the JPY/EUR and the JPY/USD exchange rates appear to be more significant than in the EUR/USD exchange rates. Also, the estimated values are different across the time zones suggesting that the FX markets may not be integrated fully and the long memory volatility could be only market specific.

Generally, the long memory volatility is found to be the greatest during the period of a trading day in which the reference domestic market is at the busiest trading activity and the second greatest during the period of the trading day in which the counterpart foreign market is at the busiest trading activity. For instance, the long memory volatility in the returns of the EUR/USD exchange rate is the greatest at the value of 0.43 during the trading period of 16-20 hour in which the US market is the busiest in trading and is the second greatest at the value of 0.38 during the period of 8-12 hour in which the European market is the busiest in trading. The similar phenomenon occurs in the case of the JPY/EUR and the JPY/USD exchange rates. Thus, the long memory volatility pattern seems to be closely related to the trading activities in the two main exchange markets(domestic reference market and counterpart foreign market) involved with the exchange rates.

〈Table 4〉 Estimation of the FIGARCH Model for the Long Memory Volatility in 4-hour Period Returns across Time Zones

(a) EUR/USD Exchange Returns

Time(GMT) Time Zone	0-4 JP	4-8 JP/EU	8-12 EU	12-16 EU/US	16-20 US	20-24 US
μ	0.0001 (0.0008)	0.0003 (0.0013)	0.0042*** (0.0016)	-0.0011 (0.0023)	0.0008 (0.0017)	-0.0021 (0.0019)
d	**0.2870*** (0.0436)**	**0.2317*** (0.0566)**	**0.3810*** (0.0523)**	**0.2754*** (0.0526)**	**0.4385*** (0.0868)**	**0.3503*** (0.1908)**
ω	0.0001	0.0005***	0.0006**	0.0013**	0.0002**	0.0010***
	(0.0000)	(0.0002)	(0.0003)	(0.0008)	(0.0001)	(0.0003)
β	0.7388***	0.6445***	0.7641***	0.7215***	0.8716***	0.7624***
	(0.0548)	(0.1037)	(0.0793)	(0.1208)	(0.0396)	(0.1404)
φ	0.4457***	0.4456***	0.5675***	0.5527***	0.6074***	0.4124***
	(0.0766)	(0.1028)	(0.1014)	(0.1330)	(0.0598)	(0.1134)
m3	0.277	0.359	-0.201	-0.287	-0.192	-1.622
m4	5.472	5.097	6.027	7.791	8.658	6.175
Q(50)	54.690	48.523	41.848	47.497	42.858	46.092
$Q^2(50)$	32.278	26.869	34.324	49.624	18.554	13.091
LL	5702.492	4293.045	3294.373	2327.730	3562.307	5070.988

(b) JPY/EUR Exchange Returns

Time(GMT) Time Zone	0-4 JP	4-8 JP/EU	8-12 EU	12-16 EU/US	16-20 US	20-24 US
μ	0.0000 (0.0015)	-0.0003 (0.0017)	-0.0027 (0.0021)	0.0018 (0.0024)	0.0048*** (0.0016)	0.0036*** (0.0012)
d	**0.4528*** (0.0664)**	**0.3657*** (0.0550)**	**0.4550*** (0.0458)**	**0.3301*** (0.0528)**	**0.4291*** (0.0962)**	**0.4212*** (0.0620)**
ω	0.0002**	0.0003***	0.0007***	0.0006**	0.0001	0.0002**
	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0001)
β	0.7901***	0.8053***	0.7118***	0.8249***	0.8672***	0.7441***
	(0.0497)	(0.0555)	(0.0577)	(0.0934)	(0.0795)	(0.1107)
φ	0.4569***	0.5774***	0.4135***	0.6580***	0.6579***	0.4473***
	(0.0597)	(0.0921)	(0.0641)	(0.1235)	(0.0856)	(0.1424)
m3	-0.130	0.091	-0.222	-0.130	0.083	-0.501
m4	6.508	8.473	5.996	6.984	10.932	15.188
Q(50)	48.332	54.423	62.710	32.591	49.220	57.991
$Q^2(50)$	37.473	65.956	51.780	62.608	74.808	23.515
LL	3222.855	2865.891	2065.779	1735.854	2980.786	3520.855

(c) JPY/USD Exchange Returns

Time(GMT) Time Zone	0-4 JP	4-8 JP/EU	8-12 EU	12-16 EU/US	16-20 US	20-24 US
μ	-0.0015 (0.0014)	-0.0012 (0.0016)	0.0021* (0.0014)	0.0031 (0.0022)	0.0051*** (0.0015)	0.0048*** (0.0013)
d	**0.3414***** **(0.0698)**	**0.2790***** **(0.0928)**	**0.3078***** **(0.0538)**	**0.2777***** **(0.0516)**	**0.3880***** **(0.1387)**	**0.3148***** **(0.0594)**
ω	0.0003***	0.0003*	0.0003***	0.0013***	0.0006	0.0005**
	(0.0001)	(0.0002)	(0.0001)	(0.0005)	(0.0005)	(0.0003)
β	0.6953***	0.7984***	0.6735***	0.6357***	0.7295***	0.4446***
	(0.0726)	(0.1335)	(0.0773)	(0.0975)	(0.1682)	(0.1961)
φ	0.3644***	0.6086***	0.3434***	0.4366***	0.5669***	0.1111
	(0.0704)	(0.2344)	(0.0709)	(0.1056)	(0.1586)	(0.1731)
m3	0.011	0.421	-0.412	0.013	-0.043	0.320
m4	6.812	12.372	6.783	9.741	13.473	20.365
Q(50)	54.906	57.858	57.246	54.282	45.806	51.787
$Q^2(50)$	35.324	27.208	43.419	66.594	13.113	31.197
LL	3595.248	3609.957	3531.188	2371.213	3272.925	4152.419

Note: The values in the parentheses are the standard error of the estimated coefficients. LL presents the values of the maximized log likelihood function, m_3 and m_4 are the sample skewness and kurtosis of the standardized residuals, and Q(50) and $Q^2(50)$ are the Ljung-Box statistics with 50 degrees of freedom based on the standardized residuals and squared standardized residuals. And,(*),(**), and(***) represent the significance level at 1%,5% and 10%

For the comparison, this paper also uses the semi-parametric frequency domain method which is suited to estimate the long memory dependencies in the volatility process in the 4-hour period returns of the high frequency exchange rates(Bollerslev and Wright, 2000; Phillips and Shimotsu, 2001). In particular, Taqqu and Teverovsky (1997; 1998) have reported the detailed simulation studies of various semi-parametric estimators for long-range dependency and find the Local Whittle estimator performs well in extreme non-Gaussian cases. Thus, this paper applies the semi-parametric Local Whittle estimation method proposed by Krüsh (1987) and Taqqu and Teverovsky (1997; 1998) to estimate the long memory dependencies in the volatility process of the 4-hour period absolute returns of the high frequency exchange rates across the time zones.

Let X_j be a mean zero time series with spectral density $f(v;\eta)$ with $-\pi < v < \pi$. For semi-parametric estimators like the Local Whittle estimator, only the long run persistence of the time series is assumed and the long run persistence parameter is estimated. The semi-parametric Local Whittle estimator is based on the periodogram of the time series. Thus, if $f(v_j)$ is the spectral density of the absolute returns series, then the Local Whittle estimator only requires specifying the form of the spectral density close to the zero frequency. The Local Whittle estimator then minimizes the quantity,

$$R(d) = \ln(\frac{1}{m})\sum_{j=1}^{m}[\mathrm{I}(v_j)v_j^{2d}] - (\frac{2d}{m})\sum_{j=1}^{m}[\ln(v_j)] \tag{7}$$

where $I(v_j)=(2\pi T)^{-1} \mid \Sigma_{t=1,T} \mid y_t \mid \exp(itv_j) \mid ^2$ and is the periodogram of the absolute returns series.

Particularly, for the choice of the values of(m), this paper follows the method of Shimotsu and Phillips (2000) because the optimal method for choosing the M value is not available. The consistency and asymptotic normality of the Local Whittle estimator have been shown by Robinson (1995), Velasco (1999) and Phillips and Shimotsu (2001) for various ranges of(d).

The estimates of the long memory parameters for the absolute returns of the 4-hour period returns across the time zones by the Local Whittle method are presented in Table 5. The estimated values range from 0.26 to 0.29 for EUR/USD, 0.29 to 0.30 for JPY/EUR, and 0.27 to 0.29 for JPY/USD, and they are found to be relatively smaller than the values of the FIGARCH model in Table 4. But they are all statistically significant at the conventional significance level confirming the existence of the long memory volatility in the absolute 4-hour period returns of the high frequency exchange rates across the time zones. And, the general pattern of the long memory volatilities across the time zones presented by the Local Whittle method is also quite in consistent with the pattern from the FIGARCH model.

〈Table 5〉 Estimation of the Local Whittle Method for the Long Memory Volatility Parameter(d) in 4-hour Period Returns across Time Zones

Time(GMT) Time Zone	0-4 JP	4-8 JP/EU	8-12 EU	12-16 EU/US	16-20 US	20-24 US
EUR/USD	0.2776***	0.2645***	0.2909***	0.2732***	0.2960***	0.2767***
	(0.0079)	(0.0076)	(0.0076)	(0.0077)	(0.0079)	(0.0089)
JPY/EUR	0.3006***	0.2965***	0.3055***	0.2952***	0.2970***	0.2959***
	(0.0078)	(0.0079)	(0.0075)	(0.0077)	(0.0080)	(0.0090)
JPY/USD	0.2907***	0.2728***	0.2809***	0.2806***	0.2946***	0.2846***
	(0.0079)	(0.0083)	(0.0076)	(0.0077)	(0.0083)	(0.0083)

Note: (*),(**), and(***) represent the significance level at 1%, 5% and 10%.

These findings indicate that the long memory volatility of the 4-hour period returns appears to be different across the time zones and only market specific suggesting that the different FX markets may not be integrated fully, and they support the heat wave hypothesis proposed by Engle et al. (1990) as the cause of the long memory volatility clustering in the 4-hour period returns, which is quite consistent with Baillie et al. (1990). Similarly to the time-of-day pattern in the 4-hour period returns in the previous section, the possible theories for the pattern of the long memory volatility across the time zones also could be related to the asymmetric information and the liquidity effect. Following the liquidity effect, that the general pattern of the concentrated trading volume and price variability in the market specific periods can be generated because of the interaction between strategic informed traders and strategic liquidity traders(Admati and Pfleiderer, 1988).

And, it is interesting to note that the estimated values of the long memory parameters from the FIGARCH model and the Local Whittle method during the trading period in which two different markets are trading simultaneously like the period of 4-8 hour(JP/EU) and 12-16 hour(EU/US) are found to be statistically significant at the conventional significance level even with relatively smaller values and the findings suggest the possibility of the long memory volatility spillover effects between the two markets(meteor shower hypothesis) as if the markets perfectly and instantaneously adjusts to the news when new information comes in clusters(Baillie and Bollerslev, 1990).[7]

Ⅳ. Conclusions

This paper considers the important features of the high frequency 1-hour EUR/USD, JPY/EUR and JPY/USD exchange rates and investigates the 4-hour period returns of the high frequency exchange rates across different time zones. Special attention is devoted to the time-of-day pattern and the long memory volatility in the 4-hour returns of the high frequency exchange rates in order to deepen our understanding of the time-of-day pattern and the long memory volatility across the different time zones. First, this paper investigates the time-of-day pattern over different time zones in FX markets by using the 4-period returns of the high frequency exchange rates and undertakes the two-sample t-test to check the statistical significance of the time-of-day pattern in the means of the 4-hour period returns across the time zones. The

7) Some papers like Dimpfl and Jung (2012) and Golosnoy et al. (2012) have examined the volatility spillover across the stock markets in Europe and the US and presented that there exist both the heat wave effect within the stock markets and the meteor shower effect across the stock markets.

results of the tests generally confirm the time-of-day pattern in the means of the 4-hour period returns across the different time zones, which is consistent with the theoretical explanations of the asymmetric information and the liquidity effect in FX markets.

Then, this paper analyzes the volatility features of the 4-hour period returns of the high frequency EUR/USD, JPY/EUR and JPY/USD exchange rates focusing on the volatility clustering and the long memory volatility across different time zones. For the purpose, this paper adopts the parametric FIGARCH model and the semi-parametric Local Whittle estimation method. The general results show that there exist the persistent long memory volatility in the 4-period returns of the high frequency exchange rates and that the long memory volatility seems to be significantly different across the time zones and only market specific. Also, the long memory volatility of the high frequency returns is found to be significant even when two different markets are trading simultaneously as if the two markets perfectly and instantaneously adjusts to the news when new information comes in clusters, which shows the spillover effects between the two markets. These findings support the heat wave hypothesis in the FX markets presenting that the long memory property could be only market specific and also suggest some possibility of the meteor shower hypothesis indicating the volatility spillover effects. In this context, the empirical results appear to be in line with the theories of the asymmetric information and the liquidity effect in the FX markets.

Consequently, this paper can provide additional evidence that there may well be supportive of the main features, the time of day pattern and the long memory volatility in the high frequency exchange rates across different time zones with some theoretical explanations based on the asymmetric information and the liquidity effect in FX markets. In this aspect, this paper can provide the increased ability to analyze finer details of the behavior of different market participants in the FX markets since the two features are in their own right importance in explaining the high frequency exchange rate dynamics.

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Abstract

본 논문에서는 다른 거래시간대에 따른 환율에서 나타나는 두 가지 중요한 특성인, 일중 시간별 거래패턴과 장기기억 변동성에 대해 1-시간 간격의 유로/달러, 엔/유로, 엔/달러 고빈도 환율 데이터를 이용하여 알아본다. 먼저 본 논문에서 서로 다른 통화들과 거래시간대에 따라 국내(외국)거래 시간 동안에는 국내화폐가 절하(절상)하는 경향이 나타나는 환율에서의 일중 시간대 거래 패턴에 대한 통계적인 증거를 파악하였다. 또한 FIGARCH모형과 Local Whittle 추정법을 이용하여 고빈도 환율에서 나타나는 장기기억 변동성을 분석하여 장기기억 변동성이 거래 통화와 거래시간대에 따라 다르게 나타날 뿐만 아니라 시장 특정적인 형태를 가지고 있음을 파악하였다. 아울러 본 논문에서는 환율의 일중 시간대 거래패턴과 장기기억 변동성에 대한 이론적 설명을 외환시장에서의 비대칭적 정보와 유동성 효과 측면에서 제시하였다.

※ 국문 색인어: 고빈도 환율, 일중 시간대 패턴, 장기기억 변동성, FIGARCH 모형, Local Whittle 추정