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Abstract

In this study, we model realized volatility constructed from intra-day high-frequency data. We explore the possibility of confusing long memory and structural breaks in the realized volatility of the following spot exchange rates: EUR/USD, EUR/JPY, EUR/CHF, EUR/GBP, and EUR/AUD. The results show evidence for the presence of long memory in the exchange rates' realized volatility. From the Bai–Perron test, we found structural breakpoints that match significant events in financial markets. Furthermore, the findings provide strong evidence in favour of the presence of long memory.

Keywords: foreign exchange markets, realized volatility, high-frequency data, long memory, structural change

JEL Classification: C22, C32, C58, F31, G15

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1 Introduction

Given the rapid growth of financial markets and the continued development of new and complex financial instruments, there is increased need for theoretical and empirical knowledge about the volatility of financial returns. In fact, volatility presents a complex phenomenon in finance. Volatility affects a multitude of decisions in financial markets. Despite its importance, volatility is still an ambiguous term; it is usually defined as an indicator of the size of price movements. Gençay *et al.* (2001) described volatility as the visible 'footprint' of less observable variables in financial markets. Therefore, understanding the dynamics of volatility would enable strategies to be implemented for coping with unpredictable fluctuations.

Several researchers have considered and studied volatility as a latent variable. However, it has turned out that this latent volatility approach cannot identify all the properties of financial returns. Thus, research on volatility has been developed, and an alternative approach has emerged, namely, realized volatility. This approach considers volatility as an observable variable based on high frequency return measures. Since the introduction of the realized volatility measure by Andersen and Bollerslev (1997a, 1997b), there has been significant interest in modelling this measure. These authors proposed realized volatility, built from intraday returns, as a measure of actual volatility. Today, realized volatility is widely used in measuring historical price movements.

Recently, a debate has emerged about the nature of the volatility process of financial returns in general and of exchange rates returns in particular. Researchers have become interested in whether these series are characterized by a process of long memory or structural breaks.

We start our analysis by considering a characteristic often quoted in financial literature: exchange rate volatility persistence in the foreign exchange market. Persistence means dependence between distant observations, which might conveniently be described by a long memory process. Thus, Andersen, Bollerslev, Diebold, and Labys (2001, 2003), Andersen, Bollerslev, Diebold, and Ebens (2001), Koopman *et al.* (2005), and Ohanissian *et al.* (2008) suggested that the realized volatility of financial returns and of exchange rate returns is often known and well modelled as a long memory process. In particular, the presence of long memory in the foreign exchange market might explain the highest order of the volatility correlation structure. Thus, consideration of the presence of this property is important for practitioners, investors, as well as for financial institutions requiring risk management and trading strategies.

Andersen *et al.* (2003) used a fractional autoregressive model to capture the long memory properties of exchange rate realized volatility. Several authors, such as McAleer and Medeiros (2008) and Corsi (2009), have shown the presence of long memory in series on volatility. Therefore, several studies have applied long memory models to the volatility of financial returns (Cheung, 1993; Baillie, 1996; Breidt *et al.*, 1998; Davidson, 2004; Kumar and Maheswaran, 2015).

However, other studies explain the long memory of the volatility process by the presence of structural breaks. According to Diebold and Inoue (2001), the presence of long memory might be a consequence of breakpoints which are not taken into account, resulting in biased estimation of the long memory parameter. Similarly, Lamoureux and Lastrapes (1990) found that the introduction of these structural break points reduces the presence of long memory. Moreover, Granger and Teräsvirta (1999) concluded that a short memory process with structural breaks provides a biased fractional integration parameter, giving a spurious long memory. Recent studies in this field suggest that several non-linear models exhibit long memory but they incorporate a form of structural breaks (Liu, 2000; Granger and Hyung, 2004; Yalama and Celik, 2013).

In this study, we explore the possibility of confusing long memory and structural breaks in the daily exchange rate realized volatility for parity in the following exchange rates: EUR/USD, EUR/JPY, EUR/GBP, EUR/CHF, and EUR/AUD. We model the series with an autoregressive fractionally integrated moving average (ARFIMA) model.

The rest of this paper is organized as follows. Section 2 reviews the literature related to the presence of long memory and structural breaks in the foreign exchange market. Section 3 presents the methodology used in this study. The data are described in Section 4. Section 5 reports the empirical results. Finally, section 6 concludes.

2 Literature review

The gradual integration of international financial markets has led to rich literature on the properties of exchange rate volatility in the foreign exchange market. The long memory issue has attracted the attention of several researchers.

Mandelbrot and Wallis (1968) argued that the long memory phenomenon or long-term dependency was described in the Bible and the Qur'an as 'seven years of great plenty throughout the land of Egypt, but seven years of famine will follow them'. Hurst (1951) discussed the concept of long memory in a study about long-term dependency of the series of Nile water flow. He noted that long periods of drought were followed by long periods of flooding. Thus, the long memory process has been applied in various fields, such as economics, meteorology, and geophysics (Lawrance and Kottegoda, 1977; and McLeod and Hipel, 1978).

Granger and Ding (1996) defined a time series as having long memory behaviour when it has a slowly decreasing autocorrelation structure. Baillie (1996) and Baillie and King (1996) showed that in a series with a long memory, time dependence exists even between distant observations. This means that actual exchange rate volatility might have an impact on future volatility for a long period.

Mandelbrot and Taqqu (1979) applied the long memory phenomenon or Joseph effect in the field of finance. The successful application of long memory models to financial time series has been widely proven. Empirically, Baillie *et al.* (1996) and Tse

(1998) argued that the long memory process has been very successful in describing the volatility of financial series. Then, Cheung (1993) using the Geweke–Porter-Hudack (GPH) test for exchange rates series showed the presence of long memory. Furthermore, he gave evidence that the ARFIMA model is the most appropriate for these series. Similarly, Beran and Ocker (1999) and Velasco (1999) provided the same evidence for the exchange rate series.

A large body of empirical literature has highlighted the presence of long memory in the volatility process. Diebold *et al.* (1991), Ding *et al.* (1993), and Taylor and Xu (1997) found that exchange rate volatility is characterized by a slowly hyperbolic decreasing autocorrelation, inducing a long memory process. Ding and Granger (1996) examined the long memory property in volatility series on the stock market and foreign exchange market. They found that evidence of long memory is stronger in the foreign exchange market. According to Baillie *et al.* (2000), long memory is a fundamental characteristic in the volatility process. They observed that the exchange rate volatility of the DEM/USD is generated by a long memory process for different frequencies. Moreover, the authors found that the fractionally integrated generalized autoregressive conditional heteroscedasticity (FIGARCH) model can adequately describe the volatility of the DEM/USD.

Many empirical studies, using high-frequency data, have examined the presence of long memory in exchange rate realized volatility. Andersen and Bollerslev (1997a, 1997b) and Andersen *et al.* (1999) suggested that the volatility built from high frequency data facilitates the detection of the presence of long memory in the volatility process. Andersen and Bollerslev (1998) demonstrated the existence of a long-term dependency in volatility in the foreign exchange market. Andersen, Bollerslev, Diebold, and Labys (2001) showed that the exchange rate realized volatility of the DEM/USD and JPY/USD seems to be well described by a fractionally integrated process due to the presence of a strong dependence in their processes. In addition, Chiriac and Voev (2011) and Varneskov and Voev (2013) noted that the volatility series exhibit characteristics comparable to a fractionally integrated process or long memory.

The existant literature provides considerable evidence for the presence of long memory in the exchange rate volatility. To account for this behavior of high persistence, several models were introduced in the empirical literature. Bollerslev (1986), Hsieh (1989), and Baillie and Bollerslev (1990) concluded that volatility series are characterized by high persistence and can be well described by an integrated generalized autoregressive conditional heteroscedasticity (IGARCH) model.

Beran and Ocker (1999) proposed a semiparametric fractional autoregressive model, to estimate exchange rate volatility in the foreign exchange market. Baillie *et al.* (1996) introduced the FIGARCH model, which enables the introduction of the long memory process in conditional variance. The authors proved the performance of this model for describing the exchange rate volatility of the DEM/USD.

Vilasuso (2002) reviewed nominal exchange rates of six industrialized countries, which correspond to the CAD/USD, FRF/USD, DEM/USD, ILT/USD, JPY/USD, and GBP/USD during 1979–1997. The author proved the ability of the FIGARCH model to detect the main features of the exchange rate volatility involved. Davidson (2004) proposed the hyperbolic generalized autoregressive conditional heteroscedasticity (HYGARCH) model. This model presents a generalized version of the FIGARCH model, and can generate long memory even if the value of the fractional integration parameter is very close to 1 in the exchange rate series.

For realized volatility, Andersen, Bollerslev, Diebold, and Ebens (2001) proposed the ARFIMA model for many financial series. Then, Andersen, Bollerslev, Diebold, and Labys (2001) applied the ARFIMA model on exchange rates volatility, they demonstrated the success of this model in modeling the realized volatility series and its ability to capture the long memory properties. Furthermore, Andersen *et al.* (2003) proposed a vector autoregressive model to estimate realized volatility.

Pong *et al.* (2004) argued that the ARFIMA model proposed by Granger and Joyeux (1980) outperforms other traditional models in forecasting exchange rate realized volatility of the GBP/USD and the DEM/JPY. Recently, Chortareas *et al.* (2011) showed the performance of the ARFIMA model in capturing the long memory properties of the exchange rate realized volatility of parity for the EUR/USD, EUR/CHF, EUR/GBP, and EUR/JPY.

Despite the evidence of the presence of long memory in the volatility of exchange rates, recent studies, like Yang and Chen (2014), showed that the realized volatility of financial returns generally exposes both long memory properties and structural breaks.

We argue that the literature contains confusing evidence regarding the presence of long memory in the volatility process. Engel and Hamilton (1990) modelled exchange rate volatility with structural break models. The authors suggested that these models take into account latent shocks that might influence the exchange rate.

Long memory might be an artefact due to structural breakpoints which are not considered. In this case, we talk about the presence of spurious long memory that leads us to analyse long memory with great caution. Modelling volatility without considering breaks might overestimate the long memory parameter. The origin of this problem was raised by Perron (1989, 1990). Zivot and Andrews (1992) suggested that the presence of structural breaks could lead to a biased result of the augmented Dickey-Fuller (ADF) test.

Liu (2000) demonstrated that the presence of long memory in the volatility process of financial returns could be spurious as it could be attributed to the negligence of structural breaks. In addition, Granger and Ding (1996) argued that long memories could result from other processes, including the aggregation of several non-linear short-term processes.

Mikosch and Starica (2000, 2004) supported the hypothesis of non-stationarity in the volatility series in financial markets. They found that long-term dependence is the result of the impact of non-stationarity in estimation procedures. The authors demonstrated that the apparent long memory in the series of the S&P500 and the DEM/USD could be an artefact induced by the presence of structural breaks.

Granger and Hyung (2004) reported that it is difficult to distinguish between long memory and structural breaks. They compared a model of structural breaks and a long memory model to analyse the volatility of the S&P500. The authors found that occasional structural breaks produce autocorrelations which decay slowly. Then, long memory behaviour could be generated by the presence of structural breaks.

Choi and Zivot (2007) examined the presence of long memory or structural breaks in exchange rate series. First, they estimated the long memory parameter without considering the structural breakpoints. Then, they estimated a structural break model and re-estimated the long memory parameter after the deletion of the breakpoints. Finally, they opted for a Monte Carlo simulation to evaluate the estimation of the structural breaks in the presence of long memory. They found that taking into account breakpoints remarkably reduced persistence in the exchange rate process. However, after removing structural breakpoints, the authors found strong evidence of the presence of long memory. These results confirmed the importance of structural breaks in exchange rate volatility.

Structural breaks can cause high persistence in the autocorrelation function, which generates spurious long memory. In addition, a growing number of structural breaks make the series process more persistent. Motivated by the results of Perron and Qu (2007), Perron and Qu (2010) reported that a short memory process contaminated with structural breakpoints might bias estimation of the fractional long memory parameter upward and cause autocorrelations to decrease slowly, which suggests the presence of long memory or spurious long memory. These authors modelled the volatility of certain financial assets and proposed a simple test to discriminate long from short memory processes with structural breaks.

Morana and Beltratti (2004) studied the properties of the exchange rate volatility of the DM/USD and the JPY/USD. Through an analysis with various parametric and semi-parametric models, the study provided evidence of the presence of structural breaks. Choi *et al.* (2010) explored the possibility of the presence of structural breaks in the volatilities of the DM/USD, JPY/USD, and JPY/DM, which appear to be characterized by long memory observed behaviour. The authors found that these series are generated by a structural break process.

Varneskov and Perron (2015) introduced structural breaks in the ARFIMA model. They demonstrated that the inclusion of structural breaks is essential and can improve the modelling of volatility in financial markets. Several structural change models have been applied to describe the dynamics of exchange rate volatility. Hamilton (1990) and Engel and Hamilton (1990) demonstrated that exchange rate volatility can be described adequately by the regime-switching models of Markov. Recently, Lee and Chen (2006) and Nikolsko-Rzhevskyy and Pordan (2012) showed that Markov regime-switching models adequately describe the exchange rate with a floating exchange rate regime. All these contradictions have motivated us to study the characteristics of exchange rate volatility and more precisely, realized volatility, constructed with high frequency data.

3 Methodology

In this study, we conduct three types of tests for each series: (i) long memory tests, (ii) structural break test, and (iii) a long memory versus structural break test. Once the realized volatility series show a long memory process, the ARFIMA model is used for the estimation.

3.1 Realized volatility measure

The availability of high frequency data enables us to measure the realized volatility very simply. The notion of using only realized returns was introduced by French *et al.* (1987), who estimated monthly realized volatility built through daily returns. Let r_t be the logarithmic return process. The realized variance over interval $[t-h,t]$ is defined as follows

$$RVar_{t,h} = \sum_{i=1}^{n} r^2_{t-h+\left(\frac{i}{n}\right)h}, \tag{1}$$

where n is the number of observations over interval $[t-h,t]$.
Thus, realized volatility, as the square root of the variance, is calculated as follows:

$$RV_{t,h} = \sqrt{RVar_{t,h}}, \tag{2}$$

3.2 Long memory tests

To test the presence of a long memory process for the series of exchange realized volatility, we use different techniques used in the empirical literature.
The first long memory process presented in the literature is the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model developed by Granger and Joyeux (1980) and Hosking (1981). A process $\{X_t\}_1^T$, with $t \in Z$ follows an ARFIMA (p,d,q) process if:

$$\phi(L)(1-L)^d X_t = \theta(L)\varepsilon_t, \tag{3}$$

where d is the order of fractional integration and L is the lag operator i.e. $LX_t = X_{t-1}$. $\phi(L)$ and $\theta(L)$ are the autoregressive and the moving average polynomials of order p and q, and ε_t is a white Gaussian noise. If $-\frac{1}{2} < d < 0$, the series are antipersistent, the autocorrelations decrease hyperbolically and tend to zero and the spectral density is dominated by the high frequency components. If $d = 0$, the series have short memory behavior and can be modeled by a standard ARMA model. If $0 < d < \frac{1}{2}$, the series are stationary with long memory behavior. The autocorrelations are positive, decrease hyperbolically, and tend to zero when the delay increases. The spectral

density is concentrated around the low frequencies and tends towards infinity when the frequencies tend towards zero.
The testing method for the presence of a long memory behavior consists on testing the null hypothesis of a short memory behavior against the alternative hypothesis of long memory behavior:

$$\begin{cases} H_0 : d = 0 \\ H_1 : d \neq 0 \end{cases}$$

We start with the rescaled range statistic (R/S), introduced by Hurst (1951). This statistic enables the classification of time series according to their nature and memory by referring to a coefficient H, known as the Hurst exponent. Let $y_t, t = 1, \ldots, T$, a time series with an average $\overline{y}_t$, of T series; the R/S statistic, denoted as $\mathcal{Q}_T$, is written as:

$$\begin{aligned} \mathcal{Q}_T &= R/S_T = \\ &= \frac{1}{\left[\frac{1}{T}\sum_{j=1}^{T}\left(y_j - \overline{y}_T\right)^2\right]^{1/2}} \times \left[\max_{1\leq k\leq T}\sum_{j=1}^{k}\left(y_j - \overline{y}_T\right) - \min_{1\leq k\leq T}\sum_{j=1}^{k}\left(y_j - \overline{y}_T\right)\right] \end{aligned} \quad (4)$$

This statistic is proportional to T^H, where $0 < H < 1$, and is given by $H \sim \frac{\log \mathcal{Q}_T}{\log T}$. It allows to classify the time series according to their level of dependency. If $0 < H < \frac{1}{2}$, antipersistence structure exists. If $H = 0$, the process is white niose. When $\frac{1}{2} < H < 1$, the long memory structure exists. If $H \geq 1$, the process is non-stationary and has infinite variance.
After Hurst (1951), Geweke and Porter-Hudak (1983) proposed a first semi-parametric method in order to estimate the long memory parameter d. The semi-parametric estimator of log-periodogram, called the GPH is extensively used. Let y_t be the exchange rate volatility, the GPH estimator of the long memory parameter d for y_t can be determined using the following periodogram:

$$\log\left(I\left(w_j\right)\right) = \alpha + \beta \log\left(4\sin^2\left(\frac{w_j}{2}\right)\right) + \varepsilon_j, \ j = 1, 2, \ldots, m, \quad (5)$$

where α is a constant, $w_j = \frac{2\pi j}{T}$, ε_j is the residual term , T is the sample size, w_j represents the $m = \sqrt{T}$ Fourier frequencies (it is required that m grows slowly with respect to the sample size). $I\left(w_j\right)$ denotes the sample periodogram defined as

$$I\left(w_j\right) = \frac{1}{2\pi T}\left|\sum_{t=1}^{T} y_t e^{-w_j t}\right|^2$$

Where y_t is assumed to be a covariance stationary times series. The estimated d of parameter integration $\hat{d}$ is -$\widehat{\beta}$ and it can be estimated by ordinary least square (OLS), an asymptotically distributed estimator for $0 < d < \frac{1}{2}$, yielding:

$$\sqrt{m}\left(\hat{d}_{GPH} - d\right) \rightarrow N\left(0, \frac{\pi^2}{24}\right), \tag{6}$$

Robinson (1995) proposed an alternative estimation, which has been used often in volatility series. Through analysis of the local Whittle estimator suggested by Künsch (1987), he developed a local Whittle estimator, d_r. The estimator of the long memory parameter for a covariance stationary series, which is consistent and asymptotically normal for $0 < d < 1/2$. It can be expressed as follows:

$$\sqrt{m}\left(\hat{d}_r - d_0\right) \rightarrow N\left(0, \frac{1}{4}\right), \tag{7}$$

m is less than [T/2] in order to evade aliasing effects; d_0 represents the true value of d, with the only additional requirement that $m \rightarrow \infty$ slower than T, $\frac{1}{m} + \frac{1}{m} \rightarrow 0$ as $T \rightarrow 0$.
Andrews and Guggenberger (2003) proposed an extension of the GPH estimator to make it even more robust; this extension is called the AG test. They kept the same asymptotic distribution of the GPH estimator. To reduce estimation bias, they replaced the constant in the specification of the periodogram with $\sum_{r=0}^{R} \alpha w_j^{2r}$. The regression is as follows:

$$\log\left(I\left(w_j\right)\right) = \sum_{r=0}^{R} \alpha w_j^{2r} + \beta d \log\left(w_j\right) + \varepsilon_j, \tag{8}$$

3.3 Structural break test

To test the possibility of the presence of structural breaks in the exchange rate realized volatility, we use the test of multiple structural breaks proposed by Bai and Perron (1998, 2003). The m-rupture ($m + 1$ break) model can be defined as follows:

$$y_t = c_j + u_t, t = T_{j-1} + 1,\ T_{j-1} + 2, \ldots, T_j, \tag{9}$$

where $j = 1, 2, \ldots, m + 1$, y_t is the logarithm of the realized volatility and c_j is the average of the logarithmic realized volatility. Structural breakpoints $(T_1, T_2, \ldots, T_m)$ are treated as unknown. The error term u_t might be serially correlated and heteroscedastic. The test is applied to each j regime with observations between the dates $\widehat{T}_{j-1}+ 1$ and $\widehat{T}_j$ $(j = 1,\ 2,\ \ldots,\ m + 1)$, we consider sup $F_T(l)$, noting that the F statistic for the hypothesis of no structural breakpoints is against the alternative containing an arbitrary number of structural breakpoints, and we define $M = 5$ as the maximum allowed number of breakpoints. We define the double maximum statistic $UD_{\max} = \max_{1 \leq l \leq M} \sup F_T(l)$, and the weighted double maximum statistic

$WD_{\max} = \max_{1 \leq l \leq M} w_l \sup F_T(l)$, where weights w_l are such that the marginal p-values are equal across values of l.
The null hypothesis H_0 of the test is the absence of structural breakpoints against the hypothesis of the presence of an unknown number of structural breakpoints. The sequential $\sup F_T(l+1|l)$ tests the null hypothesis of l breaks against the assumption of $l+1$ breaks. To estimate the number of breakpoints, we use $UD_{\max}$ and $WD_{\max}$ to determine whether at least one break occurred. If there is evidence of a structural break, we choose the number of structural breakpoints using $\sup F_T(l+1|l)$. Thus, the test can be defined as follows:

$$F_T(l+1/l) = \left\{ Q_T\left(\hat{T}_1, \ldots, \hat{T}_l\right) - \min_{1 \leq i \leq l+1} \inf_{\lambda \in \Lambda_{i,n}} Q_T\left(\hat{T}_1, \ldots, \hat{T}_{i-1}, \lambda, \hat{T}_i, \ldots, \hat{T}_l\right) \right\} \frac{1}{\hat{\sigma}^2}, \tag{10}$$

where $\Lambda_{i,n} = \{\lambda; \hat{T}_{i-1} + (\hat{T}_i - \hat{T}_{i-1})\eta \leq \lambda \leq \hat{T}_i - (\hat{T}_i - \hat{T}_{i-1})\eta\}$, and $\hat{\sigma}^2$ is a consistent estimator of σ^2 under the null hypothesis.

3.4 Long memory versus structural break test

A simple test, based on the estimation of the log-periodogram, enables us to distinguish the long and short memory contaminated by structural breaks proposed by Perron and Qu (2010). Known as the PQ test statistic, this is given, under the null hypothesis of realized volatility characterized by a long memory process against the alternative hypothesis of a short memory process affected by structural breaks or spurious long memory process. If $0 < a < b < 1$ and $b < 4/5$, the test statistic is as follow:

$$t_d\left(a, b\right) = \sqrt{\frac{24\left[T^a\right]}{\pi^2}} \left(\hat{d}_a - \hat{d}_b\right) \xrightarrow{d} N(0,1), \tag{11}$$

for $\hat{d}_a$ and $\hat{d}_b$ denote the log-periodogram estimate of the of the long memory parameter for the frequencies, $m_a = T^a$ and $m_b = T^b$, respectively. We follow Perron and Qu (2007) and implement the test with $a = 1/2$ and $b = 4/5$.

3.5 ARFIMA model

The ARFIMA specification is chosen once the series show a long memory process. The ARFIMA model (p, d, q) proposed by Granger and Joyeux (1980) for stationary process y_t is as follows:

$$\phi\left(L\right)\left(1 - L\right)^d \left(y_t - \mu\right) = \theta\left(L\right)\varepsilon_t, \tag{12}$$

where d is the order of fractional integration and L is the lag operator in t. The polynomial components AR and MA are given by $\phi\left(L\right) = 1 + \phi_1 L + \cdots + \phi_p L^p$ and $\theta\left(L\right) = 1 + \theta_1 L + \cdots + \theta_q L^q$, respectively, where μ is the mean of y_t, which is defined as the logarithm of the logarithmic daily realized volatility $\log(RV_t)$, and ε_t is a white

Gaussian noise.
Several studies, such as, Andersen, Bollerslev, Diebold and Labys (2001, 2003), Pong *et al.* (2004), and Koopman *et al.* (2005), have suggested that the ARFIMA model outperforms other traditional models for modelling exchange rate realized volatility. According to the work of Andersen *et al.* (2003) and Chortareas *et al.* (2011), the specification of the ARFIMA model (p, d, q) in the context of the realized volatility is as follows:

$$\phi(L)(1-L)^d(\log(RV_t)-\mu)=\theta(L)\varepsilon_t, \tag{13}$$

4 Data and descriptive statistics

In our study, we use high frequency data that cover the spot exchange rates of EUR/USD, EUR/JPY, EUR/GBP, EUR/CHF, and EUR/AUD provided by Reuters FX. The data cover the period from 1 January 2004 to 30 October 2014. To avoid microstructure noise, we choose a 30-minute interval based on the work of Martens (2001), Andersen *et al.* (2003), Koopman *et al.* (2005), and Pooter *et al.* (2008). The currency pairs used in this study were chosen based on their importance in the global foreign exchange market and the fact that most studies focus on the volatility of the US dollar, despite the importance of the euro in the foreign exchange market. First, we compute intraday returns $r_{i,t}$ from the fluctuations between t and $t+l$. Then, we build 48 intervals of 30 minutes each from 21:00 GMT to 21:00 GMT the following day. The expression of realized volatility, based on French *et al.* (1987), is as follows:

$$RV_T=\sqrt{\sum_{i=1}^{48} r_{i,t}^2}, \tag{14}$$

We obtain 2722 observations. We mention that the foreign exchange market is open 24 hours a day, 7 days a week but transactions during weekends and holidays are less important. Therefore, we follow the standard approach of Andersen and Bollerslev (1998), and adjust the data to avoid the holiday effect by discarding the weekend period from Friday 21:00 GMT to Sunday 21:00 GMT as well as public holidays. The holiday period incorporates Christmas (24–26 December), New Year (31 December–2 January), Labour Day, and Thanksgiving Day and the day thereafter.
Table 1 provides descriptive statistics for the daily realized volatility and logarithmic realized volatility. The skewness coefficients are negative for the logarithmic realized volatility of EUR/CHF, which indicates a left-skewed distribution. For the other series, the skewness coefficients differ from zero and are positive, indicating a right-skewed distribution. The excess kurtosis indicates a leptokurtic distribution with values concentrated around the mean and fat tails in the case of all series. Jarque–Bera statistics confirm the rejection of the normality hypothesis for all series, indicating non-linear behavior.
Figure 1 describes the evolution of the realized volatility for the five exchange rates.

Table 1: Descriptive statistics

		Mean	Standard errors	Skewness	Excess Kurtosis	Min	Max	Jarque-Bera
EUR/USD	RV_t	0.396	0.474	4.871	37.5923	0.0068	6.401	166459.428
	LRV_t	−1.327	0.094	0.324	0.324	−4.983	1.856	15.583
EUR/YEN	RV_t	0.706	1.432	8.736	111.861	0.014	27.623	1416415.828
	LRV_t	−0.976	1.021	0.447	0.602	−4.266	3.318	128.791
EUR/CHF	RV_t	0.194	1.063	38.244	1722.401	0	49.245	328091758.371
	LRV_t	−2.83	1.532	−0.333	1.226	−8.672	3.896	215.191
EUR/GBP	RV_t	0.269	0.368	4.816	32.909	0.01	4.84	129779.526
	LRV_t	−1.766	0.888	0.458	0.373	−4.541	1.576	108.151
EUR/AUD	RV_t	0.517	1.387	19.24	538.212	0.027	47.036	32136017.809
	LRV_t	−1.183	0.85	0.894	2.142	−3.594	3.851	859.589

The figure show periods of high volatility followed by periods of high volatility, and periods of low volatility followed by periods of low volatility, which indicates volatility clustering. For the EUR/USD, we note an important spike of volatility between 2004 and 2008.

We observe in the figure of the EUR/USD an acceleration of volatility in the last months of 2004, which can be explained by the depreciation of the US dollar that began in 2002. The US dollar depreciated to record lows against the euro in late 2004. In August 2004, news issued by central banks about foreign exchange reserves of the United States highlighted the weakness of the US dollar. This weakness accelerated the appreciation of the euro to the US dollar in the financial market against the dollar and the yen. The euro seems to have remained stable against the British pound and the Australian dollar and depreciated relative to the Swiss franc.

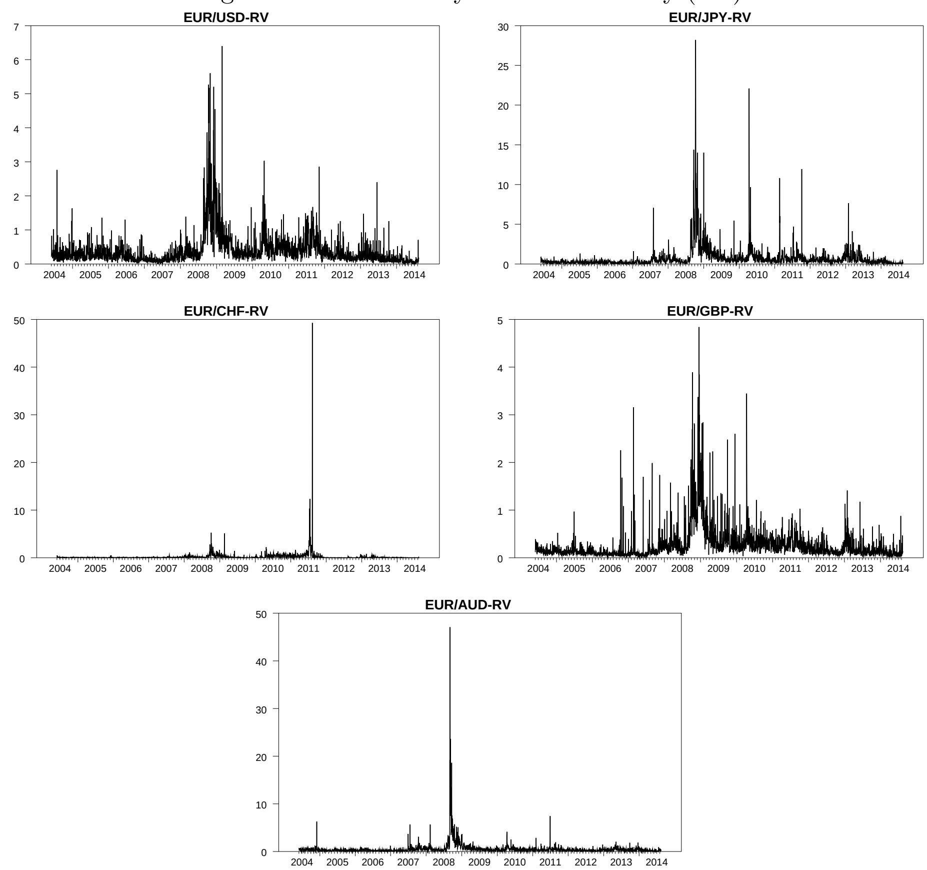
In 2007, there is a significant spike in the volatility of the EUR/JPY. This seems to have been the result of monetary policy to depreciate the yen followed by Japan's central bank. In 2008, the foreign exchange market showed a sharp increase in volatility for all currency pairs involved in this study. This very high level of volatility was the result of the subprime crisis, which strongly affected the foreign exchange market.

After August 2007, the appreciation of the euro led to high volatility, due to the sentiments of investors that the eurozone was a less risky refuge. In late 2008, the yen sharply appreciated against the euro, as the eurozone was affected by the subprime crisis. The high cluster of volatilities during 2007 and 2008 came amid the recession of the UK economy. The volatility of the EUR/AUD experienced a bullish acceleration after the financial crisis.

Figure 2 shows the autocorrelation functions of the realized volatility and the logarithm of the realized volatility.

We note that these functions have a hyperbolic slow decay; moreover, they exhibit greater persistence in the autocorrelation functions of the logarithmic realized volatility series, which can indicate the presence of long memory. Then, in accordance

Figure 1: Plots of daily realized volatility (RV)



with the previous literature (Andersen *et al.*, 2003, Choi *et al.*, 2010), we consider the logarithmic specifications of the realized volatility.
Table 2 presents different stationarity tests. For the ADF and PP tests, we test the null hypothesis of presence of unit root against the alternative hypothesis of absence of unit root, i.e. a stationary process. For the KPSS test, the null hypothesis is the presence of stationarity process. According to ADF, PP and KPSS test results, we can reject the non-stationarity hypothesis.

Figure 2: Autocorrelation plots for daily realized volatility (RV) and daily logarithmic realized volatility (LRV)

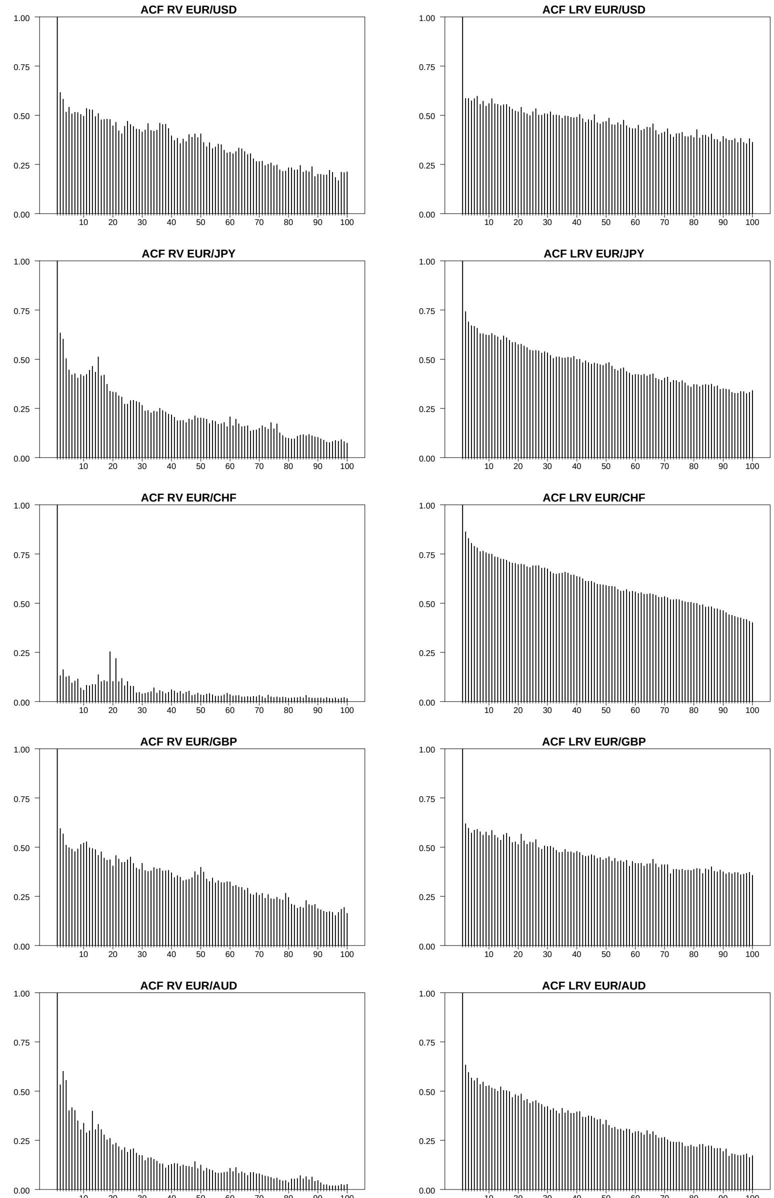


Table 2: Stationarity tests

LRV_t	ADF	PP	KPSS
EUR/USD	-5.832	-26.445	0.02
EUR/YEN	-12.421	-17.704	0.079
EUR/CHF	-6.033	-11.328	0.139
EUR/GBP	-3.067	-24.3902	0.11
EUR/AUD	-10.494	-22.654	0.128
Critical-value	-1.95	$.-2.863$	0.146

5 Dynamics of forex realized volatility

5.1 Long memory test

As mentioned in the methodology, we first conduct the long memory tests. The presence of long memory was firstly tested using Hurst exponent (H) produced by the Rescaled range statistic. The value of H are indicating that the series have long memory structure since $\frac{1}{2} < H < 1$. Table 3 shows the estimation results of long memory parameter d for the logarithmic realized volatility. For the GPH, Robinson, and AG tests, we choose m frequency based on the previous literature. For the Robinson test, to estimate the fractional integration parameter, Robinson (1995) proposed $m = T^{0.5}$. For the GPH and AG tests, we rely on the work of Simotsu (2006), Aloy *et al.* (2011), and Charfeddine and Guégan (2011). Thus, we take $m = T^{0.5}$, $T^{0.6}$, $T^{0.7}$, $T^{0.8}$.
We find that the Hurst coefficients are well above 0.5 for the different series, which indicates the presence of a long memory process. The results of the other tests are nearly the same. The values of long memory parameter d are between 0.322 and 0.541. We observe a decline over the estimation of the long memory parameter based on the periodogram method. There might well be long memory in the logarithmic realized volatility of the five exchange rates. Therefore, a shock that occurs at some point will affect the future evolution of the series over a relatively long period. The series tend to move back to equilibrium values very slowly. The presence of a long memory process in the realized volatility of the exchange rate of returns shows that shocks are not permanent. A long-range dependent process might contain information which makes forecasting more significant. One possible explanation for the long memory in the process of volatility can be found in news about the market. This news might be grouped in time. Thus, the shift in investor responses to this news, for example, might cause autocorrelation in volatility. In addition, the long memory is connected to the heterogeneity of market participants. Investors with limited rationality form heterogeneous expectations about the future level of volatility.
The test results of GPH and AG show that parameter d is clearly unstable. This instability might result from the presence of structural breaks. Therefore, long

Table 3: Long memory test results

LRV_t	H	Robinson	m	GPH	AG
EUR/USD	0.822	0.494	0.5	0.552	0.396
			0.6	0.347	0.342
			0.7	0.368	0.49
			0.8	0.113	0.114
EUR/YEN	0.85	0.47	0.5	0.337	0.301
			0.6	0.541	0.572
			0.7	0.278	0.495
			0.8	0.231	0.477
EUR/CHF	0.829	0.46	0.5	0.454	0.322
			0.6	0.371	0.389
			0.7	0.391	0.361
			0.8	0.595	0.193
EUR/GBP	0.832	0.48	0.5	0.5	0.409
			0.6	0.415	0.58
			0.7	0.385	0.369
			0.8	0.125	0.133
EUR/AUD	0.815	0.49	0.5	0.4	0.407
			0.6	0.392	0.406
			0.7	0.242	0.55
			0.8	0.608	0.242

memory and structural breaks might be confused. Davidson and Sibbertsen (2009) suggest the existence of a bias in the log-periodogram regressions of a time series believed to be long memory. Short-run autocorrelation being likely to feature in a long memory process. Furthermore, Agiakloglou *et al.* (1993) suggest the presence of short-run dynamic components can still severely bias the GPH estimator in finite samples, and falsely indicating the existence of long memory.

5.2 Structural breaks test

In order to identify the possible presence of structural breaks in the realized volatility process of the different exchange rates, we use the test proposed by Bai and Perron (1998, 2003). The test results are reported in Table 4. These results show points of structural breaks that seem to reflect the experience of the financial markets and particularly the foreign exchange market. We can say that structural breakpoints seem to coincide with historical events and major incidents related to financial markets. The first breakpoint in June 2004 coincides with the end of the period of depreciation of the US dollar against the euro, when US dollar appreciation affected other currencies. The second breakpoint led to an increase in volatility and is associated with the financial crisis of 2008 that spread worldwide. The crisis, which began in August 2007, has affected the entire financial system and generated high volatility in the foreign exchange market. The financial crisis has caused strong appreciation of the euro against the US dollar.

The two breakpoints of 2009 and 2011 coincided with the beginning and end of the

Table 4: Structural breaks test results

LRV_t	EUR/USD	EUR/YEN	EUR/CHF	EUR/GBP	EUR/AUD
T1	2004:06:29	2004:09:24	2004:08:05	2006:02:02	2005:03:02
T2	2007:10:23	2008:10:09	2007:07:23	2007:11:14	2007:07:13
T3	2008:06:17	2009:06:24	2009:06:15	2008:09:18	2008:08:14
T4	2010:01:07	2009:09:16	2010:04:28	2009:04:06	2009:01:21
T5	2011:09:19	2011:06:13	2011:06:29	2011:11:24	2011:09:12

sovereign debt crisis in the euro area. During this crisis, the exchange rates of the euro against the currencies considered in this study, especially the British pound and Swiss franc, were extremely volatile. The breakpoint of 2011 for the EUR/CHF coincides with the successful intervention of the Swiss National Bank in support of a minimum exchange rate of 1.20 Swiss franc per euro; the break led to a decline in realized volatility. It seems that structural change is an empirical property of exchange rate realized volatility. In fact, we find that most breakpoints mainly arise from significant events in the financial market. Based on previous results, long memory and structural breaks are two important features of the data related to exchange rate realized volatility.

5.3 Long memory versus structural break test

The presence of spurious long memory leads us to analyse long memory with great caution. The test proposed by Perron and Qu (2010) enables us to distinguish long memory from short memory contaminated by structural breaks. We test the null hypothesis of the presence of long memory against the alternative hypothesis of the presence of short memory with structural breaks. The results, shown in Table 5, indicate that the null hypothesis is not rejected for all series reported. The results indicate that no structural break has affected the long memory of the exchange rate realized volatility involved in the study. Therefore, we retain the null hypothesis of the presence of long memory. We argue that, despite the persistence of the shocks, the presence of very large spikes and the instability of the long memory parameter, realized volatility remains determined by long memory process, and seems to follow a long-range trend. Thus, in this case, the significant events in the financial markets, such as crisis, might affect, only in a short-run way, the long memory property of foreign exchange market volatility. In other words, exchange rate realized volatility follows a long memory process in stable periods. However, during period of crisis, this process becomes unstable.

Pesaran and Timmerman (2004) and Beltratti and Morana (2006) suggested that the volatility series can be affected by occasional structural breaks that might be caused by various factors, like financial crisis, speculative bubbles, and changes in monetary policy. However, we note that the presence of long memory involves volatility persistence. This persistence reveals that uncertainty is a key determinant in the

Table 5: Perron and Qu test results

LRV_t	EUR/USD	EUR/YEN	EUR/CHF	EUR/GBP	EUR/AUD
PQ statistics	-1.7844	0.802	-0.793	-0.7534	-0.337
Critical-value 95%			± 1.96		

behaviour of exchange rate returns. Thus, this property is of significant importance to investors and for forecasting.
Based on results above in this section (long memory versus structural break test), we use the ARFIMA specification for modelling the exchange rate realized volatility.

5.4 ARFIMA results

Based on the work of Andersen *et al.* (2003), the long memory parameters d are obtained by implementing Robinson's estimator for each series. Thus, we consider the ARFIMA$(5, d, 0)$ model. The optimal lag lengths for both the AR and MA are selected using the Akaike information criteria (AIC). We consider a number of alternative models, and based on the AIC, the order $(5, d, 0)$ is the most reliable. Our specification is consistent with the specification of the ARFIMA model in Andersen *et al.* (2003) and Chortareas *et al.* (2011).
The results of the estimated parameters of ARFIMA$(5, d, 0)$ model are presented in Table 6, indicating a high degree of dependence for different series. In addition, the Q test results for the standardized residuals show that the ARFIMA model captures the realized volatility dependency well.

Table 6: Results of $ARFIMA(5, d, 0)$

LRV_t	EUR/USD	EUR/YEN	EUR/CHF	EUR/GBP	EUR/AUD
d	0.494	0.47	0.46	0.48	0.49
AR(1)	-0.280** (-14.6)	-0.057** (-2.95)	0.054** (2.84)	-0.216** (-11.3)	-0.137** (-7.20)
AR(2)	-0.115** (-5.81)	-0.031 (-1.554)	0.077** (4.02)	-0.087** (-4.46)	-0.031 (-1.61)
AR(3)	-0.058** (-2.95)	0.006 (0.296)	0.041** (2.18)	-0.079** (-4.06)	-0.014 (-0.771)
AR(4)	0.009 (0.466)	0.056** (2.778)	0.040** (2.11)	-0.010 (-0.523)	-0.011 (-0.601)
AR(5)	0.075** (3.93)	0.050** (2.487)	0.074** (3.88)	0.032** (1.68)	0.057** (3.02)
Residual test					
Q(30)	138.233**	113.017**	188.884**	143.171**	106.760**

Note: The t-statistics are given in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

6 Conclusions

This study aimed to model the realized volatility of daily foreign exchange rates using high frequency data. We explored the possibility of confusing long memory and structural breaks in daily realized volatility. The results of long memory tests showed evidence of the presence of long memory in the realized volatility of the different exchange rates used in this study. We applied the Bai–Perron (1998, 2003) test in order to detect the structural breaks. We identified structural breakpoints that match significant historical events in financial markets. Furthermore, Perron and Qu (2010) who distinguished between long memory and spurious long memory provided strong evidence in favour of long memory.

In fact, long memory plays an important role in describing realized volatility exchange rates. Moreover, we found that significant events in financial markets might affect the long memory property of the realized volatility in the foreign exchange market only in a short-run way. These findings reveal that uncertainty is a key determinant of the behaviour of exchange rate returns and are important for investors and forecasters.

A long-range dependent process might contain information, which makes forecasting more significant. We show that the ARFIMA model is more appropriate for modelling exchange rate realized volatility.

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