DOCUMENTO DE TRABAJO N° 393

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DEPARTAMENTO DE ECONOMÍA

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Diciembre, 2014

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DE **ECONOMÍA**

DOCUMENTO DE TRABAJO 393
http://files.pucp.edu.pe/departamento/economia/DDD393pdf

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Lima, Departamento de Economía, 2014
(Documento de Trabajo 393)

PALABRAS CLAVE: Cambio Estructural, Jumps, Procesos de Larga Memoria, Integración Fraccional, Estimados en las Frecuencias, Cambios de Nivel Aleatorios, Volatilidades del Mercado Bursátil y Cambiario en Perú.

Hecho el Depósito Legal en la Biblioteca Nacional del Perú Nº 2015-02553.
ISSN 2079-8466 (Impresa)
ISSN 2079-8474 (En línea)

Impreso en Kolores Industria Gráfica E.I.R.L.
Jr. La Chasca 119, Int. 264, Lima 36, Perú.
Tiraje: 100 ejemplares

Volatility of Stock Market and Exchange Rate Returns in Peru: Long Memory or Short Memory with Level Shifts?

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Abstract

Though the econometrics literature on this area is extensive, in Peru few studies have been dedicated to the analysis of financial returns in general and volatility in particular. As part of an empirical research agenda suggested by Humala and Rodríguez (2013), this paper represents one of the first attempts to distinguish between long- and short-memory (with level shifts) in volatility of Peru's stock market and exchange rate returns. We utilize the statistical approach put forward by Perron and Qu (2010). The data is end-of-day and span the period January 3, 1990 to June 13, 2013 (5,831 observations) for the stock market returns, and January, 3 1997 until June 24, 2013 (4,110 observations) for exchange rate returns. The analysis of the ACF, the periodogram and the fractional parameter estimation for the two volatilities suggest that the theoretical predictions of Perron and Qu's simple mixture model (2010) are correct. The results are more conclusive for stock market volatility in comparison with those of the exchange rate. The application of one of the statistics employed by Perron and Qu (2010) suggest the rejection of a long-memory hypothesis for both volatilities. Nonetheless, the other statistics provide weak evidence against the null hypothesis, above all for the exchange rate market. To reinforce the findings, some results associated with other investigations are presented.

JEL Classification: C22. **Keywords:** Structural Change, Jumps, Long Memory Processes, Fractional Integration, Frequency Domain Estimates, Random Level Shifts, Stock Market and Forex Rate Volatilities in Peru.

Resumen

Aunque la literatura econométrica en esta área es extensa, en Perú pocos estudios se han dedicado al análisis de los retornos financieros en general y la volatilidad en particular. Como parte de un programa de investigación empírica sugerido en Humala y Rodríguez (2013), este trabajo representa uno de los primeros intentos para distinguir entre larga y corta de memoria (con cambios de nivel) en la volatilidad de los mercados bursátil y cambiario de Perú. Utilizamos el enfoque estadístico presentado por Perron y Qu (2010). Los datos son diarios y cubren el período del 3 de Enero 1990 al 13 de Junio 2013 (5831 observaciones) para los rendimientos bursátiles, y del 3 de Enero de 1997 al 24 de Junio de 2013 (4110 observaciones) para los retornos cambiarios. El análisis de la ACF, el periodograma y la estimación del parámetro fraccional para las dos volatilidades sugieren que las predicciones teóricas del modelo de mezcla simple de Perron y Qu (2010) son correctas. Los resultados son más concluyentes para la volatilidad del mercado de valores en comparación con los del tipo de cambio. La aplicación de una de los estadísticos sugeridos por Perron y Qu (2010) sugieren el rechazo de la hipótesis de largo memoria para ambas volatilidades. No obstante, los otros dos estadísticos proporcionan débil evidencia contra la hipótesis nula, sobre todo para el mercado cambiario. Para reforzar los hallazgos, se presentan algunos resultados relacionados con otras investigaciones.

Classificación JEL: C22. **Palabras Claves:** Cambio Estructural, Jumps, Procesos de Larga Memoria, Integración Fraccional, Estimados en las Frecuencias, Cambios de Nivel Aleatorios, Volatilidades del Mercado Bursátil y Cambiario en Perú.

Volatility of Stock Market and Exchange Rate Returns in Peru: Long Memory or Short Memory with Level Shifts?[1]

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1 Introduction

One of the often mentioned characteristics in the literature on financial econometrics is the high persistence in the volatility of financial returns. Persistence is usually analyzed by using both the autocorrelation function (ACF) and the spectral density function. The peculiarity of the ACF in the context of the fractional integration model is that it decays much more slowly than in the case of an ARMA model (in which the fall is exponential); that is, the shocks are highly persistent. This characteristic is known as the long-memory effect or long-range dependency. This property implies that the autocovariances have a functional form given by $\gamma_k = c_k k^{2d-1}$, where c_k is a slowly varying function. This form of autocovariances enables the hyperbolic decay of the ACF, providing evidence of the long-memory characteristic. Moreover, in the frequency domain, this model suggests that the spectral density at the zero frequency is unrestricted; that is, tending towards infinity. In formal terms: $f_\omega(\omega) = c_\omega \omega^{-2d}$, where c_ω is a constant and where $f_\omega(\omega) \Rightarrow \infty$ when $\omega \Rightarrow 0$.

The first approximation to volatility modeling of financial returns are the ARFIMA(p,d,q) models. These models were put forward by Granger and Joyeux (1980) and Hosking (1981). Some consequences or inferences of these models are that if $-0.5 < d < 0.5$ then the process is stationary. Note that this rank guarantees, according to Hosking (1981), the stationarity and the invertibility of the series. On the other hand, if $d > 0$ the process will have a long memory, as it implies that the summation of the autocorrelations is infinite[3]. On the other hand, if $d < 0$, the process will have short memory.

For the estimation of the fractional parameter (d), the basic reference is Geweke and Porter-Hudak (1983). The estimation is based on a regression using the log-periodogram for a set of frequencies: $\ln\{I(\omega_{j,T})\} = \ln\{\sigma^2 f_u(0)/2\pi\} - d\ln\{4\sin^2(\omega_{j,T}/2)\} + \ln\{f_u(\omega_{j,T})/f_u(0)\} + \ln\{I(\omega_{j,T}/f_u(\omega_{j,T})\}$, where $I(\omega_{j,T})$ is the periodogram; that is, the spectral density estimator, $\omega_{j,T} = 2\pi j/T$ are the so-called Fourier frequencies, $j = 1, 2, \ldots, m$; where m denotes the number of frequencies to be used in the estimation. The parameter d is estimated by OLS and Geweke and Porter-Hudak (1983) show that the estimator is consistent for the case $d < 0$. Robinson (1995) tests consistency in a more general fashion and derives the Normal asymptotic distribution of the estimator. For a complete review, see Beran (1994) and Baillie (1996).

Ding et al. (1993) find that market returns are well characterized by long-memory models, especially powers of the form $|r_t|^d$, where r_t are the returns. Moreover, Lobato and Savin (1998)

[1] This paper is drawn from the Thesis of Andrés Herrera Aramburú at the Department of Economics, Pontificia Universidad Católica del Perú. We thank useful comments of Paul Castillo (Central Bank of Peru), Pierre Perron and Z. Qu (Boston University).

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[3] A practical definition of long memory is to state that the sum of the autocorrelations is infinite; that is, $\lim_{T\Rightarrow\infty} \sum_{j=-T}^{T} |\rho_j| = \infty$.

propose a semiparametric statistic whose null hypothesis is short memory and applies it to the S&P500 index returns and their different powers. The results they obtain are a non-rejection at the level of returns and rejection for the case of the squared returns; the statistic rejects the absolute value returns more strongly, which is a similar result to that found by Ding, et al. (1993). Nonetheless, Lobato and Savin (1998) attribute the results, in the case of the squared returns, to the non-stationarity of the series, mean shifts, for example; and in the case of the absolute value returns, the cause of long memory could be the effect of the aggregation.

Other studies have suggested that the evidence of long-memory is due to the presence of structural changes[4]. For example, Diebold and Inoue (2001) analyze the simple mixture model (formed by the sum of a mean and one disturbance), the permanent stochastic break model of Engle and Lee (1999), and Hamilton's well-known Markov Switching model (1989). Using Monte Carlo experiments, Diebold and Inoue (2001) show that under certain conditions, regime switching processes can cause the series to present characteristics of long-memory processes. These conditions, in the three cases, require the probabilities of structural changes occurring to be small.

For their part, Granger and Hyung (2004) state that it is difficult to distinguish between a fractional model and a breaks model, such as those responsible for the slow ACF decay. Therefore, it is possible that the confusion arises when the structural breaks are not taken into consideration. Another related difficulty is that the statistics for finding the number of structural breaks are contaminated when the underlying process is fractionally integrated I(d). The results show that both models adjust similarly to the series and that one possible combination of both can improve the volatility predictions.

Mikosch and Stărică (2004a) analyze, in addition to the relationship between structural changes and long-memory, its implications on the known GARCH effects of financial returns. They conclude that both characteristics may be caused by structural breaks in the unconditional mean and the unconditional variance. In addition, Mikosch and Stărică (2004b) put forward a statistic to identify whether a series can be modelled as a GARCH process. The statistic is based on the spectral density, and it is shown that the rejection of the hypothesis of a GARCH model is associated with shifts in the unconditional variance. Given that the structural breaks found are associated with periods of recession, the authors analyze the form of the ACF and find that the process is short-memory until before 1973; that is, when they omit the period of high volatility associated with the petroleum crisis. However, it will suffice to include the subsequent four years so that the ACF changes dramatically and shows signs of a long-memory process. Thus, a GARCH model is not appropriate for modeling returns due to the presence of structural changes. On the other hand, Stărică and Granger (2005) argue that the returns are well represented by an independent random variables model with conditional variance that changes over time.

Recently, Perron and Qu (2010), proposed a simple mixture model, comprised of a short-memory stationary process added to a random level shifts variable. The authors analyze the statistical properties of the ACF and the periodogram, as well as the asymptotic properties of the fractional parameter estimation[5]. The conclusion is that the volatility of returns displays the characteristics of the proposed model more than the long-memory models. The conclusion is reinforced with the application of a statistic that allows a distinction to be made between a fractional integration model and a mixture model.

[4]This is a similar hypothesis to that of Perron (1989) who documented how random walk processes may be confused with stationary series with structural breaks in the deterministic components.

[5]See also Perron and Qu (2007).

Though the econometrics literature on this area is extensive, in Peru few studies have been dedicated to the analysis of financial returns in general and volatility in particular. For a complete statistical evaluation of the stylized facts of financial and exchange rate returns in Peru, see Humala and Rodríguez (2013). As part of an empirical research agenda, this paper represents one of the first attempts to distinguish between long- and short-memory (with level shifts) in the volatility of Peru's stock market and exchange rate returns. We therefore utilize the statistical approach put forward by Perron and Qu (2010). The data is end-of-day and span the period January 3, 1990 to June 13, 2013 (5,831 observations) for the stock market returns, and January, 3 1997 until June 24, 2013 (4,110 observations) for exchange rate returns. The analysis of the ACF, the periodogram and the fractional parameter estimation for the two volatilities suggest that the theoretical predictions of Perron and Qu's simple mixture model (2010) are correct. The results are more conclusive for stock market volatility in comparison with those of the exchange rate. The application of one of the statistics employed by Perron and Qu (2010) suggest the rejection of a long-memory hypothesis for both volatilities. Nonetheless, the other statistics provide weak evidence against the null hypothesis, above all for the exchange rate market. To reinforce the findings, some results associated with other investigations are presented.

The paper is structured as follows. Section 2 presents the methodology put forward by Perron and Qu (2010). Section 3 presents and discusses the empirical results for Peru's stock market and exchange rate returns. Section 4 presents the conclusions.

2 Methodology

Henceforth, we use the Perron and Qu notation (2010). The data-generating process is a combination of a short-memory process and a random level shift component that follows a Bernoulli distribution. With $\{y_t\}_{t=1}^{T}$ being the series under analysis, the specification of the random level shifts model (RLS) is as follows:

$$\begin{aligned} y_t &= c + v_t + u_{T,t} \qquad (1) \\ u_{T,t} &= \sum_{j=1}^{t} \delta_{T,j} \\ \delta_{T,j} &= \pi_{T,t}\eta_t, \end{aligned}$$

where c is a constant; v_t is a short-memory process that satisfies $v_t = C(L)e_t$ with $e_t \sim i.i.d.\ (0, \sigma_e^2)$ and $E|e_t|^r < \infty$ for $r > 2$. The polynomial $C(L)$ satisfies $C(L) = \sum_{i=0}^{\infty} c_i L^i$, $\sum_{i=0}^{\infty} i|c_i| < \infty$ and $C(1) \neq 0$. For the level shift component $u_{T,t}$, we have $\eta_t \sim i.i.d.\ (0, \sigma_\eta^2)$ and $\pi_{T,t}$ is a variable with Bernoulli distribution that takes the value of 1 with a probability p/T; that is, $\pi_{T,t} \sim i.i.d.\ (p/T, 1)$. It is also assumed that $\pi_{T,t}$, η_t and v_t are mutually independent. In the model, p is independent of the sample size T, which is a necessary construction for guaranteeing that the structural breaks are infrequent.

Using the previous model, Perron and Qu (2010) analyze the ACF, the periodogram and the estimation of the parameter d. It is said that the process is long memory if the spectral density function is such that $f_y(\omega) = g(\omega)\omega^{-2d}$, when $\omega \Rightarrow 0$, where $g(\omega)$ is a function of slow variation in accordance with $\omega \Rightarrow 0$. Equivalently, the ACF of the long-memory process is defined by $\rho_y(h) = c(h)h^{2d-1}$, when $h \Rightarrow \infty$, where $c(h)$ is a function of slow variation in accordance with

$h \Rightarrow \infty$. In the case of the spectral density function, it is sufficient that $d > 0$ so that the function tends towards infinity. In the case of the ACF for $0 < d < 1/2$, the function displays a hyperbolic decay. Both characteristics are evidence of long memory and depend on the value of the parameter d.

Perron and Qu (2010) put forward two approximations to analyze the autocovariance function in terms of h and T. The first is an asymptotic approximation for h-fixed; that is, $h/T \Rightarrow 0$ when $T \Rightarrow \infty$. Given that this approximation is not appropriate for for long values of h, the second asymptotic approximation for h-long is based on $h/T \Rightarrow \kappa$ when $T \Rightarrow \infty$. In the first case, the distribution limit of the autocovariance function has two components: the autocovariance of the short-memory process and the accumulated level-shift process, which does not depend on the lag. Therefore, for lags that are not very distant, the first component will dominate, while, as h increases, the second component will have more influence. This is because the autocovariance of the short memory process decays exponentially and becomes less relevant after some lags. On the other hand, under the second approximation, that is, if $h/T \Rightarrow \kappa$, when $T \rightarrow \infty$, the short-memory is no longer present, and the autocovariance function decays as κ increases (very distant lags), albeit at a very slow rate. Therefore, for very long lags, the autocovariance function will be completely dominated by the level shift component. Perron and Qu (2010) derive the ACF and its asymptotic convergence. In particular, it seems clear that the ACF of a short memory process with random level shift is best represented by the first approach (in which the ACF of the short memory process predominates) for small lags and, conversely, is better described by the approximation in which the random level shift predominates for very long lags[6]. To show this, we replicate the simulation performed by Perron and Qu (2010), presented in Figure 1. This Figure shows that the simulated ACF (the mean of the autocorrelations) and the approximations according to both approaches. The short memory process is an AR(1) with coefficients $\rho = 0.5$ in one case and $\rho = 0.9$ in the other, with disturbances $e_t \sim i.i.d.\ N(0, 1)$. The level-shift component is like that described by (1) with $p = 5$ and $\eta_t \sim i.i.d.\ N(0, 1)$. The size of the sample is $T = 500$, the number of replications is 10,000, and Figure 1 shows the ACF up to lag 150. The ACF decays slowly as a long-memory process. Then it is observed that for short lags h, the asymptotic approximation h-set is appropriate while the other approximation is not appropriate. But for long lags h, the opposite occurs. The other observation is that the values of h, for which the two approximations are appropriate, depend on the value of the autoregressive parameter (ρ). When $\rho = 0.5$, the approximation h-fixed is appropriate up to $h = 4$ and the other approximation appears to be appropriate for $h > 5$. When $\rho = 0.9$, the approximation h-fixed is appropriate for h up to 20 and the other approximation is appropriate for $h > 40$. In summary, both approximations are complementary.

Given the purpose of comparing the model (1) with the long memory model, it is important to center on the analysis of very distant lags, for which the second approach will be of more use to us, so the ACF considered will be in function of κ. The most important characteristic of the ACF, put in this way, is that its form will fundamentally depend of the size of the sample, as for different values of T there will be different values of κ, given the lag h. In particular, when $\kappa \approx 0.3$, the autocorrelation function goes from being positive to negative (at approximately 30% of the sample). When $\kappa \approx 0.6$, it attains a minimum value (at approximately 60% of the sample) and then begins to increase and approach zero. Conversely, in the context of long memory, the ACF will cross the zero line earlier than is the case of short memory, depending on the value of the

[6]See Propositions 1 and 2 of Perron and Qu (2010).

fractional parameter, d and not on the size of the sample T (see Figure 1).

In the case of the periodogram, this can be approximated by $I_{y,T}(\omega_j) = I_{v,T}(\omega_j) + I_{u,T}(\omega_j) + 2I_{vu,T}(\omega_j)$. For a given frequency, the variability of the series can stem from three sources: the short memory process, the level shift process, or the interaction between both. Given the assumption of independence between both processes, the third term has an expected value equal to zero. The properties of the periodogram derived in Perron and Qu (2010) provide the theoretical foundations to what had been documented via simulations up to that point: that these models can be confused with long memory due to the bias in the estimation of the fractional parameter. In consideration of this, Perron and Qu (2010) analyze what occurs with each component of the periodogram for given frequencies. In particular, they show that for low frequencies (such as $j = o(T^{1/2})$ as T grows), the term that corresponds to the level shift is that which dominates the periodogram. Moreover, for high frequencies (that satisfy $T/j^2 = o(1)$) the first component predominates, but this takes values that are increasingly small. To illustrate these characteristics, we replicate the simulation presented in Perron and Qu (2010). Figure 2 shows the three components of the periodogram of an AR process (1) with $\rho = 0.7$ and errors *i.i.d.* $N(0,1)$ plus the level shift component with $T = 500$, $p = 5$ and $\eta_t \sim$ *i.i.d.* $N(0,1)$. In Figure 2 it can be seen that in the frequencies close to zero, the level shift component predominates, while as the frequencies increase, the AR(1) process predominates; in addition, it is shown that the interaction between both components has no relevant effect on the form of the periodogram.

In the short memory model with level shifts, the periodogram decays more rapidly than in the long memory model, which indicates that the level shift component is more important only after a few frequencies close to zero. This characteristic is relevant since the estimation method for the fractional parameter will be sensitive to the number of frequencies utilized in the log-periodogram regression: the greater the number of frequencies employed, the less the estimation will be affected by the level shift component and the greater the influence the short-memory process will have.

The regression using the log-periodogram is performed with OLS and utilizes a given number of frequencies. Let the sample periodogram, $I_{y,T}(\omega_j)$, for each j-th Fourier frequency $\omega_j = 2\pi j/T$ ($j = 1, \ldots, [T/2]$). The estimator $\widehat{d}$ is obtained from the following regression: $\log[I_{y,T}(\omega_j)] = c - 2d\log[2\sin(\omega_j/2)] + \epsilon_j$, utilizing the first m frequencies ($j = 1, \ldots, m$). The estimated parameter has the following form: $\widehat{d} = (1/2S_T)\sum_{j=1}^{m} a_j \log[I_{y,T}(\omega_j)]$, where $a_j = -\log[2\sin(\omega_j/2)] + (1/m)\sum_{j=1}^{m}\log[2\sin(\omega_j/2)]$ and $S_T = \sum_{j=1}^{m} a_j^2$. It is common in the literature to use $m = T^{1/2}$ as a rule. Nonetheless, in the case of a short memory model with level shift, estimating the fractional parameter through the use of this rule leads to the conclusion that the model is long memory, with an $\widehat{d}$ close to 0.5.

Perron and Qu (2007) have shown the characteristics of the distribution limit of $\widehat{d}$ when the process is short memory with level shift. They find that there is considerable discontinuity in the asymptotic distribution when different growth rates in the number of frequencies (m) are used in the log-periodogram regression. Thus, when m takes values close to $T^{1/3}$, $\widehat{d}$ will be around 1. When m increases from $T^{1/3}$ to $T^{1/2}$, $\widehat{d}$ decays noticeably, provided that the stationary component starts to have an influence on the asymptotic distribution of the estimator. Finally, when m increases at a higher rate than $T^{1/2}$, the estimated fractional parameter decays even more; this is primarily because the stationary short-memory component dominates the periodogram. On the other hand, when the data generating process is a long memory process, the estimator $\widehat{d}$ stays the same, despite utilizing different growth rates to m; therefore, the asymptotic distribution remains unchanged.

Perron and Qu (2010) propose a statistic to identify whether the series stems from a long memory process or a short memory process with level shift. The null hypothesis is that the series displays long memory. The idea underlying the statistic is that the estimated fractional parameter ($\widehat{d}$) undergoes significant changes to its asymptotic distribution when different frequencies are utilized (m), provided that the data generating process is the sum of a short memory process with random level shifts. If the process is long memory, the estimated fractional parameter will not change drastically despite the change in the number of frequencies used in the log-periodogram regression. Utilizing the Perron and Qu notation (2010), $\widehat{d}_{a,c}$ denotes the estimated fractional parameter when the number of frequencies considered in the log-periodogram regression is $m_{a,c} = c[T^a]$. Under the long memory null hypothesis, Perron and Qu (2010) derive the following: $\sqrt{c[T^a]}(\widehat{d}_{a,c} - d_0) \Rightarrow N(0, \pi^2/24)$. In this way, the statistic put forward by these authors is $t_d(a, c_1; b, c_2) = \sqrt{24c_1[T^a]/\pi^2}(\widehat{d}_{a,c_1} - \widehat{d}_{b,c_2})$, where the statistic has a Normal distribution (0,1) under the null hypothesis and when the parameters a and b satisfy $0 < a < b < 1$, and $a < 4/5$. For further details see Perron and Qu (2010).

On the other hand, under the alternative hypothesis (short memory and level shifts) the statistic diverges towards $+\infty$, given that on the limit $\widehat{d}_{a,c_1}$ and $\widehat{d}_{b,c_2}$ differ, with the latter smaller than the former. The statistic allows two fundamental facts to be verified. Firstly, from the frequency $T^{1/2}$ onwards, the estimation of the fractional parameter displays a steady decline. Therefore, the statistic to be utilized will be:

$$t_d(a, c_1; b, c_2) = t_d(\frac{1}{2}, 1; \frac{4}{5}, 1). \quad (2)$$

Secondly, we must evaluate whether the fractional parameter estimation undergoes a sharp drop for the frequencies between $T^{1/3}$ and $T^{1/2}$. It is here that two problems arise. Following (2), we can consider utilizing a statistic such as $t_d(\frac{1}{3}, 1; \frac{1}{2}, 1)$. Nonetheless, this is not the most appropriate, as the maximum value of $\widehat{d}$ is not exactly attained in $T^{1/3}$ (first problem). Therefore, Perron and Qu (2010) propose two variations in the statistic already presented. These variations refer to the maximum and average value of $t_d(\frac{1}{3}, c_1; b, c_2)$ with $b = 1/2$ and c_1 between 1 and 2:

$$\sup t_d = \sup_{c_1 \in [1,2]} t_d(\frac{1}{3}, c_1; b, 1), \quad (3)$$

$$mean\ t_d = mean_{c_1 \in [1,2]}\ t_d(\frac{1}{3}, c_1; b, 1). \quad (4)$$

The second problem is that the distribution limit of (3) and (4) is not available, and the sample distribution would be affected by the data generating process under the null hypothesis. Therefore, to calculate the appropriate critical values, a parametric bootstrap is utilized, where the parameterization will be given by the estimated coefficients of an ARFIMA (1,d,1) model.

3 Empirical Evidence

3.1 The Data

The data is end-of-day and covers the period from January 3, 1990 to June 13, 2013 (5,831 observations) for stock market returns, and from January 3, 1997 to June 24, 2013 (4,110 observations) for exchange rate returns. The returns are calculated as $r_t = [\log(P_t) - \log(P_{t-1})] \times 100$, where P_t represents the closing price that takes the variable in its original form in the period t. Taking the lead from Perron and Qu (2010) and the literature in general, we utilize the log-squared returns as a proxy for volatility. For practical effects, $y_t = \log(r_t^2 + 0.001)$ is used to account for returns equal to zero and where y_t is the variable specified in (1).

In Figure 3, daily stock market returns (panel a), and daily exchange rate returns (panel b) are shown. Both series show the stylized fact of similar periods of volatility, which is a sign of exchange rate volatility over time. Moreover, the stock market has movements in returns greater that those which occur in the exchange rate market[7]. Both characteristics are made more evident in Figure 4 where both panels display squared returns (stock market and exchange rate, respectively). Apparently, the volatilities have a similar form; nonetheless, on observing the scale, the difference in the turbulence of both markets is clearly seen. Equally, it is shown how the recent financial crisis affected both markets, with large fluctuations in the period running from 2008 to 2009.

3.2 Results

The Figure 5 shows the sample ACF of the volatilities. In panel (a), the results for the stock market are presented, while in panel (b) the ACF of the volatility of exchange rate returns is shown. A simple visual inspection allows us to note a certain resemblance between the behavior predicted by theory and the volatility of both returns. In the case of the volatility of stock market returns, it can be seen that the ACF crosses the line of zero in the lags close to 1100 (approximately $0.22T$)[8]; reaches a minimum value close to the half-way point of the sample (approximately $0.50T$); to then increase towards values close to zero. In the case of the volatility of exchange rate returns, we find values similar to these thresholds.

In Figure 6, the estimation of the smoothed ACF is shown using a non-parametric kernel[9]. This procedure is applied for different sample sizes, takes the same initial observation, and the estimates for four different sample sizes are presented. In all cases, the behavior sampled by the data coincides with the behavior suggested by theory. All functions cross the line of zero at the height of $0.30T$, reach a minimum of around $0.50T$ or $0.60T$ and return to the level of zero for more distant lags. This is important because this theoretical behavior is consistent with the empirical evidence shown in Figure 5. Moreover, these results are interesting in that they demonstrate that the evidence of long-memory can change drastically with the sample size. The bigger the sample size, the stronger the evidence. This may be one of the explanations for the empirical results found below.

We now move on to the analysis of the frequencies using both the periodogram and the fractional parameter estimation. Figure 7 shows the estimation of the periodogram from frequency 0 to frequency $\pi/50$, for the volatility of stock market returns (panel a) and exchange rate returns (panel b). It is observed that for frequencies close to zero, the influence of the level shift component is that which dominates the periodogram and shows relatively high values. As the frequencies increase, the stationary component takes more relevance and the periodogram reduces abruptly and significantly. For exchange rate volatility, the results are not as evident as in the case of the stock market. Nonetheless, certain coincidences can be seen with the theoretical approximation. The Figure 7 (panel b) shows the periodogram for exchange rate volatility. It can be seen here that the periodogram does not decrease so abruptly as the frequencies increase, and only takes small

[7] This may due to the exchange rate interventions of the Central Reserve Bank of Peru, which contribute to a reduction in the volatility of this market.

[8] The result is similar to that found in Perron and Qu (2010) for the S&P500.

[9] Following from Perron and Qu's experiment (2010), we use a Normal kernel with a fixed bandwidth in $T^{-1/3}$.

values for frequencies that are somewhat distant from zero.

The Figure 8, for its part, shows the estimation of the fractional parameter for different values of m in the regression by using the log-periodogram for the volatility of stock market returns (panel a) and exchange rate returns (panel b). As we pointed out earlier, Perron and Qu (2007) find values of m for which the distribution changes significantly: when m is close to $T^{1/3}$, when it is between $T^{1/3}$ and $T^{1/2}$ and when it is greater than $T^{1/2}$. In Figure 8 (panel a) it is shown that the estimation of $\widehat{d}$ undergoes dramatic changes in the stated intervals (identified by a vertical line). It is observed that in the first section, the estimated parameter is around 0.7 (for $m = T^{1/3} = 18$) which is a sign of long memory. In the following interval (up to $m = T^{1/2} = 76$), the estimate takes values close to 0.4, to then descend even more and position itself close to 0.2 in the final interval (up to $m = T^{2/3} = 324$). Meanwhile, Figure 8 (panel b) displays a behavior that differs somewhat from what is expected in terms of the estimation of the parameter d. In the first interval (up to $m = 16$), $\widehat{d}$ takes values close to 0.5, but when m is found between $T^{1/3}$ ($m = 16$) and $T^{1/2}$ ($m = 64$), the estimate increases towards values of between 0.7 and 0.8. Subsequently, for values greater than m, the estimation shows the pattern already known and starts to decrease, albeit with a certain degree of persistence; thus, when $m = T^{2/3} = 257$, the $\widehat{d}$ is, on average, 0.4. Even for values of m beyond $T^{2/3}$, the estimated parameter shows a decrease of close to 0.3.

According to the afore-mentioned Figures (5-8), both volatilities show characteristics that, according to theory, correspond to a short-memory process with level shift. In the case of the stock market, the evidence is stronger than in the case of the exchange rate market, given that the ACF, the periodogram and the estimation of $\widehat{d}$ conform most closely with the theory put forward by Perron and Qu (2010). On the other hand, in the case of the volatility of exchange rate returns, the ACF, the periodogram and the fractional parameter estimation are not conclusive.

We now utilize (2), (3) and (4) to formally test for the existence of long memory in the two volatilities. The results are shown in Table 1. Firstly, it can be seen that the values of the statistic $t_d(\frac{1}{2}, c_1; \frac{4}{5}, 1)$ reject the null hypothesis at 1% for both financial series. Therefore, under this first approximation, we see that the behavior of the volatility of our series shows signs of corresponding to a short-memory process with level shifts.

Table 1 also shows the results obtained for the statistics $\sup t_d$ and *mean* t_d. The results indicate that the only rejection is obtained for the volatility of stock market returns at 10% significance and using the statistic *mean* t_d. For the volatility of exchange rate market returns, the null hypothesis that this series follows a long memory process using both statistics cannot be rejected. Different sample sizes were utilized but the results are similar. It should be stressed that both the calculated values of the statistics and the critical values correspond to a flexibility of c_1 between 1 and 2, but they were also calculated with different values. The best results were obtained when the interval in which c_1 varies is restricted to 1 and 1.3. In this case, both statistics ($\sup t_d$ and *mean* t_d) reject the null hypothesis at 10% for the entire sample.

An interesting detail that helps to explain the results is the estimation of the ARFIMA(p,d,q) models for both volatilities (see Table 1). In the case of the volatility of stock market returns, the estimates are ARFIMA(0.208,0.348,0.426) and for the volatility of exchange rate returns, the estimates are ARFIMA(0.978,0.12,0.914). Compared with the results of Perron and Qu (2010), our estimates of the fractional parameter are quite different, especially the link with the volatility of exchange rate returns. In the case of Perron and Qu (2010), for all the estimated samples, the minimum value of the fractional parameter is 0.43 and the maximum value is 0.48. In general, all the estimates of the fractional parameter are very close to 0.50, which is the limit of stationarity.

In return, in our case the highest estimated value of the fractional parameter (0.343) is obtained for the volatility of the stock market returns. In the case of the volatility of exchange rate returns, it is smaller[10]. The exchange rate volatility is absorbed or explained by the autoregressive part and the moving averages, due to which the estimation of the fractional parameter is very small. All of this evidence suggests the presence of a long memory process, albeit with estimates of the fractional parameter such as 0.34 and 0.12 for the stock market and exchange rate volatilities, respectively. Thus, the dynamic of estimated ARFIMA(1,d,1) models for our two series is quite different to those estimated in Perron and Qu (2010).

The theoretical framework proposed by Perron and Qu (2010), is of an asymptotic nature, and the results can be affected by the limited size of the sample that we are using. This occurs through two mechanisms. Firstly, the random level shifts cause the bias in the estimation of the fractional parameter towards long memory; the greater the probability of breaks, the greater the bias of the estimation. Larger sample size also influences this bias, as it increases the probability of more breaks being found[11]. Taking this into account, we see that both the estimation of $\widehat{d}$ presented in Figure 8 (panels a and b), and the estimation of the ARFIMA(1,d,1) presented in Table 1, are notably smaller than the estimations reported by Perron and Qu (2010) –a sign of having less level shifts and/or a smaller sample– which directly affects the calculated value of the statistics, and these are considerably smaller than those calculated in the referenced study.

Secondly, the similar critical values increase as the sample size reduces, which renders a rejection of the null hypothesis even more difficult. This can be observed with greater clarity in Perron and Qu (2010), though in our Table 1, the trend can also be discerned.

Moreover, it is important to mention that the second aim of the statistic was to demonstrate that a sharp fall in the estimation between the frequencies $T^{1/3}$ and $T^{1/2}$ occurs (because of which the statistics $\sup t_d$ and $mean\ t_d$ were constructed). Despite the non-rejection, there is evidence that this fall occurs, as in addition to what the visual inspection in Figures 8 (panels a and b) tell us, an important fact is that the greater the flexibility that is given to c_1, the more considerably the statistic $mean\ t_d$ reduces its calculated values (especially for stock market volatility). That is, as the rank of c_1 increases, the average value of the statistic rapidly falls, and signs are shown of a sharp fall in the estimation of the fractional parameter in the interval of the frequencies $T^{1/3}$ and $T^{1/2}$.

The approach of this paper has been the use of use statistics, which tend to have deficiencies related to size and power. In this respect, Qu (2011) mentions that the statistics $\sup t_d$ and $mean\ t_d$ display low power versus the alternatives of short memory with level shifts. Results with other statistics, including Qu (2011), are documented in Pardo Figueroa and Rodríguez (2014) and the results are more conclusive in rejecting the long memory hypothesis.

Another way of arguing in favor of a short-memory model with level shifts is to leave aside the hypothesis tests and change them for the modeling and estimation of a RLS model. This is what Lu and Perron (2010), and Li and Perron (2010) propose. This line of research (modeling) is now being documented in various studies for volatilities of stock market and exchange rate volatilities for a sample of Latin American countries, including Peru; see Ojeda Cunya and Rodríguez (2014), Rodríguez and Tramontana Tocto (2014), Gonzáles Tanaka and Rodríguez (2014), and Rodríguez (2014). In this regard, this paper constitutes one of the first steps in an agenda that seeks to

[10] Moreover, in the case of this volatility, it could be stated that common factors exist both in the autoregressive part and the moving averages, given that the two coefficients are very similar.

[11] See the simulations set out in Diebold and Inoue (2001), Figure 3.

analyze stock market and exchange rate volatilities in Peru (and Latin America) from different perspectives.

Some results for our two markets can be obtained from Ojeda Cunya and Rodríguez (2014). On estimating the RLS model, the probability of level shifts is 0.000446 and 0.01824 for stock market and exchange rate volatilities, respectively. Given the number of observations, this involves around 26 and 75 level shifts for each market, respectively. Most level shifts in the exchange rate market are due to the continuous interventions of the Central Reserve Bank of Peru. Figure 9 shows the smoothed estimate of the level shift component, along with the estimate of these changes, using the method of Bai and Perron (1998, 2003)[12]. This estimation clearly shows the level shifts during the period and the greatest episodes of turbulence in both markets. What follows is to subtract the smoothed level shift component from the series of volatilities (or in its absence, to subtract the estimate obtained using the Bai and Perron method (1998, 2003)). In so doing, we can calculate the ACF of these series (residuals). This is shown in Figure 10. By comparing this ACF with that obtained in Figure 5, it is clear that the evidence of long memory has been completely eliminated. These results stand as conclusive evidence that long memory stems entirely from level shifts, in spite of the number of these being small. We can add that estimating ARFIMA(1,d,1) models for this residual series allows the obtention of $\widehat{d} < 0$, which shows that short memory exists (antipersistence).

4 Conclusions

An often mentioned and inclusive characteristic assumed in the literature on financial econometrics is the presence of long memory in the volatilities of financial returns. However, another route in the literature has suggested that this evidence may be caused by level shifts or infrequent structural breaks. The aim of this paper is to show signs of long memory or short memory with level shifts in the end-of-day series of volatilities of stock market and exchange rate returns for the Peruvian case, following the approach of Perron and Qu (2010). The analyses of the ACF, the periodograms and the fractional parameter estimates for both series of volatilities satisfy the characteristics suggested by a simple mixture model that includes a short memory component plus a level shift component governed by a Bernouilli distribution. The simulations and Figures allow it to be proven that the series analyzed behaves like a simple mixture model by canceling out the evidence of long memory. Nonetheless, due to the sensitivity of the estimation of the fractional parameter to the number of parameters used, it is necessary to resort to two additional statistics ($\sup t_d$ and $mean\ t_d$) whose critical values depend on the data analyzed. The long-memory null-hypothesis can only be rejected at 10% for stock market volatility.

A literal reading of our end-of-day results would suggest that the volatilities of exchange rate returns follow a long-memory process, while the evidence for the volatility of stock market returns is mixed. Nonetheless, the behavior of the ACF, the periodograms, and the fractional parameter estimates provide evidence in favor of a short memory model with level shifts.

The approach of this paper has been the use of statistics, which usually have deficiencies related to size and power. In this regard, Qu (2011) states that the statistics $\sup t_d$ y $mean\ t_d$ display low power compared with the short memory with level shift alternatives. Results with other statistics, including Qu (2011), are documented in Pardo Figueroa and Rodríguez (2014), and these are more conclusive in rejecting the long memory hypothesis.

[12] For further details, see Ojeda Cunya and Rodríguez (2014).

One way of arguing in favor of a short memory model with level shifts is to leave aside testing in favor of modeling and estimation of a RLS model. This is what Lu and Perron (2010), and Li and Perron (2010) propose. This line of research (modeling) is being documented in various studies for the volatilities of stock market and exchange rate returns of a sample of Latin American countries, including Peru; see Ojeda Cunya and Rodríguez (2014), Rodríguez and Tramontana Tocto (2014), Gonzáles Tanaka and Rodríguez (2014), and Rodríguez (2014). In this sense, this paper constitutes one of the first steps in an agenda for analyzing stock market and exchange rate volatilities in Latin America from different perspectives.

Some results for our two markets can be obtained from Ojeda Cunya and Rodríguez (2014). Using this approximation, we find that the probabilities of level shift is small. Nonetheless, one we eliminate the level shifts from the volatility series, all evidence of long memory is eliminated.

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Table 1. Empirical Results

Tests	Stock Market	Forex market
	1990:01-2013:06	1997:01-2013:06
	$T = 5831$	$T = 4110$
$t_d(\frac{1}{2}, 1; \frac{4}{5}, 1)$	5.517^a	7.221^a
sup t_d	1.798	0.489
mean t_d	1.204^c	-0.036
Simulated DGP ARFIMA (1,d,1)	(0.208,0.343,0.426)	(0.978,0.120,0.914)
Simulated Critical Values sup t_d	[2.082, 2.504, 3.273]	[0.722, 1.142, 1.958]
Simulated Critical Values *mean* t_d	[1.202, 1.516,, 2.151]	[-0.109,, 0.241, 0.961]

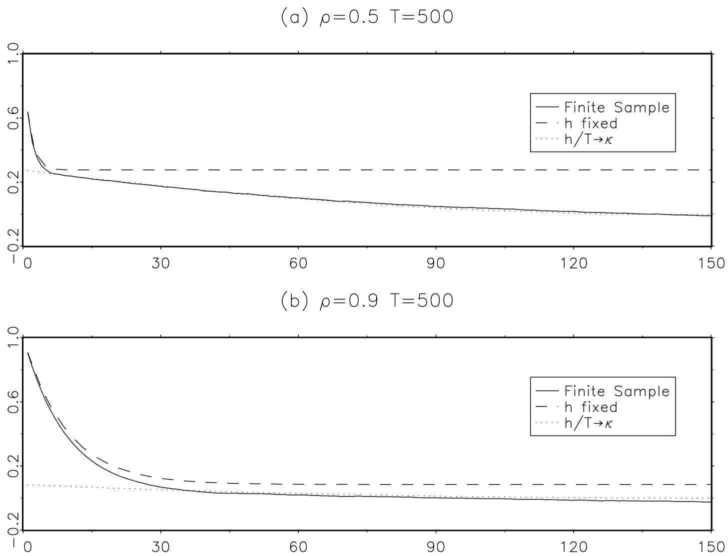


Figure 1. Median of the Autocorrelations: Finite Sample and Asymptotic Approximations

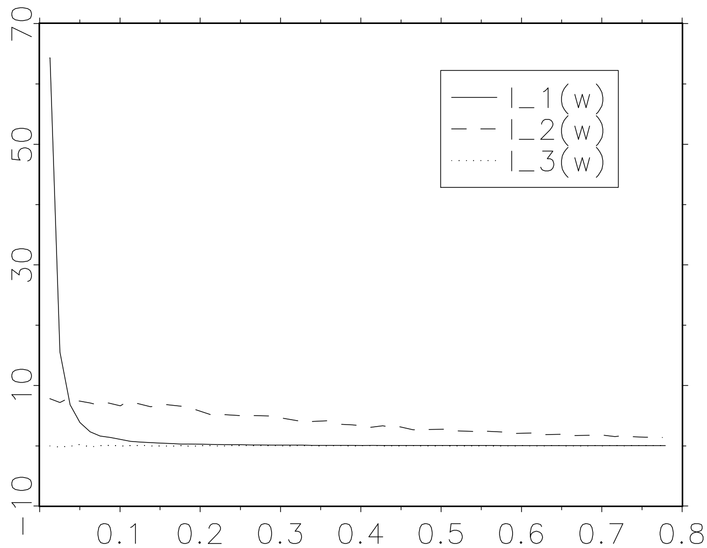


Figure 2. Median of the Periodogram at Frequencies 0 to $\pi/8$, $T = 500$, $\rho = 0.7$.

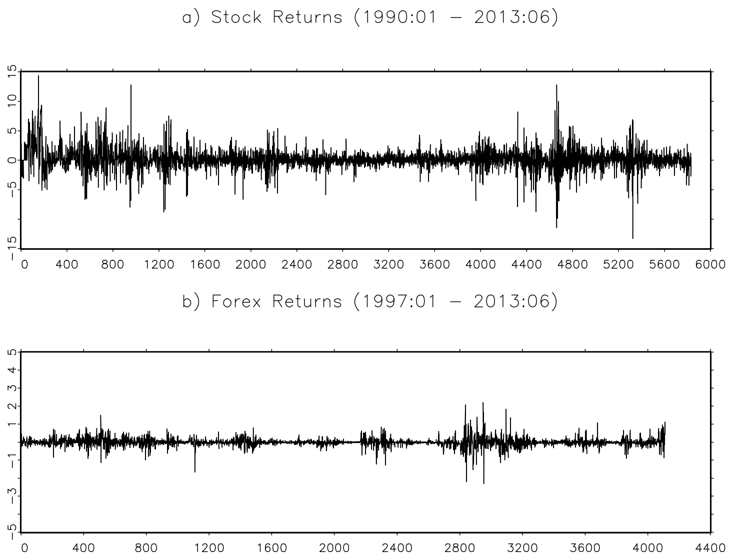


Figure 3. Daily Returns Series

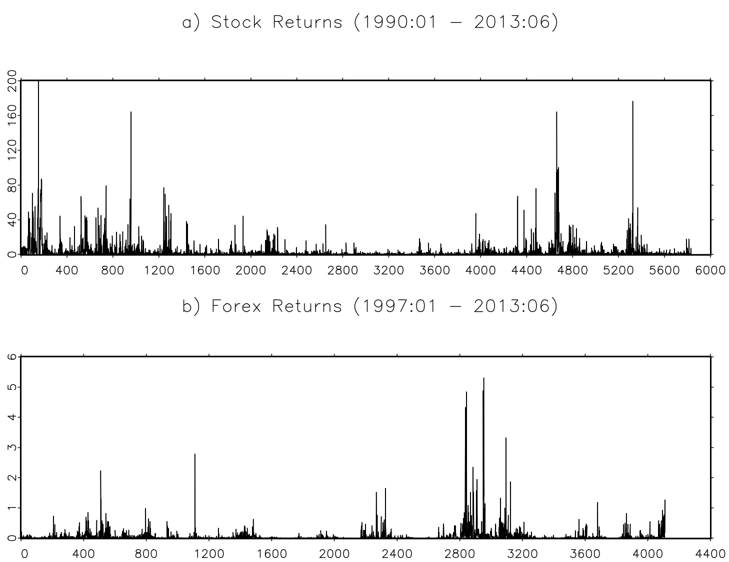


Figure 4. Daily Volatility of Returns Series

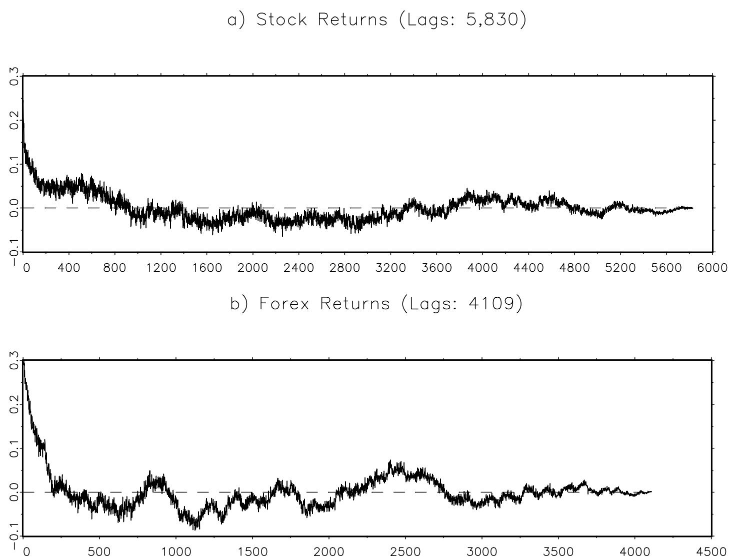


Figure 5. Sample Autocorrelation Functions (ACF) of Volatility Returns Series

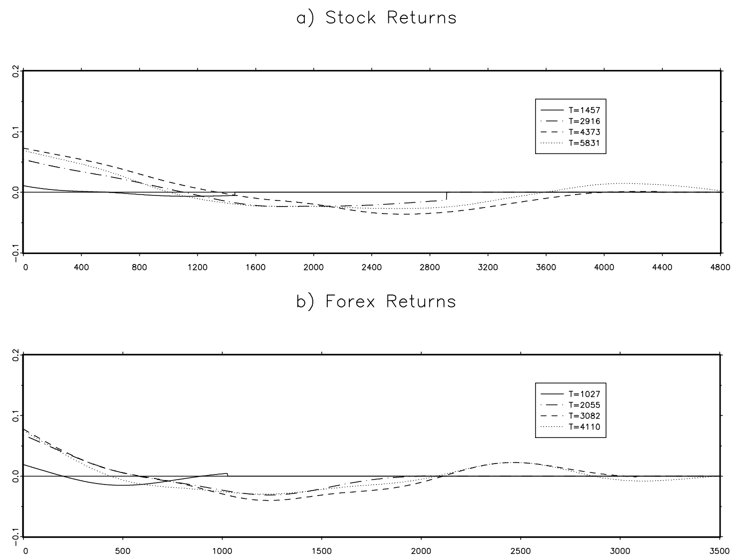


Figure 6. The Autocorrelation Functions (ACF) of Volatility Returns Series with different Sample Sizes

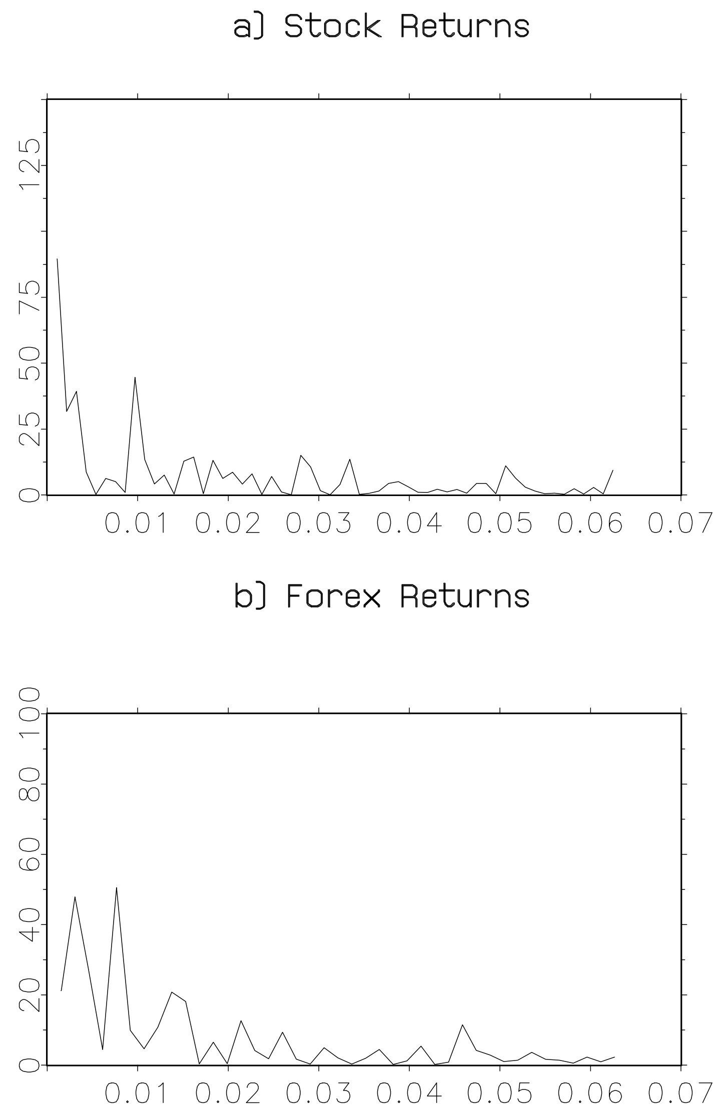


Figure 7. The Periodogram at Frequencies 0 to $\pi/50$ for Volatility Returns Series

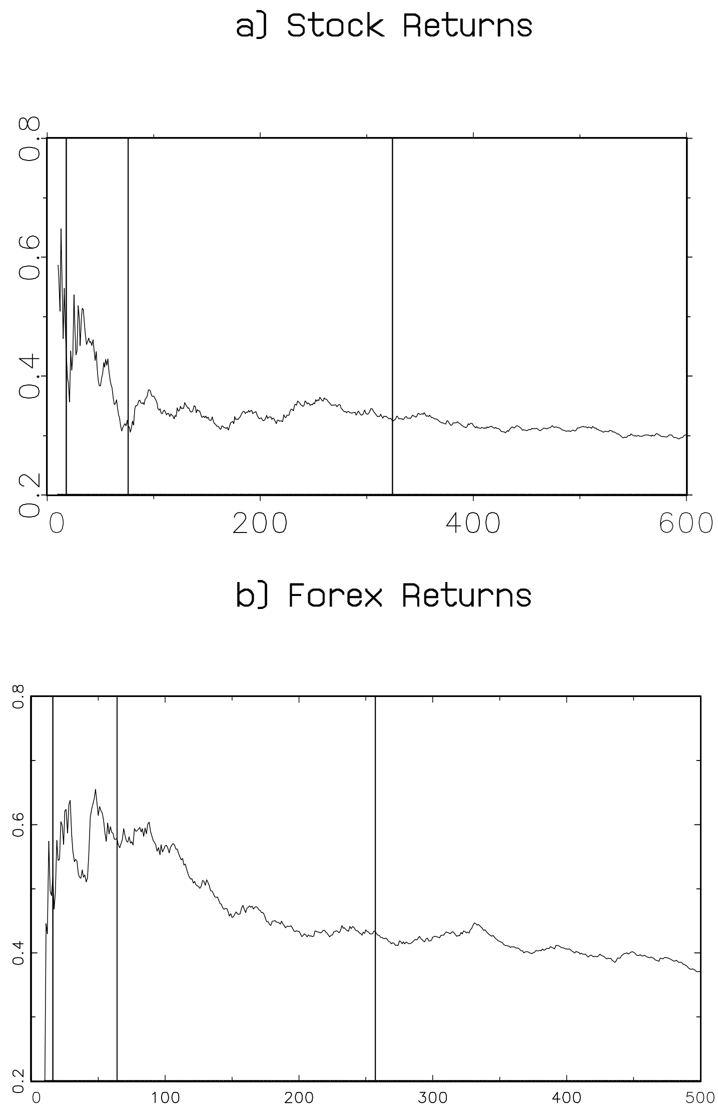
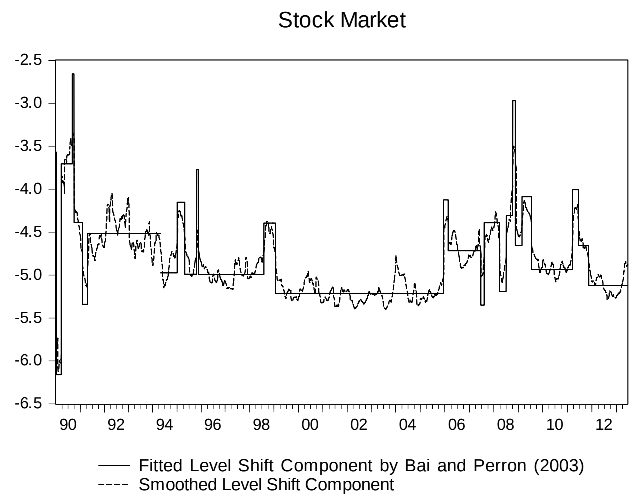


Figure 8. The Estimates of d with different m for Volatility of Returns Series



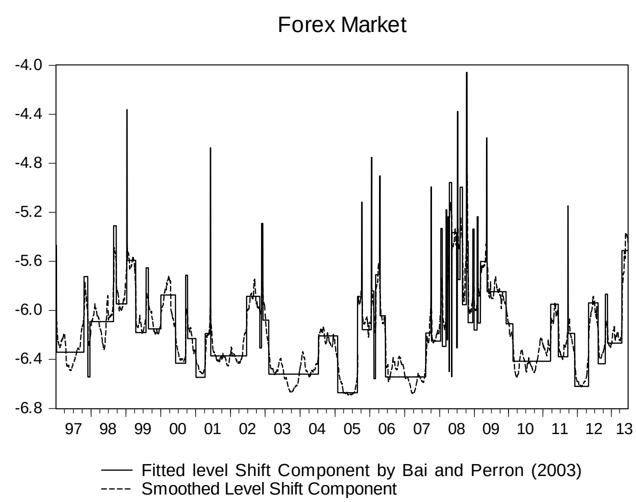


Figure 9. Level Shift Component estimated by Bai and Perron (2003) and Smoothed Level Shift Component

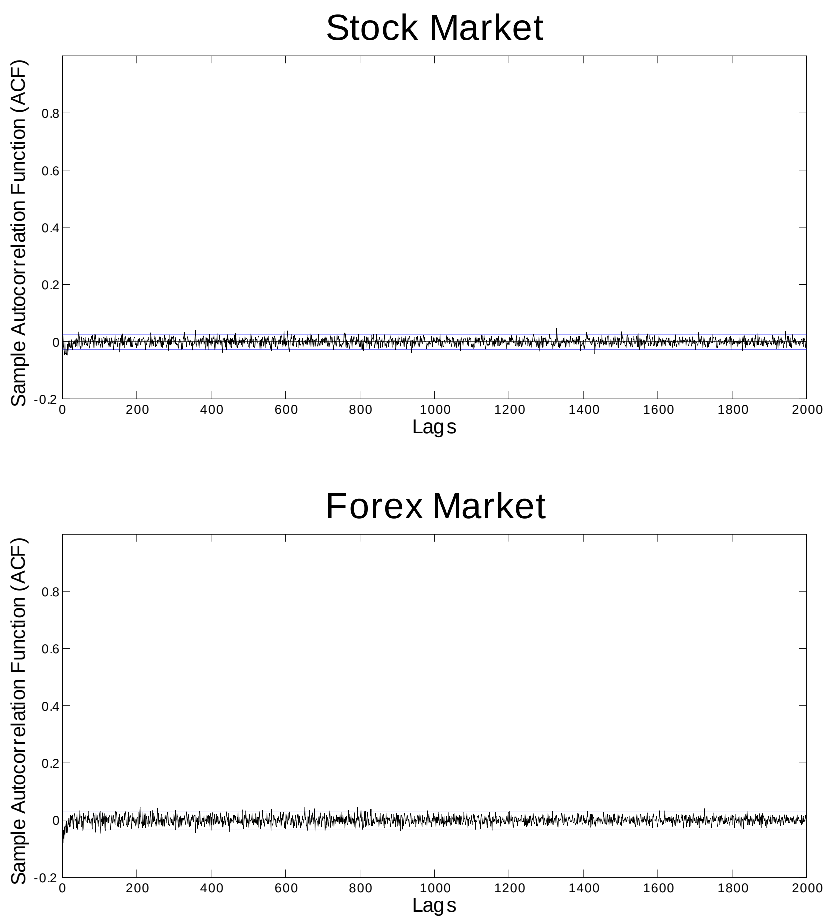


Figure 10. Sample ACF of Residuals of the RLS Model for Volatility Returns Series

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