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Abstract

In the crude oil market the phenomenon of Long Memory can be easily identified with the help of the simple (but effective) methodology of Katsumi Shimotsu. The Exact Local Whittle estimator and two testing strategies provide a strong assessment of the phenomenon. We present evidences and we suggest a profit opportunity. Furthermore, the existence of Long Memory discloses an inefficient oil market.

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1 Evidences of Long Memory reveal a profit opportunity.

The phenomenon of Long Memory implies that the prices of yesterday will impact the prices of tomorrow on a long term horizon. In other words, an autocorrelation function decaying slowly characterizes a Long Memory process.

The standard model of stock market variations implies that $\rho(h)$, the autocorrelation function of realized returns, must decrease geometrically ($\rho(h) \leqslant cr^{-h}$ with $c > 0$). Adelman (1965) and Granger (1966), however, observed a phenomenon with a hyperbolic decay called Long Dependance or Long Memory ($\rho(h) \sim ch^{2H-2}$ with $c > 0$ and $0 < H < 1$). The phenomenon lead Mandelbrot (1965), during his research on fractal, to rediscover Hurst(1951)'s law and to introduce the concept of self-similar process which later became Mandelbrot (1968) fractional Brownian motion. The Fractal approach moved to econometrics with the discrete time perspective. While the discrete time analog of Brownian motion is the random walk, the discrete time version of fractional Brownian motion is a fractionally differenced white noise.

They are many explanations for the phenomenon in financials markets, some of which are related to the various characteristics of the agents and, as a consequence, to the heterogeneity of the trading behaviors.

Econometrical models for Long Memory in mean were first introduced by Granger and Joyeux (1980) and Hosking (1981). The Autoregressive Fractionally Integrated Moving Average (ARFIMA) manifests a hyperbolic decay rate and constitutes an extension of the ARMA model (with a geometric rate). The ARFIMA framework was itself extended towards volatility models. Baillie et al. (1996) and Bollerslev and Mikkelsen (1996) introduced the Fractionally Integrated Generalized Autoregressive Conditionally Heteroskedastic (FIGARCH) models reflecting the findings that, even when the return series has no serial correlation, the autocorrelation function of the squared, log-squared, or the absolute value series of an asset return could decays slowly. Chung (2001) proposed a significant improvement of the ARFIMA-FIGARCH models to fix a problem of specification from Baillie et al. (1996)[2].

Regarding economic theory, the existence of Long Memory in financial returns goes against the efficient market hypothesis stating that the prices of assets contain all past information and so the expected profit for the speculator should be zero. Fama (1970) said that "a market in which prices always *fully reflect* available information is called *efficient*". In the *weak-form* of informationally efficient market, all past information is incorporated in the prices of assets. As a consequence, under the efficient market hypothesis, the oil market should be a *faire game* with rare opportunities of profit.

The academic literature has been highlighting Long Memory phenomenons in markets expected to be inefficient. Numerous papers have identified Long Memory in small financial markets of developing countries[3]. Intuitively, inefficient markets are expected to be small,

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[2]See Baillie (1996), Pérez and Ruiz (2001) and Walter (2009) for a review of concepts and literature.

[3]As an illustration, see Tan and Khan (2010) for the Malaysian market or Korkmaz et al. (2009) for the Turkish market.

new, or partially aggregated. With more than 86.6 million barrels per day sold in 2010[4], the crude oil market should be one of the most efficient with very few opportunity of gains. Surprisingly, although "there is more trade internationally in oil than in anything else"[5], a growing literature is showing evidences of Long Memory in the oil market, especially on volatility[6].

We demonstrate that, with the help of the simple (but effective) methodology of Shimotsu, the existence of Long Memory in the crude oil market can be easily identified.

2 A straightforward approach prevents spurious results

By spending enough time, fiddling observations and experimenting statistical tools, an econometrician can reveal spurious patterns and correlations from any dataset.

In order to reduce the problem of induction[7] embedded in the econometric approach and to prevent spurious findings from data mining, we apply a straightforward strategy:

initially, we collect the last 20 years volatility of two oil spot prices major index (Brent and WTI[8]). Secondly, we strictly replicate the methodology of Shimotsu (2008) to estimate the Long Memory parameter, d. Finally, we run the tests of Shimotsu (2006) to assess the quality of d.

To compute the volatility, we transpose the calculation of Shimotsu (2006) from a daily basis to a weekly basis. The weekly realized volatility is the sum of square of the daily returns in a week. The first return is computed using the closing price of the previous week. To avoid the disruptions created by the days without quotation, we divide the total by the number of open days in the week. Let p_τ define the price of crude oil index at time τ and the h-period return at time τ as $r_{\tau+h,h} = p_{\tau+h,h} - p_\tau$. Then, the realized weekly volatility of week t is calculated as $x^t = \frac{v^2}{\theta}$ with $v^2 = \sum_{j=1}^{1/\Delta} r_{t+j\Delta,\Delta}^2$ and θ the number of open days in the week. In our study, we analyze $X_t = \log\sqrt{x^t}$.

At every step, we do not change the values and we do not remove possible outliers. In addition, we do not adjust break points: an alternative methodology would be to identify break points using the algorithm of Sanso et al. (2004) and to adjust them using the filter of Nouira et al. (2004). Whereas the alternative methodology produces an adjusted d, our approach simply consist in the identification of a non spurious d. We use samples from 1rst January 1990 until the 31th December of 2010.

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[4]The U.S. Energy Information Administration (EIA).

[5]The U.S. Energy Information Administration (EIA).

[6]See Choi and Hammoudeh (2009) and Arouri et al. (2010).

[7]The problem of induction discloses the philosophical question of whether inductive reasoning leads to knowledge.

[8]The Brent (produced in the North Sea region) and the West Texas Intermediate (WTI - Cushing, produced in Texas and southern Oklahoma) serve as a reference or 'marker' for pricing a number of other crude streams. Source: http://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm

3 We confirm the existence of Long Memory in the crude oil market.

The volatility densities of the Brent and the WTI shows skewness and excess kurtosis, a common characteristic of financial returns[9].

The descriptive statistics and the stationary tests suggest the existence of Long Memory for the two time series: the Autocorrelation function, the Ljung-Box and Lagrange Multiplier test exhibit significant evidences of serial correlation; additionally the ADF test rejects the null hypothesis of the series being $I(1)$ and, at the same time, the KPSS tests also rejects the series being $I(0)$. Therefore modelling these series either as $I(0)$ or $I(1)$ processes appears too restrictive.

Shimotsu and Phillips (2005) proposed an consistent estimator of Long Memory, called the Exact Local Whittle estimator (ELW). Later, Shimotsu (2008) created a more generalized version under the assumption that the mean and trend of the observations are unknown: the Two Step ELW (TSELW) estimator[10]. Applying the TSELW, we find $d = 0.625$ for the Brent and $d = 0.672$ for the WTI[11].

We have to mention that the estimation of the long memory parameter is subject to a significant amount of research and controversy. Baillie and Kapetanios (2009) said that: "[Surprisingly...], one of the most heavily researched topics in this area [Long Memory], continues to be the issue of semi-parametric estimation of the long memory parameter [d]". Lopez and Mendes (2006), for instance, focused on a specific parameter in the estimation of d, the bandwidth selection. The tuning constant α defines the bandwidth m with $m = n^\alpha$ and n the sample size. In our calculation, we apply a common value of $\alpha = 0.6$ and therefore $m = 66$. The whole question of Long Memory estimation, however, does not constitutes the purpose of this article.

The presence of structural breaks in the observations can introduce spurious effects in the covariance function and, as a consequence, creates spurious evidence of fractional integration. To deal with the problem Shimotsu (2006) provided two testing strategies: In the first one, we split the sample into subsamples, then we estimate d for each subsample, and finally we compare them with the estimate of d from the full sample, using a modified Wald test. Basically, the first and the second testing strategy tend to overreject the null $d = \hat{d}$. In the second strategy, following a demeaning of the series and using an estimated d, we apply the well known KPSS and PP tests to check for stationarity of the differenced series[12]. Assuming

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[9]See Cont (2001).

[10]The ELW and the TSELW are semiparametric estimators. Shimostu modified the ELW objective function to estimate the mean by combining two estimators: the sample average, and the first observation depending on the value of d. In addition, Shimotsu dealt with the presence of a linear or quadratic time trend by first detrending the data. Above all, Shimotsu showed that the TSELW estimator has a $N(0; \frac{1}{4})$ asymptotic distribution for $d \in (-\frac{1}{2}; 2)$ (or $d \in (-\frac{1}{2}; \frac{7}{4})$ when the data has a polynomial trend).

[11]The ELW and the TSELW produced similar estimations. The complete results are available upon request. The TSELW estimator, as well as the testing strategies, are implemented using the Matlab® code provided by Katsumi Shimotsu. Other calculations are done using common features from Eviews® and Matlab®.

[12]In a review of litterature, Baillie (1996, chapter 4.3) mentioned that the Dickey-Fuller and the PP

the observations being $I(d)$, the dth difference must be $I(0)$. On the contrary, it would not be $I(0)$ with a spurious $I(d)$.

In the end, the two testing strategies validate the estimated d and we conclude in the existence of Long Memory in the crude all market[13].

3 The results bring two questions.

As a conclusion, the crude oil market appears inefficient. The results highlight profits opportunities and new questions:

Is the magnitude of the estimated effect big enough to matter?

The question is inspired by Mc Closkey and Ziliak (2008)[14]. A highly statistically significant relationship may have a very small effect and not be of substantive importance. To be more specific, are the Long Memory phenomenons big enough to provide a profit relative to the transaction cost required to exploit them? Our results indicate that modeling these series with the usual ARMA-GARCH models is inapropriate. The next step will be to evaluate how much the gain collected from ARFIMA-FIGARCH models exceeds the transaction cost.

Where does Long Memory come from?

Henry and Zaffaroni (2003) provided an exogenous explanation of a Long Memory inherited from underlying geophysical influences: oil consumption may be impacted by climatic factors containing Long Memory. They provided also an endogenous explanation: Long Memory appears because the observations are an aggregation of outputs created by heterogeneous agent with "time varying cost of adjustment". In the same way, Cont (2005) said that Long Memory appears because of the heterogeneity in the time horizon of the economic agents. Another possibility could be the agents changing their trading behavior: Cont (2005) also mention evolutionnary models with a *natural selection* of agents or investor inertia with a threshold behavior as possible cause of Long Memory. Above all, explanations for Long Memory are numerous and are left for future research.

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tests ($H0 = I(1)$) perform relatively poorly in distinguishing between the $I(1)$ null hypothesis and the $I(d)$ alternative meanwhile the KPSS and LM tests ($H0 = I(d)$) can be used to distinguish short memory from Long Memory stationary processes. Shimotsu (2006), however, showed the complementarity of KPSS and PP test and how by using the two tests it minimizes the risk of overaccept the null ($d = \hat{d}$).

[13] The statistical results are in Appendix 1 and Appendix 2. The first window (1.) represents the observations. The second window (2.) illustrates the identification of skewness and kurtosis. Windows (3.), (4.), and (5.) show the Autocorrelation function, the Ljung-Box and the Lagrange multiplier. The ADF and the KPSS tests are in (6.) and (7.). The last windows (7.) contains the results of the TSELW estimator.

[14] See McCloskey and Ziliak (2008), Chapter 8, p.89, 'How Big is Big in economics'.
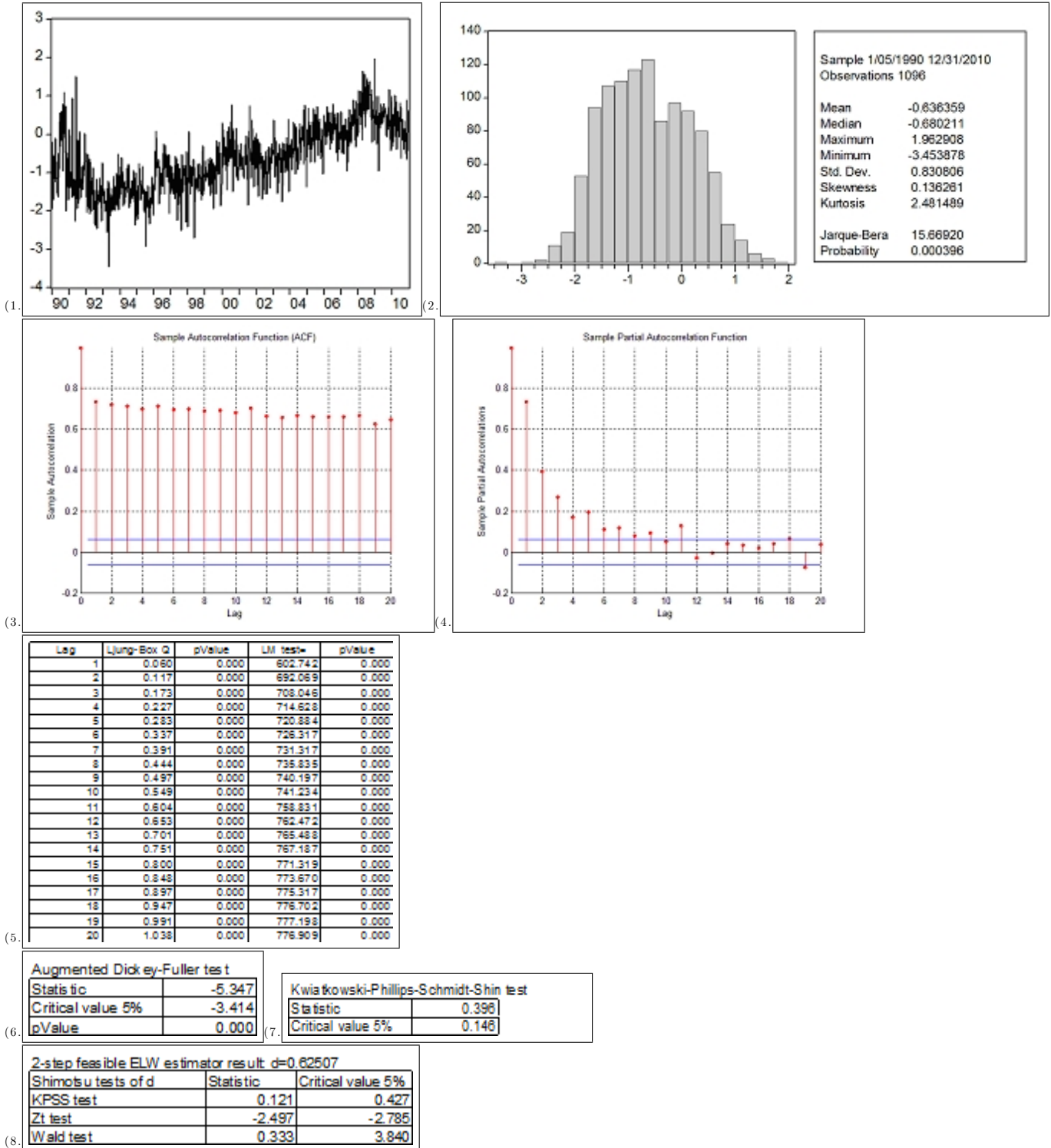
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Appendix

Appendix 1: Brent Volatility.

Lag	Ljung-Box Q	pValue	LM test=	pValue
1	0.060	0.000	602.742	0.000
2	0.117	0.000	692.069	0.000
3	0.173	0.000	708.046	0.000
4	0.227	0.000	714.628	0.000
5	0.283	0.000	720.884	0.000
6	0.337	0.000	726.317	0.000
7	0.391	0.000	731.317	0.000
8	0.444	0.000	735.835	0.000
9	0.497	0.000	740.197	0.000
10	0.549	0.000	741.234	0.000
11	0.604	0.000	758.831	0.000
12	0.653	0.000	762.472	0.000
13	0.701	0.000	765.488	0.000
14	0.751	0.000	767.187	0.000
15	0.800	0.000	771.319	0.000
16	0.848	0.000	773.670	0.000
17	0.897	0.000	775.317	0.000
18	0.947	0.000	776.702	0.000
19	0.991	0.000	777.198	0.000
20	1.038	0.000	776.909	0.000

Augmented Dickey-Fuller test	
Statistic	-5.347
Critical value 5%	-3.414
pValue	0.000

Kwiatkowski-Phillips-Schmidt-Shin test	
Statistic	0.396
Critical value 5%	0.146

2-step feasible ELW estimator result: d=0.62507		
Shimotsu tests of d	Statistic	Critical value 5%
KPSS test	0.121	0.427
Zt test	-2.497	-2.785
Wald test	0.333	3.840

Appendix 2: WTI Volatility.

(1.

(2.

Sample 1/05/1990 12/31/2010
Observations 1096

Mean	-0.545919
Median	-0.580795
Maximum	2.400528
Minimum	-3.737870
Std. Dev.	0.825420
Skewness	0.109937
Kurtosis	2.671353
Jarque-Bera	7.140144
Probability	0.028154

(3.

(4.

Lag	Ljung-Box Q	pValue	LM test=	pValue
1	0.067	0.000	587.086	0.000
2	0.129	0.000	640.671	0.000
3	0.190	0.000	669.292	0.000
4	0.251	0.000	692.423	0.000
5	0.311	0.000	706.113	0.000
6	0.369	0.000	711.343	0.000
7	0.429	0.000	720.878	0.000
8	0.487	0.000	729.173	0.000
9	0.542	0.000	730.990	0.000
10	0.599	0.000	732.839	0.000
11	0.653	0.000	734.968	0.000
12	0.708	0.000	739.029	0.000
13	0.763	0.000	741.241	0.000
14	0.818	0.000	744.286	0.000
15	0.871	0.000	744.799	0.000
16	0.922	0.000	752.495	0.000
17	0.972	0.000	754.298	0.000
18	1.020	0.000	756.514	0.000
19	1.067	0.000	757.647	0.000
20	1.115	0.000	759.852	0.000

(5.

Augmented Dickey-Fuller test	
Statistic	-4.726
Critical value 5%	-3.414
pValue	0.001

(6.

Kwiatkowski-Phillips-Schmidt-Shin test	
Statistic	0.330
Critical value 5%	0.146

(7.

2-step feasible ELW estimator result: d=0.67286		
Shimotsu tests of d	Statistic	Critical value 5%
KPSS test	0.042	0.442
Zt test	-2.768	-2.819
Wald test	0.344	3.840

(8.

9