Quantile Serial Dependence in Crude Oil Markets: Evidence from Improved Quantilogram Analysis with Quantile Wild Bootstrapping

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Abstract

We examine the quantile serial dependence in crude oil prices based on the Linton and Whang's (2007) quantile-based portmanteau test which we improved by means of quantile wild bootstrapping. Through Monte Carlo simulation, we find that the quantile wild bootstrap based portmanteau test performs better than the bound testing procedure suggested by Linton and Whang (2007). We apply the improved test to examine the efficiency of two crude oil markets – WTI and Brent. We also examine if the dependence is stable via rolling sample tests. Our results show that both WTI and Brent are serially dependent in all except the median quantiles. Interestingly, the Brent oil market is more dependent than the WTI market in the higher quantiles while the opposite is true in the lower quantiles. These findings suggest that it may be misleading to examine the efficiency of crude oil markets in terms of mean (or median) oil returns only. These crude oil markets are relatively more serially dependent in non-median ranges.

Keywords: crude oil prices, efficiency, quantile serial dependence, quantilogram, wild bootstrapping.

JEL Classification Codes: Q40, C12, C15, C22, C50

[1] Introduction

It is well-accepted that oil is very important as it can affect very significantly the performance of the economy and financial markets (see, among others, Hamilton, 2011; Huang, et al, 1996; Park and Ratti, 2008; Lee et al., 2012). Several studies have found statistically significant evidence that an increase in oil price is a contributing factor behind recessions (see, for examples, Hamilton, 1983; Barsky and Lutz, 2004). Due to oil's central role in the world economy, many parts of society count on and strive to increase the understanding of how the oil market works. For examples, central banks and economic policy makers view oil price as one of the key variables in generating macroeconomic projections and in assessing macroeconomic risks.

Ever since the issue of market efficiency was brought to the forefront by the work of Fama in the 1970s, a voluminous amount of studies has been conducted on this issue in different financial and economic markets. The scale of research on this issue in the crude oil markets is quite large. This efficiency issue has been examined through various lens or approaches. They include, for examples, variance ratio tests (Charles and Darne, 2009), unit root tests (Elder and Serletis, 2008; Maslyuk and Smyth, 2009), time varying long-range dependence (Tabak and Cajueiro, 2007), Hurst exponent dynamics from detrended fluctuation analysis (Alvarez-Ramirez et al., 2008; Wang and Liu, 2010), and neural network (Yu, et al, 2008). However, the focus in the literature has been on the first moment (level or conditional mean) or second moment (volatility) of oil prices/returns and little is known beyond the first or second moments. In addition, the research on predictability in this market has yielded mixed results (Alquist, et al, 2013). Thus, there is a need for further research on market efficiency in the crude oil market with a new perspective/approach. Our paper therefore addresses this gap in the literature.

Our approach is to look at the efficiency issue of the crude oil markets in terms of serial dependence through the application of Linton and Whang's (2007) quantile-based Portmanteau test. This approach is special as it measures serial dependence in *different quantiles* of the crude oil prices distributions, providing additional information that traditional serial correlation cannot offer. In other words, we are not just concerned about the oil price dynamics at the middle but also about other parts (upper and lower tails) of the crude oil price distribution. This is a very important issue since oil prices have been shown to exhibit fat tails (Nordhaus, 2007; Trolle and Schwartz, 2010). To the best of our knowledge, this paper is the first in the literature to examine the issue by means of Linton and Whang's test.

In addition, this paper also contributes to the econometrics literature. Instead of employing the inference strategy suggested in Linton and Whang (2007), which at times lead to inclusive results, we conduct the Linton and Whang's (2007) test by means of the quantile wild bootstrapping of Feng, et al (2011). We show, via simulations, that the bootstrap-based inference is accurate in size without compromising in power and it can effectively avoid inconclusive outcomes.

As an overview, first, our results show that by means of wild bootstrapping, we were able to improve the finite sample properties of the Linton and Whang's (2007) quantile-based Portmanteau test. When we applied this improved test to the analysis of the efficiency of WTI and Brent in crude oil markets, we found that both WTI and Brent are serially dependent in all except the median quantiles. Interestingly, the Brent oil market is with higher degree of serial dependence than the WTI market in the higher quantiles while the opposite is true in the lower quantiles. These findings suggest that it may be misleading to examine the efficiency issue of crude oil markets in terms of mean (or median) oil returns only. The result implies that these crude oil markets may be predictable in non-median ranges. The rest of the paper is organised as follows. Section 2 discusses the methodology and Section 3 presents the empirical results. Section 4 concludes the study.

[2] Methodology

In this section, we discuss the quantilogram and the quantile portmanteau test proposed by Linton and Whang (2007). Specifically, we discuss the strengths and limitations of the associated inference of these statistics and how we improve the inference through quantile wild bootstrapping. We present the results of the Monte Carlo simulation which demonstrate the improvement.

2.1. Quantilogram and quantile portmanteau test

Suppose that Y_1, Y_2,… are random variables drawn from a stationary process whose marginal distribution has quantile μ_q for $0<q<1$. Linton and Whang (2007) define the quantilogram for any quantile q as

$$\rho_q(k) = \frac{E[\psi_q(Y_t - \mu_q)\,\psi_q(Y_{t+k} - \mu_q)]}{E[\psi_q^2(Y_t - \mu_q)]}, \text{ k=1,2,…,} \quad (1)$$

where $\psi_q(x) = q - 1(x < 0)$ is the check function (or, a.k.a. quantile hits). Since the quantilogram $\rho_q(k)$ consider the dynamic association in terms of the direction of deviation from a given quantile, it can be used to measure the serial dependence of the stochastic process $\{Y_t\}_{t=1}^{\infty}$. The issue is whether the past information set of Y_t can or cannot improve the prediction about whether Y_t will be above or below the quantile μ_q. Under the null hypothesis of no serial dependence (for a given *q*), $\rho_q(k)=0$ for all k. Alternatively, if $\rho_q(k)\neq 0$ for some k, $\{Y_t\}_{t=1}^{\infty}$ is serially dependent.

Let $\hat{\mu}_q$ be the sample quantile obtained by solving $\hat{\mu}_q = \arg\min_{\mu\in R}\sum_{t=1}^{T}\Theta_q(Y_t-\mu)$ where $\Theta_q(x)=x[\alpha-1(x<0)]$. The sample counterpart of $\rho_q(k)$ can be computed as follows:

$$\hat{\rho}_q(k)=\frac{\sum_{t=1}^{T-k}\psi_q(Y_t-\hat{\mu}_q)\psi_q(Y_{t+k}-\hat{\mu}_q)}{\sqrt{\sum_{t=1}^{T-k}\psi_q^2(Y_t-\hat{\mu}_q)}\sqrt{\sum_{t=1}^{T-k}\psi_q^2(Y_{t+k}-\hat{\mu}_q)}}, \text{ k=1,2,…, T-1.} \quad (2)$$

Since $\hat{\rho}_q(k)$ is constructed as a sample autocorrelation of the check function (the correlation of $\psi_q(Y_t-\hat{\mu}_q)$ and $\psi_q(Y_{t+k}-\hat{\mu}_q)$), $\hat{\rho}_q(k)\in[-1,1]$. To test the null hypothesis of no directional predictability at quantile *q* (i.e. $\rho_q(k)=0$ for k=1,…,p), Linton and Whang (2009) suggest a quantile version of Box-Ljung Q test (henceforth, QQ):

$$QQ_q(p)=T(T+2)\sum_{k=1}^{p}\hat{\rho}_q^2(k)/(T-j). \quad (3)$$

As the usual portmanteau Q test, the interpretation of the $QQ_q(p)$ test is straightforward, if the null hypothesis cannot be rejected, there exhibits insufficient evidence against serial dependence (at the q quantile); instead, if the null hypothesis is rejected, the underlying series is serially dependent. The inference of $\hat{\rho}_q(k)$ and $QQ_q(p)$ is, however, not straightforward. Specifically, under the null hypothesis, the asymptotic distribution of $\hat{\rho}_q(k)$, as shown by Theorem 2 in Linton and Whang (2007), is

$$\sqrt{T}\begin{bmatrix}\hat{\rho}_q(1)\\ \vdots \\ \hat{\rho}_q(p)\end{bmatrix} \Rightarrow N(0, V_q)\,. \qquad (4)$$

Here, V_q is a $p \times p$ asymptotic variance-covariance matrix which, in general, depends on the underlying volatility process of Y_t. Since □$Q_q(p)$ is a function of {$\hat{\rho}_q(1)$, …, $\hat{\rho}_q(p)$}, □$Q_q(p)$ is not asymptotically valid. To avoid the necessity of specifying a volatility model, Linton and Whang (2007) derived the lower and upper bounds of $V_{q,kk}$, the k[th] diagonal component of $V_q^{(p)}$, $1 \le V_{q,kk} \le 1 + \overline{v}_q$, and the (j,k) off-diagonal component, $|V_{q,jk}| \le \overline{v}_q$, where $\overline{v}_q = [\max(q, 1-q)]^2 / q(1-q)$.

Under the null hypothesis, when the upper bound is considered, we can construct the $(1-\alpha)\%$ confidence interval of $\hat{\rho}_q(k)$ as $CI_1 = \left(-z_{\alpha/2}\sqrt{(1+\overline{v}_q)/T},\, z_{\alpha/2}\sqrt{(1+\overline{v}_q)/T}\right)$. We note that, since $\overline{v}_q$ increases without limit as $q \to 0,1$, the confidence interval can be very wide. In some special circumstances (e.g. conditions that satisfy equation (6) in Linton and Whang (2007)), V_q is an identity matrix and so the lower bound can be applied, the interval shrinks to be $CI_2 = \left(-z_{\alpha/2}\sqrt{1/T}, z_{\alpha/2}\sqrt{1/T}\right)$. Linton and Whang (2007) call the larger band CI_1 conservative and the smaller band CI_2 liberal. Correspondingly, the rule for the □$Q_q(p)$ test can be either conservative or liberal: according to a conservative rule, the null hypothesis is rejected if □$Q_q(p) > (1 + p\overline{v}_q)\chi^2_\alpha(p)$ and for a liberal rule if □$Q_q(p) > \chi^2_\alpha(p)$. Such inference setups are indeed very novel in circumventing the complication of modelling the volatility process. Thus, this setup may be used even in the case where the first or even the second moment is infinite (e.g., in the case of α-stable process). However, in practice, the user needs to decide which rule – conservative or liberal – should be employed. The test would gain power at the cost of potential size distortion when the liberal rule is considered. On the other hand, with the conservative rule, the test can be very conservative for even moderate p (specially, when q is close 0 or 1) and has no power to reject the null hypothesis even if the tested process is indeed serially dependent.

2.2. Quantile wild bootstrapping

In this paper, we suggest approximating the distribution of $\hat{\rho}_q(k)$ and $\square Q_q(p)$ via quantile wild bootstrapping (QWB). Specifically, we adopt and modify the bootstrapping procedure of Feng, et al (2011) as follows.

(1) Obtain $\hat{e}_t = Y_t - \hat{\mu}_q$. Form a bootstrap sample of T observations $Y_t^* = \hat{\mu}_q + \omega_t \,|\, \hat{e}_t \,|$ where the weights ω_t is generated $\omega_t = \begin{cases} 2(1-q) \text{ } with \text{ } probability \text{ } p = 1-q \\ -2q \text{ } with \text{ } probability \text{ } p = q. \end{cases}$

(2) Compute $\hat{\rho}_q(k)$ and $\square Q_q(p)$ based on $\{Y_t^*\}_{t=1}^T$ and label the associated statistics: $\hat{\rho}_q^*(k)$ and $\square Q_q^*(p)$.

(3) Repeat (1) and (2) B times to form bootstrap distributions of $\hat{\rho}_q(k)$ and $\square Q_q(p)$: $\{\hat{\rho}_{q,b}^*(k)\}_{b=1}^B$ and $\{\square Q_{q,b}^*(p)\}_{b=1}^B$, respectively .

For the individual quantilogram, a $100(1-\alpha)\%$ confidence interval for $\hat{\rho}_q^*(k)$ can be obtained as $\left[\hat{\rho}_q(k) - T^{-1/2} c_{1k,\alpha}^*, \hat{\rho}_q(k) + T^{1/2} c_{2k,\alpha}^*\right]$ where $\left(c_{1k,\alpha}^*, c_{2k,\alpha}^*\right)$ are from the bootstrap distribution of $\{\sqrt{T}(\rho_{q,b}^*(k) - \rho_q(k))\}_{b=1}^B$ such that $\Pr(c_{1k,\alpha}^* \le \sqrt{T}(\hat{\rho}_{q,b}^*(k) - \hat{\rho}_q(k)) \le c_{2k,\alpha}^*)$

$=1-\alpha$. For the test of no directional predictability ($\widehat{QQ}^*_q(p)$), a critical value, $c^*_{QQ,\alpha}$, for a significance level α is given by the $(1-\alpha)100\%$ percentile of B test statistics $\{\widehat{QQ}^*_{q,b}(p)\}_{b=1}^{B}$ such that $c^*_{QQ,\alpha} = \inf\left\{c : \Pr\left(\widehat{QQ}^*_{q,b}(p) < c\right) \geq 1-\alpha\right\}$.

2.3. Monte Carlo simulation results

The simulation design basically follows that of Linton and Whang (2009). Specifically, we consider three models: (A) I.I.D. Normal: $Y_t \sim N(0,1)$; (B) GARCH_1: $Y_t \sim \varepsilon_t \sigma_t$ with $\sigma_t^2 = 0.2 + 0.45\sigma_{t-1}^2 + 0.35Y_{t-1}^2$ where $\varepsilon_t \sim N(0,1)$; (C) GARCH_2: $Y_t \sim \varepsilon_t \sigma_t$ with σ_t^2 $= 0.2 + 0.9\sigma_{t-1}^2 + 0.06Y_{t-1}^2 + 0.03Y_{t-1}^2 1(Y_{t-1} < 0)$. We choose sample size T=500, 1000, and 5000 and quantile q=0.1, 0.3, 0.5, 0.7, and 0.9. The Monte Carlo simulation is conducted via the warp-speed method of Giacomini et al (2013) with 10,000 replications and done by GAUSS. According to Linton and Whang (2009), Model (A) is completely under the null hypothesis of no directional predictability for *all* quantiles, while (B) and (C) are under the null for the *median* but under the alternative. We report the simulation results of the 5% nominal level of $\widehat{QQ}_q(p)$ in Table 1. For the purpose of comparison, we report inference results of $\widehat{QQ}_q(p)$ via both bootstrapping (QWB) and the liberal rule.

Table 1 shows that in the cases when the null is true (Model (A) and q=0.5 in Models (B) and (C)), the bootstrapping inference is corrected sized regardless lag (p), sample size (T), and quantile (q) (Model (A)). In contrast, the testing result can become rather over-sized when the liberal decision rule is applied, particularly when p is large (p=50 or 100) and T is moderate (T=500 or 1000). For example, in Model (A), while the rejection rate at q=0.5 for the bootstrap test is around 0.05 regardless p and T, the rejection rate for the liberal test can range from 0.051 (p=1 and T=1000) to 0.240 (p=100, T=500). In the cases under the alternative (Model (B) and (C) with $q \neq 0.5$), Table 1 shows that the bootstrap test exhibit as competitive power as the liberal test in most cases – for example, in all the cases with p=1 and 5. We note that for those cases that the liberal test is significantly more powerful than the bootstrap test, the liberal test also suffers considerable size distortion but the bootstrap test does not – for example, when p=50, 100 and T=500, 1000. Overall, our simulation results support the use of QWB.

[3] Empirical analysis of crude oil markets

We apply the proposed QWB-based quantilogram in analysing the quantile serial dependence in two major crude oil markets: WTI and Brent. We are the first to apply the quantilogram analysis in energy markets.

3.1. Data

For the two crude oil markets, we collect daily spot prices from Energy Information Administration website.[1] Both prices collected end on December 1, 2014 but with different starting dates (due to data availability): WTI is from January 2, 1986 with 7,207 observations and Brent is from May 20, 1987 with 6,923 observations. We plot the WTI and Brent crude oil prices & returns (log-returns) in Figure 1. In general, the two price series move closely to each other and both returns are very volatile. We also present descriptive statistics for the

[1] http://www.eia.gov/

two oil returns in Table 2. In summary, the two returns are statistically insignificantly different from zero, volatile, left-skewed and leptokurtic.

3.2. Empirical results

We first report the full-sample results of the quantilogram and the corresponding quantile portmanteau test for WTI and Brent returns in Figure 2 and Table 3. We consider the cases with lags up to 100 at five various quantiles (q=0.1, 0.3, 0.5, 0.7, 0.9). We also show the QWB-based 95% confidence intervals (centred to zero) for the quantilogram and the QWB-based 5% critical values (Figure 2) and p-values (Table 3) for the quantile-portmanteau test. The bootstrapping is performed with 1,000 replications. For both WTI and Brent returns, there seems to be some evidence of serial dependence, but only in higher and lower quantiles – as shown in Table 3, the null hypothesis of no serial dependence is rejected at 5% level in nearly all cases when $q \neq 0.5$ but not otherwise (i.e., when *q*=0.5*)*. The autocorrelation at q=0.5 is evidently non-existent for the WTI returns and while there is some evidence of positive median autocorrelation for Brent in a few lags (e.g. p=1 and 14), the evidence is weak. Therefore, overall, there is not much evidence of dependence in the median. This result is consistent with the well-documented fact that the conventional autocorrelation of asset/commodity returns is often zero (Pagan, 1996). Recall from Table 1 that the crude oil returns are not statistically different from zero, this means that the autocorrelation at *q*=0.5 corresponds to the autocorrelation of the sign of oil returns. If there is a lot of positive autocorrelation, one may earn money buying those oil contracts that went up, and a lot of negative autocorrelation means one should buy those oil contracts that went down, either way one can arbitrage the autocorrelation away. In other words, autocorrelation is expected to be zero because it is limited by arbitrage.

In the lower quantiles, when q=0.1 in particular, there are many cases of individually significant positive serial dependence and the dependence appears to be very persistent. Comparing the two markets, Brent seems to be with somewhat higher degree of dependence than WTI in the lower quantiles. Thus, when there are large losses in one period, the chance of having large losses in the next few periods is high (higher than 10% in the case of q=0.1, unconditionally). Similar results are also shown for the higher quantiles, there are significant long-lasting, positive serial-correlations – implying when there are large gains in one period the chance of having large gains in the next few periods is also high. This result indicates the presence of volatility clustering that is, as first noted in Mandelbrot (1963), recognized as a stylized property present in many speculative price time series. This volatility clustering effect has given rise to the development of stochastic models – GARCH models and stochastic volatility models are intended primarily to model this phenomenon in oil returns.

To examine if the dependence is stable across time, we also run rolling quantile portmanteau test ($QQ_q(p)$) with a four-year window (each with 1,008 daily returns) moving up by three months (63 observations). For WTI, there are 95 rolling results and for Brent 90 results. We report the results using p=50 at 5% significance level with various q's in Figure 3 and summarize the rejection percentage in Table 4. As shown in Table 4, for both oil returns, there are significantly more rejection sub-periods in the lower and upper quantiles than in the middle. Interestingly, in the case of Brent (but not in WTI), it appears that the market is more dependent in the higher quantiles than in the lower quantiles.

Moreover, Brent appears somewhat more dependent than WTI in the higher quantiles while it is opposite when lower quantiles are considered. As is well known in the crude oil literature, there are at least two reasons that the WTI and Brent markets and their prices are different. First, the inland U.S. WTI and the seaborne Brent crude oil have been traded in partly segregated markets (see, for example, Büyükşahin et al, 2013). Second, infrastructure constraints in Cushing, Oklahoma, have historically influenced the price differential between WTI crude oil trades against Brent crude oil trades (Fattouh, 2010; Borenstein and Kellogg, 2012).[2] This effectively makes Cushing oil stocks insulate the WTI market from the price pull stemming from strong world demand, suggesting that WTI is more sensitive to US conditions while Brent is more sensitive to the world conditions.

We also observe from Figure 3 that the dependent sub-periods at q=0.1 and 0.9 for both oil markets (WTI, especially) tend to concentrate on the first 13/14 sampling years (around 1986 to 1999) and the last 10/11 years (roughly, 2003/2004 to 2014). A closer look at Figure 1, especially the return series of WTI and Brent, reveals that there were many large (positive or negative) returns during the two periods. In addition, these large returns tend to cluster with each other, confirming the volatility clustering effect depicted in Table 3. By browsing the chronology of economic or political events in the world crude oil market, it is not difficult to understand why there were so many largest positive and negative returns in these two periods.[3]

[2] Several new crude transportation projects came online in early 2013, including pipelines and crude-by-rail terminals. This new infrastructure helped clear transportation bottlenecks in U.S. Midcontinent, particularly around Cushing, Oklahoma.

[3] The chronology is available at the links below:
https://en.wikipedia.org/wiki/Chronology_of_world_oil_market_events;
https://en.wikipedia.org/wiki/2001_world_oil_market_chronology;
https://en.wikipedia.org/wiki/World_oil_market_chronology_from_2003.

[4] Conclusion

We examined the quantile serial dependence of crude oil prices based on an improved version of the Linton and Whang's (2007) quantile-based portmanteau test. We improved the test by means of quantile wild bootstrapping. Through Monte Carlo simulation, we found that the quantile wild bootstrap based portmanteau test corrects the over-sizing problem of the standard portmanteau test. We applied the improved test to examine the efficiency of two crude oil markets – WTI and Brent. Our results showed that both WTI and Brent are dependent in all except the median quantiles. Interestingly, the Brent oil market is more dependent than the WTI market in the higher quantiles while the opposite is true in the lower quantiles. These findings suggest that it may be misleading to examine the efficiency of crude oil markets in terms of mean (or medium) oil returns only. These crude oil markets are relatively more dependent in non-median ranges.

References

Alquist, R., Kilian, L. and Vigfusson, R.J. (2013) Forecasting the price of oil, in: G. Elliott and A. Timmermann (eds*.), Handbook of Economic Forecasting*, 2, Amsterdam: North-Holland, 427-507.

Alvarez-Ramirez, J., Alvarez, J. and Rodriguez E. (2008) Short-term predictability of crude oil markets: A detrended fluctuation analysis approach. *Energy Economics*, 30, 2645–2656.

Barsky, R. B. and Kilian L. (2004) Oil and the macroeconomy since the 1970s, *The Journal of Economic Perspectives*, 18, 115-134.

Borenstein, S. and Kellogg, R. (2012) The incidence of an oil glut: who benefits from cheap crude oil in the midwest? *NBER Working Paper No*. 18127, June.

Büyükşahin, B., Lee, T.K., Moser, J.T. and Robe, M.A. (2013) Physical markets, paper markets and the WTI-Brent spread, *Energy Journal*, 34, 129–51.

Charles, A. and Darne, O. (2009) The efficiency of the crude oil markets: Evidence from variance ratio tests, *Energy Policy*, 37, 4267–4272.

Elder, J. and Serletis, A. (2008) Long memory in energy futures prices, *Review of Financial Economics*, 17, 146-155.

Fama, E.F. (1970) Efficient capital markets: A review of theory and empirical work, *The Journal of Finance*, 25, 383-417.

Fattouh, B. (2010) The dynamics of crude oil price differentials. *Energy Economics* 32: 334–342.

Fen, X., He, X. and Hu, J. (2011) Wild bootstrap for quantile regression, *Biometrika,* 98, 995-999.

Giacomini, R., Politis, D.N. and White, H. (2013) A warp-speed method for conducting Monte Carlo experiment in solving bootstrap estimator, *Econometric Theory*, 29, 567-589.

Hamilton, J. D. (1983) Oil and the macroeconomy since World War II*, The Journal of Political Economy*, 91, 228-248.

Hamilton, J.D. (2011) Nonlinearities and the macroeconomic effects of oil prices, *Macroeconomic Dynamic*, 364-378.

Huang, R., Masulis, R. and Stoll, H. (1996) Energy shocks and financial markets, *Journal of Futures Markets*, 16*,* 1-27.

Lee, B.J., Yang, C.H. and Huang, B.H. (2012) Oil price movements and stock market revisited: a case of sector stock price indexes in the G7 countries, *Energy Economics*, 34, 1284–1300.

Linton, O. and Whang, Y.-J. (2007) The quantilogram: with an application to evaluating directional predictability, *Journal of Econometrics*, 141, 250-282.

Maslyuk, S. and Smyth, R. (2009) Unit root properties of crude oil spot and futures prices, *Energy Policy*, 31, 109–118.

Nordhaus, W., (2007) Who's afraid of a big bad oil shock? *Brookings Papers on Economic Activity*, 2007:2.

Pagan, A. (1996) The econometrics of financial markets. *Journal of Empirical Finance*, 3:15-102.

Park, J. and Ratti, R. A. (2008) Oil price shocks and the stock markets in the U.S. and 13European countries, *Energy Economics*, 30(5), 2587-2608.

Tabak, B.M. and Cajueiro, D.O. (2007) Are the crude oil markets becoming weakly efficient over time? A test for time-varying long-range dependence in prices and volatility, *Energy Economics*, 29, 28–36.

Trolle, A. B. and Schwartz, E. S., (2010) Variance risk premia in energy commodities. *The Journal of Derivatives* 17.3, pp. 15–32

Wang, Y.-D. and Liu, L. (2010) Is WTI crude oil market becoming weakly efficient over time? New evidence from multiscale analysis based on detrended fluctuation analysis, *Energy Economics*, 32, 987–992.

Yu, L. A., Wang, S.-Y. and Lai, K. K., (2008) Forecasting crude oil price with an EMD-based neural network ensemble learning paradigm, *Energy Economics*, 30, 2623–2635.

Table 1 Simulation – size and power with quantile wild bootstrapping (QWB)

(A) IID-N(0,1)

		T=500		T=1000		T=5000	
Quantile (q)	lag(p)	QWB	Liberal	QWB	Liberal	QWB	Liberal
0.1	1	0.051	0.039	0.048	0.046	0.049	0.048
	5	0.052	0.051	0.050	0.049	0.047	0.048
	50	0.053	0.094	0.051	0.070	0.048	0.054
	100	0.054	0.205	0.051	0.119	0.048	0.061
0.3	1	0.049	0.055	0.051	0.050	0.051	0.051
	5	0.052	0.057	0.055	0.056	0.047	0.051
	50	0.049	0.105	0.051	0.076	0.050	0.054
	100	0.049	0.228	0.052	0.126	0.048	0.061
0.5	1	0.048	0.048	0.044	0.051	0.053	0.053
	5	0.051	0.060	0.048	0.051	0.053	0.051
	50	0.050	0.111	0.050	0.077	0.053	0.057
	100	0.051	0.240	0.048	0.122	0.051	0.064
0.7	1	0.048	0.054	0.052	0.053	0.051	0.049
	5	0.048	0.054	0.050	0.052	0.051	0.050
	50	0.049	0.106	0.052	0.077	0.051	0.056
	100	0.050	0.227	0.049	0.122	0.050	0.062
0.9	1	0.049	0.047	0.050	0.054	0.053	0.050
	5	0.048	0.051	0.049	0.052	0.054	0.050
	50	0.052	0.094	0.051	0.070	0.054	0.056
	100	0.050	0.209	0.055	0.116	0.051	0.061

[B] GARCH_1 (see Linton & Whang (2007), Case [2], pages 272-273)

		T=500		T=1000		T=5000	
Quantile (q)	lag(p)	QWB	Liberal	QWB	Liberal	QWB	Liberal
0.1	1	0.548	0.548	0.772	0.772	1.000	1.000
	5	0.548	0.552	0.825	0.827	1.000	1.000
	50	0.323	0.409	0.583	0.636	1.000	1.000
	100	0.245	0.477	0.461	0.592	0.998	0.998
0.3	1	0.109	0.110	0.160	0.159	0.557	0.556
	5	0.089	0.099	0.132	0.137	0.521	0.517
	50	0.071	0.131	0.084	0.118	0.258	0.268
	100	0.061	0.260	0.067	0.162	0.179	0.212
0.5	1	0.049	0.049	0.049	0.049	0.047	0.049
	5	0.050	0.055	0.049	0.053	0.050	0.050
	50	0.046	0.104	0.050	0.073	0.054	0.058
	100	0.047	0.229	0.048	0.120	0.052	0.065
0.7	1	0.096	0.114	0.165	0.162	0.551	0.560
	5	0.092	0.097	0.129	0.131	0.526	0.522
	50	0.064	0.126	0.086	0.118	0.261	0.275
	100	0.059	0.250	0.070	0.163	0.179	0.209
0.9	1	0.496	0.480	0.798	0.800	1.000	1.000
	5	0.531	0.545	0.827	0.823	1.000	1.000
	50	0.315	0.404	0.577	0.628	1.000	1.000
	100	0.231	0.472	0.455	0.588	0.998	0.998

[C] GARCH_2 (see Linton & Whang (2007), Case [3], pages 272-273)

		T=500		T=1000		T=5000	
Quantile (q)	lag(p)	QWB	Liberal	QWB	Liberal	QWB	Liberal
0.1	1	0.198	0.195	0.286	0.286	0.832	0.831
	5	0.405	0.403	0.643	0.644	0.999	0.999
	50	0.367	0.439	0.626	0.660	0.998	0.999
	100	0.280	0.494	0.530	0.628	0.996	0.997
0.3	1	0.065	0.068	0.079	0.079	0.177	0.178
	5	0.090	0.097	0.123	0.130	0.433	0.430
	50	0.084	0.145	0.120	0.156	0.443	0.450
	100	0.073	0.268	0.091	0.190	0.345	0.373
0.5	1	0.051	0.051	0.049	0.049	0.049	0.052
	5	0.050	0.056	0.049	0.052	0.053	0.052
	50	0.048	0.103	0.050	0.076	0.048	0.055
	100	0.050	0.231	0.050	0.126	0.049	0.061
0.7	1	0.055	0.063	0.064	0.066	0.106	0.107
	5	0.065	0.072	0.081	0.084	0.194	0.194
	50	0.065	0.120	0.081	0.106	0.187	0.199
	100	0.057	0.242	0.067	0.151	0.147	0.170
0.9	1	0.125	0.120	0.248	0.250	0.683	0.692
	5	0.317	0.317	0.497	0.503	0.988	0.988
	50	0.293	0.366	0.489	0.529	0.989	0.990
	100	0.222	0.431	0.400	0.512	0.975	0.978

Table 2: Descriptive Statistics (Daily Oil Returns)

	WTI	Brent
Mean	0.008642	0.017231
Median	0.056101	0.021148
Maximum	19.15065	18.12974
Minimum	-40.63958	-36.12144
Std. Dev.	2.505625	2.262667
Skewness	-0.794085	-0.678947
Kurtosis	18.42884	18.61910
Jarque-Bera (p-value)	72241.62 (0.000)	70903.07 (0.000)
Sample	Jan 2, 1986 - Dec 1, 2014	May 20, 1987 - Dec 1, 2014
Observations	7207	6923

Table 3: Quantile Portmanteau Test (Daily Crude Oil Returns)

WTI

Lag/Quantile	q=0.1	q=0.3	q=0.5	q=0.7	q=0.9
P=1	59.24	6.743	1.570	0.338	12.36
	(0.000)	(0.007)	(0.213)	(0.555)	(0.001)
P=10	291.4	25.42	9.272	40.67	194.0
	(0.000)	(0.004)	(0.501)	(0.000)	(0.000)
P=50	962.2	104.0	47.18	239.0	911.4
	(0.000)	(0.000)	(0.599)	(0.000)	(0.000)
P=100	1444	160.2	88.38	384.7	1379
	(0.000)	(0.000)	(0.801)	(0.000)	(0.000)

Brent

Lag/Quantile	q=0.1	q=0.3	q=0.5	q=0.7	q=0.9
P=1	48.27	22.42	3.994	2.343	13.87
	(0.000)	(0.000)	(0.050)	(0.126)	(0.001)
P=10	214.4	64.75	11.43	64.61	128.7
	(0.000)	(0.000)	(0.338)	(0.000)	(0.000)
P=50	566.7	158.4	54.7	237.7	687.7
	(0.000)	(0.000)	(0.306)	(0.000)	(0.000)
P=100	841.6	236.0	117.5	407.4	1223
	(0.000)	(0.000)	(0.125)	(0.000)	(0.000)

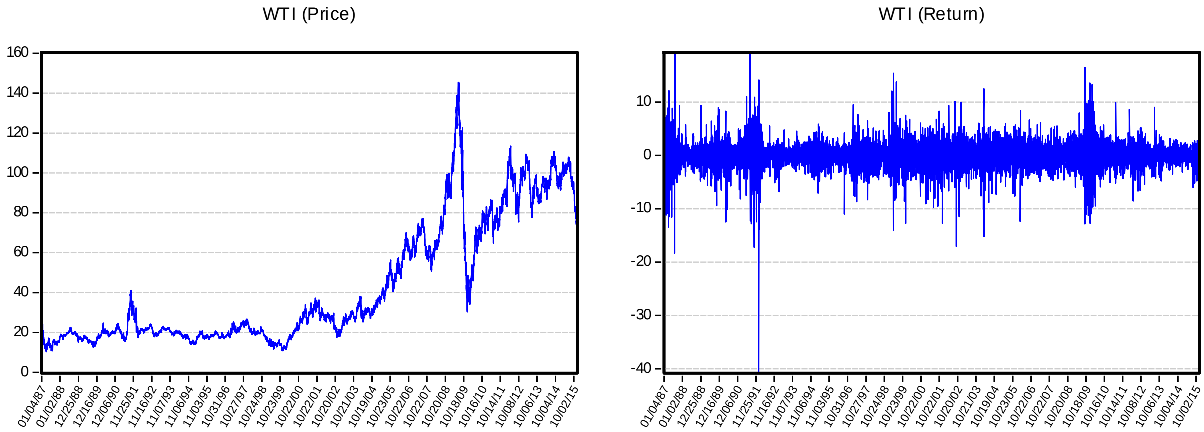
Note: P-values in the parentheses (obtained via wild quantile bootstrapping)

Table 4: Percentage of rejection at 5% level over the rolling samples

Quantile	WTI	Brent
q=0.1	67.36%	71.11%
q=0.3	22.10%	63.33%
q=0.5	7.37%	20.00%
q=0.7	35.79%	21.11%
q=0.9	63.16%	54.44%

Figure 1: WTI and Brent Oil Daily Prices & Returns

WTI



Brent

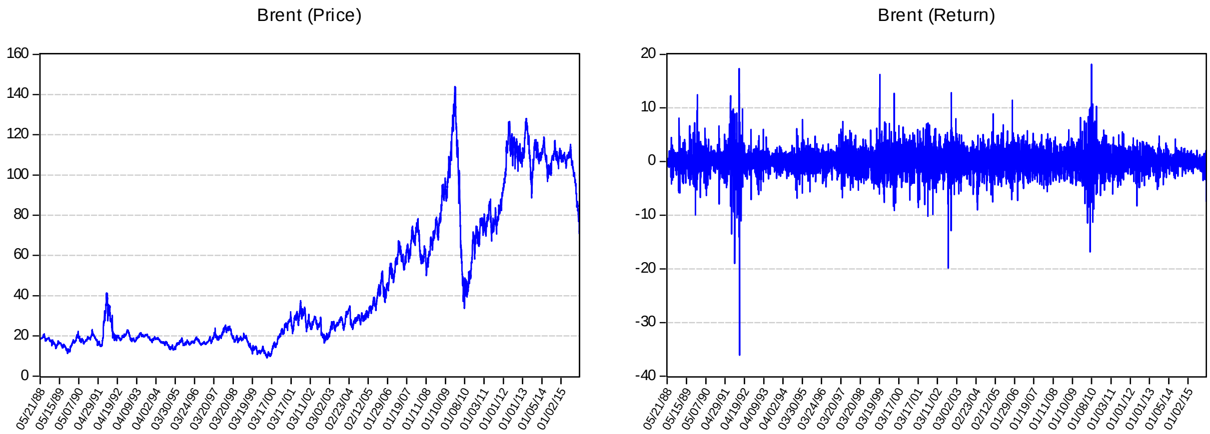
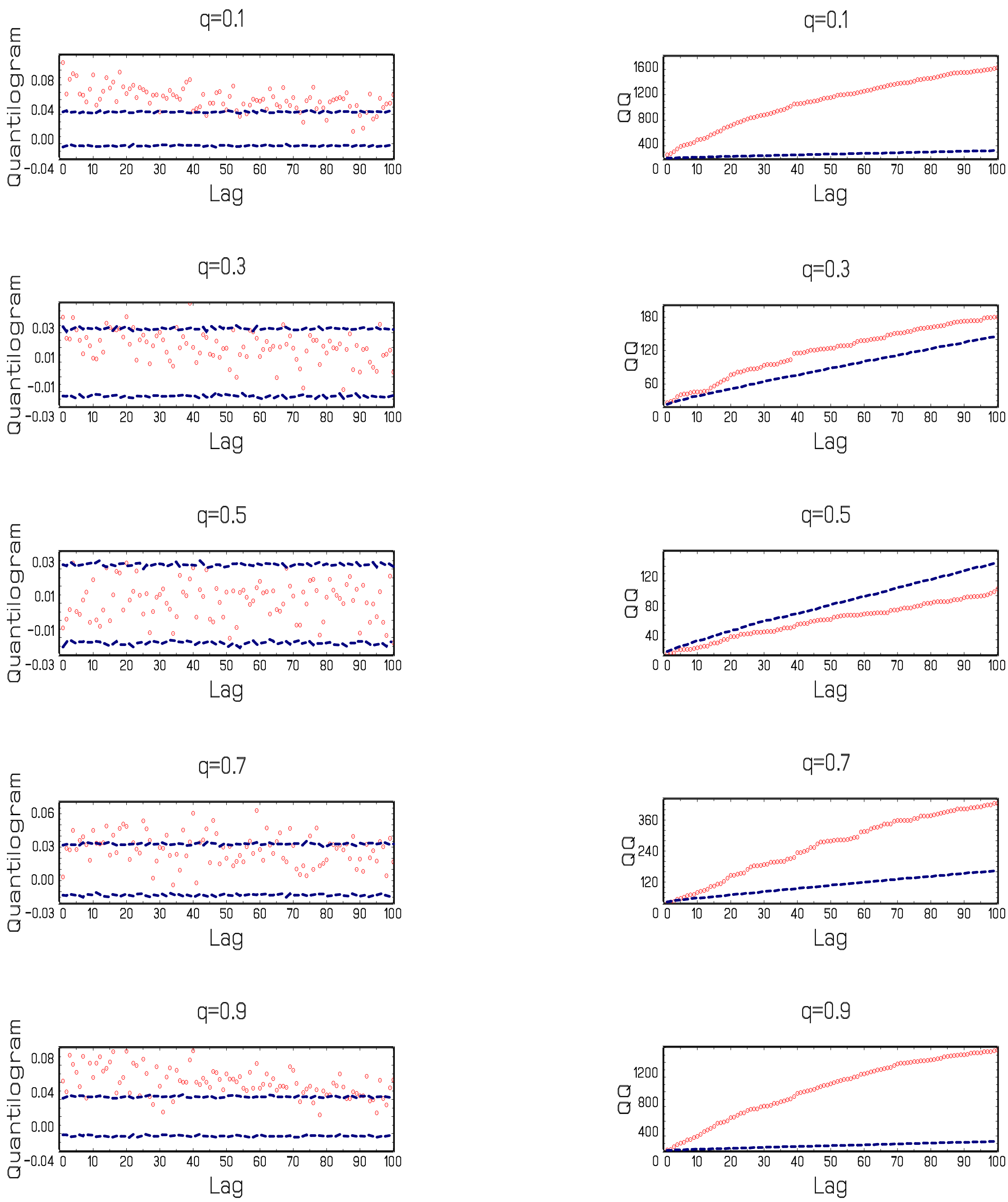


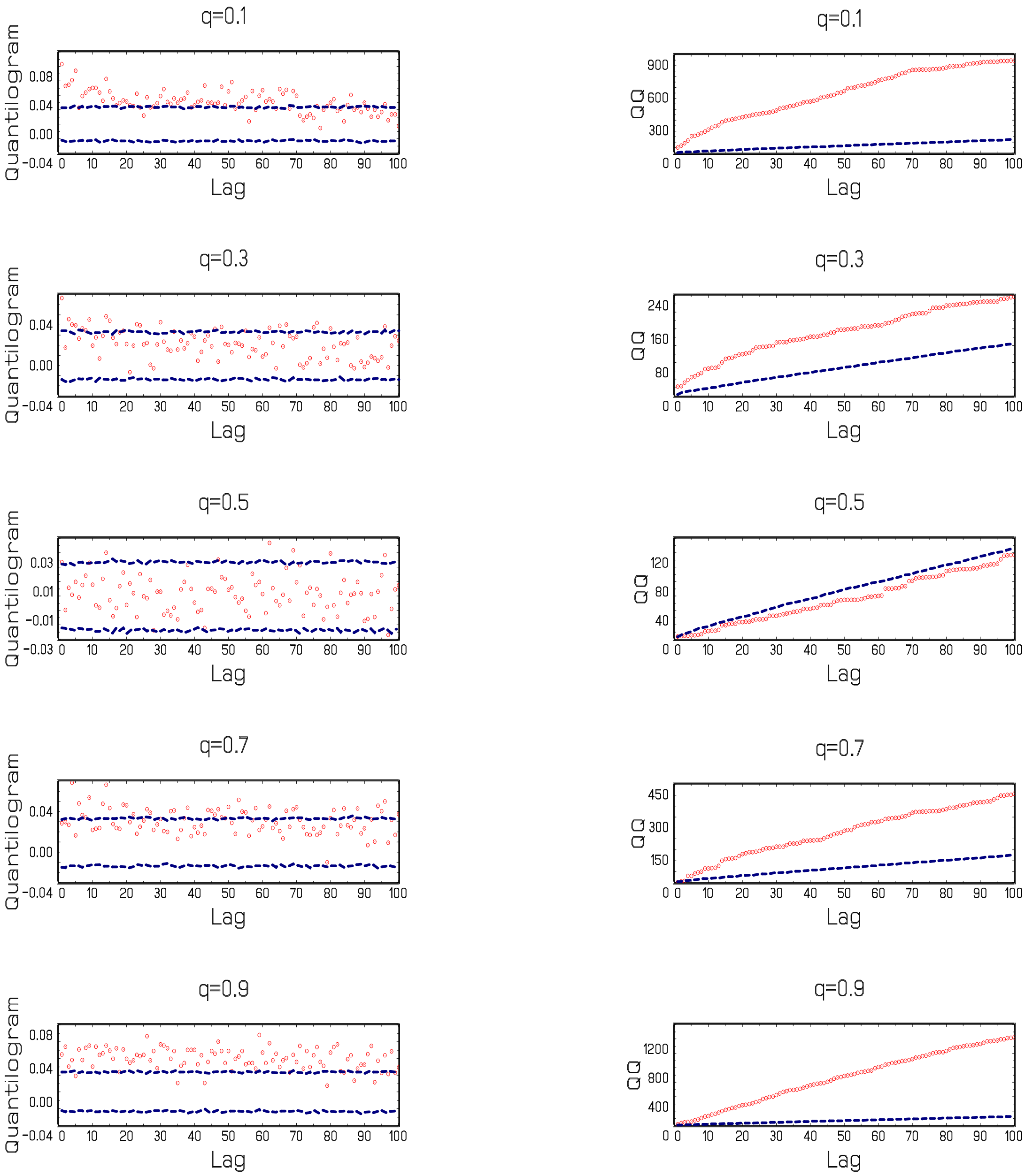
Figure 2: Quantilogram and Quantile Portmanteu Test (lag=1,…,100)

(Left column) Red dots for the quantilogram; blue dash lines for 95% confidence intervals cantered at zero. (Right column) Red dots for the QQ test; blue dash lines for 5% critical values.

(A) WTI



(B) Brent

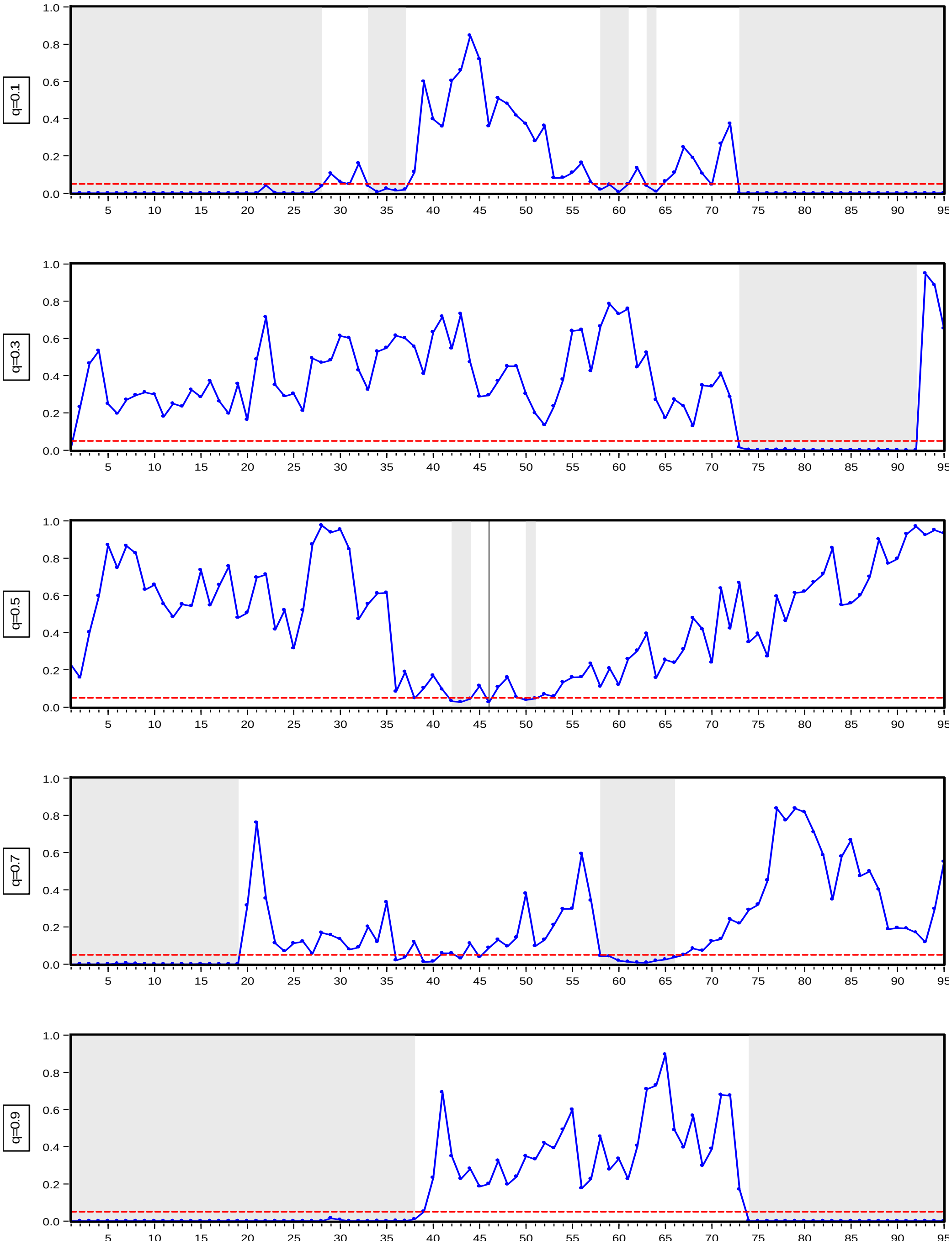


q=0.1
Quantilogram
0.08
0.04
0.00
−0.04
0 10 20 30 40 50 60 70 80 90 100
Lag
q=0.1
QQ
900
600
300
0
Lag
q=0.3
Quantilogram
0.04
0.00
−0.04
Lag
q=0.3
QQ
240
160
80
0
Lag
q=0.5
Quantilogram
0.03
0.01
−0.01
−0.03
Lag
q=0.5
QQ
120
80
40
0
Lag
q=0.7
Quantilogram
0.04
0.00
−0.04
Lag
q=0.7
QQ
450
300
150
0
Lag
q=0.9
Quantilogram
0.08
0.04
0.00
−0.04
Lag
q=0.9
QQ
1200
800
400
0
Lag

Figure 3: Rolling Window (p-value: QQ_{50})

Note: the p-value of 5-year (i.e. 1260 observations) rolling samples with 3-month (i.e. 63 observations) shift with 95 (for WTI) and 90 (for Brent) overlapped subsamples. Shade areas cover subsample periods with rejection of zero quantilogram (i.e. p<0.05).

WTI



Brent