TRUSTING IN ECONOMETRIC TOOLS? A MULTIBREAKPOINT ANALYSIS OF CRUDE OIL PRICES

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Abstract

Statistical investigation of economic data is very often a posterior analysis. Econometric tools are not an exception, despite some cutting-edge instruments adopted by some pioneers to gaze into "crystal ball". Clearly, among such (ex-post) techniques the main difference is between methods able to (reasonably) capture past issues in inherent modeling approach or not. In the present contribution, a quite recent multibreakpoint analysis of time series is proposed with the aim to overcome traditional constraints the researcher has to face. As a matter of fact, common applied methods are able to identify one (or at best two) structural break(s) in time series. By investigating oil crude prices, we propose a quite different approach applying a not (at the moment) widespread econometric technique to detect more than a single structural break in empirical data analysis. Hence, a brief discussion is developed to compare resulting outcomes with real historical facts. The aim is to test endogenous capability of the technique in pairing changes in statistical properties of oil price time series with salient chronological events.

Keywords: multibreakpoint analysis, oil prices, structural change, time series, Bellman principle

JEL codes: C01, C13, C22, C87, Q40

1. Introduction

Statistical and econometric procedures are widespread in quantitative economics as methods to investigate and verify hypothesis and theories. As every technique, they have relative merits and shortfalls. Some of them are more accepted (hence widely adopted by scholars), while others are less employed (with a lower degree of acceptance by the majority of academics). In order to gaining proper approval, methods must be previously known, implemented, applied, discussed and validated in their specific research boundary. Despite the relevant efforts and important contributions found in literature, reliable time series forecasting is still currently a very complex field of research even if properly and professionally managed. Whoever in empirical time series approaching forecasting methods faced relevant issues in results for medium-long exercises. A wealth of techniques have been developed also in describing, representing and modeling the past. Obviously, past (descriptive) and future (forecast) needs in research activity are characterized by proper requirements. Following this reasoning, the efficiency of an econometric method to analyze past must be assessed taking into consideration relative “ability” to fit the phenomenon is asked to depict and explain. In the present paper a relative new methodology is presented to detecting multiple breaks in time series. To the best of our knowledge, and without pretension to exhaustion, this is probably one of the very first attempts adopting such a technique in the literature on economics of commodity markets (oil in our case). Honestly speaking, it is already possible to find in empirical literature contributions pertaining structural break point analysis. On this point we cite two recent cases as merely examples, and without pretension to exhaustion. In their paper, Mayer et al. (2017) analyzing the metal markets process a rolling three-years window within the whole time frame without addressing a specific statistical approach. In further interesting literature on financialization of commodity markets, Adams and Glück (2015) employ the Galeano and Wied (2014) two steps-algorithm to identify a substantial single “cut-off” division between the pre- and the post-financialization period. Without entering into the merits of the above mentioned contributions, the common feature of available literature focused on the topic (what is technically labeled as a “breakpoint”) is that main binding constraint lies in the inner procedure able to detect and process one single structural change within the time series object of investigation. Also the Galeano and Wied (2014) algorithm has the aim to detect possible multiple breaks in time series, but its application is devoted to the analysis of the correlation structure of the random variables to verify its substantial constancy over time. Therefore, only when such a constancy is not present the method tends to estimate the number and the timing of possible breaks. Thus, to be successful, it has to process almost two series. For this reason is neither chosen nor adequate for our case given that a single time series is investigated. The task of the present work is to apply the multiple break detection procedure to oil prices to verify whether changes in statistical properties are located in the near presence of significant historical facts affecting the chronological sequence of data. Relevant information to retrieve will be the statistical impact such an event exerted on prices. Thus, a good detection may be evaluated as a encouraging premise for further research implementations.

2. Methodology

With the aim to deeply analyzing behavior, and hence possible changes in statistical properties, of oil prices, we apply a quite recent (and interesting) statistical technique developed to dating multiple structural changes (aka breakpoints, i.e unexpected shifts) in time series data as proposed by Bai and Perron (2003 and 1998). Estimation applied in the present work considers general forms of serial correlation and heteroskedasticity in the errors, lagged dependent variables, trending regressors, different distributions for the errors and the regressors across segments. Thus, the multiple break detection is endogenously derived from data by applying least-squares method to a linear model. The main feature of such a framework lies in the approach the researcher proposes in the analysis. Considering more than one single endogenous break when actually more than one change exists is a need well outlined by several studies Lumsdaine and Papell (1997). Statistical and econometric literature propose a wealth of work concerning typical designed (also at unknown date) single or, at most, double change tests (for example and without pretension to exhaustion: Lütkepohl et al., 2004; Lee and Strazicich, 2003; Papell and Prodan, 2003; Ohara, 1999; Clemente et al., 1998; Lumsdaine and Papell, 1997; Perron, 1997; Banerjee et al., 1992; Zivot and Andrews, 1992; Brown et al., 1975). A further widespread procedure was proposed by Chow (1960), but its implementation steps require an exogenous specification by the researcher of the null hypothesis for (also in this case for just) one structural change in data, and then perform the test. Instead, and this is the main difference, to identify and locate the structural changes in longitudinal series, the present method leaves the statistical procedure to endogenously detect the unknown dates where they could be present. This is a non-subjective and mathematically supported choice, and is less open to critics by skeptical readers. The method here briefly summarized starts from the standard linear regression model, and proceeds in determining *m* breakpoints within dataset (and *m* + 1 partition segments), where the coefficients of the regression relationship shift from one stable relation to a different one. For interested readers, proofs and formal developments can be found in Bai and Perron (2003 and 1998) as well as in Zeileis et al. (2003) for computing details. Hence, having the linear regression model expressed as :

$$y_t = x_t \beta_t + \varepsilon_t \text{ with } (t = 1, \ldots . n), \qquad (1)$$

where at time t, y_t is the observed dependent variable, x_t is a vector of regressors ($k \times 1$), and β_t is the corresponding $k \times 1$ vector of regression coefficients varying over time. The hypothesis of the constancy of regression coefficients holds whether:

$$H_0 : \beta_t = \beta_0 \ (t = 1, \ldots . n),$$

and *m* reasonable breakpoints lead to *m* + 1 segments wherein the model (1) can be re-written as:

$$y_t = x_t\,\beta_j + \varepsilon_t \text{ with } (t = t_{j-1}+1,\ldots, t_j,\ j = 1,\ldots\ldots, m+1),$$

having j as the segment index and $T_{m,n} = \{\, t_1,\ldots\ t_m \,\}$ as the set of breakpoints (or m-partition) by convention represented with $t_0 = 0$ and $t_{m+1} = n$.

Within the m-partition, the least-squares estimate of the β_j leads to the Residual Sum of Squares (RSS) as:

$$RSS = \sum_{j=1}^{m+1} rss\left(t_{j-1}+1, t_j\right)$$

with $rss\left(t_{j-1}+1, t_j\right)$ is the minimal residual sum of squares in the j_{th} segment of the partition.

Dating and locating structural changes, it is necessary to identify the breakpoints $t'_1,\ldots\ldots t'_m$ resulting from the minimization the objective function over all partitions with $t_j - t_{j-1} \geq n_h \geq k$:

$$(t'_1,\ldots\ldots t'_m) = \operatorname*{argmin}_{1\leq t\leq m} RSS \qquad (2)\ .$$

Solutions to obtain global minimization of the objective function in (2) are computationally burdensome for all $m > 2$ (even in the hypothesis to have a reasonable sample of size n). The order of the grid search would be $O(n^m)$. Hence, hierarchical algorithms have to be applied to do recursive portioning or joining sub-samples. Segment sizes are determined with $h \times n$ observations, where h is a bandwidth parameter chosen to include 15% (h =0.15) of observation n within each segment. However, it is possible to selected another trimming value to refine the analysis. Some examples of such applications can be found both in Bai (1997) and Sullivan (2002). Nonetheless, such algorithms will not necessarily find the solutions in terms of global minimizers. Otherwise, applying an approach in dynamic programming of order $O(n^2)$ for each m time a change occurs is much easier to implement. Bai and Perron (2003) calculate a dynamic algorithm fit for pure and partial structural change models within an Ordinary Least Squares (OLS) regression context. Such a proposal is able to obtain an optimal time-segmentation by the recursive solution of the problem following the Bellman's principle (1952), wherein the stochastic event is analyzed by adopting a recursive calculation strategy where each obtained result is applied to the determination of the subsequent one. Hence, in achieving the optimal segmentation the algorithm is derived from:

$$RSS\ (T_{m,n}) = \min_{mn_h \leq t \leq n-n_h} [RSS\ (T_{m-1,t}) + rss\ (t + 1, n)]\ .$$

The same procedure applied for *RSS* can be implemented for the Schwarz Bayesian Information Criterion (*BIC* or *SIC* by various authors) (Schwarz, 1978):

$$BIC = \ln\left(\frac{\sum_{t=1}^{n} \varepsilon_t^2}{n}\right) + \frac{p \ln(n)}{n} \quad .$$

Thus, it is possible to count on fitting criteria to evaluate multi-breakpoint detection procedure.

Finally, as far as treatment and possible outliers are concerned, no specific formal theoretical evaluation is conducted both to detect and model them. Outlier analysis within intervention models framework is a common econometric technique to analyze special events. Usually such procedures are implemented through iterative calculations for the case of changes in conditions occurring at unknown points of times. Nevertheless, proper cautions are needed with regard to the appropriateness of the general model specification and the inherent possibilities for over specification in the number of outliers (Box et al., 2016). Generally consisting in specific adjustments, whatsoever modeling technique -even if correctly applied- could be evaluated by critics as an artificial adjustment to induce or emphasize specific results.

3. Data, empirical results and discussion

Yearly and monthly WTI quotations data in their nominal prices are processed in the present work. Despite its argued traditional regionalization (Weiner, 1991), for depicting the unified worldwide oil price/market, WTI price is a world benchmark (Kuck and Schweikert, 2017, Ghassan and Alhajhoj, 2016, Chevallier and Ielpo, 2013 and Kaufman and Ullman, 2009). For what concerns longitudinal data, yearly prices cover the period 1861-2017, and are retrieved from Quandl (2018). Monthly quotations cover a more recent period from 1986:01 to 2018:05, and are gathered from Datastream (2018). Periods are not exactly overlapping because the attempt wishes to test the procedure in a long-term and a medium-term context as well. Additionally, it is not possible to find monthly figures starting from 1861. The longer monthly WTI price series is available from 1986 onwards. Considering the present work as an explorative one, it must pointed out that different time frequencies could also be selected for dedicated research needs.

Processing the series with trimming parameters equal to h = 0.15 and h = 0.10, we obtain the following results resumed in Table 1 (where yellow cells indicate the minimum *BIC* for various m + 1 partitions).

Table 1- Optimal partition with BIC and RSS

	Yearly (1861-2017)		Monthly (1986:01-2018:05)	
m (*h* = 0.15)	*BIC*	*RSS*	*BIC*	*RSS*
0	1,425	79,267	3,756	345,008
1	1,305	34,454	3,252	91,429
2	1,286	28,548	3,216	80,908
3	1,296	28,517	3,190	73,331
4	1,306	28,506	3,201	73,277
5	1,316	28,502	3,215	73,580
m (*h* = 0.10)	*BIC*	*RSS*	*BIC*	*RSS*
0	1,483	109,210	3,756	345,008
1	1,438	76,696	3,252	91,429
2	1,396	55,069	3,090	58,585
3	1,383	47,502	2,973	41,982
4	1,369	40,850	2,939	37,307
5	1,374	39,562	2,905	33,197
6	1,384	39,475	2,914	32,944
7	1,394	39,399	2,923	32,657
8	1,404	39,325	2,935	32,648
9	1,414	39,325	3,004	37,815

Source: Personal elaboration on Datastream (2018) and Quandl (2018)

Corresponding graphical representations are portrayed in Figures from 1 to 4. The identification of multiple breaks is preferred by adopting the *BIC* criterion. *RSS* does not coincide, but we prefer the *BIC*.

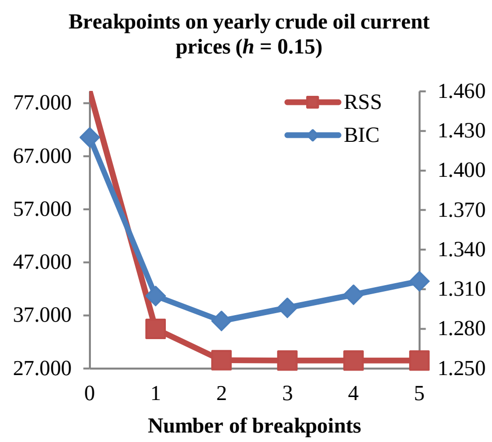

Fig. 1- Breakpoint detection within yearly WTI nominal prices (*h* =0.15)
Source: Personal elaborations on Quandl (2018)

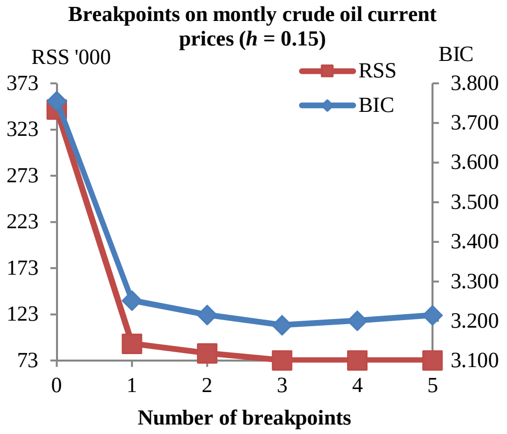

Fig. 2- Breakpoint detection within monthly WTI nominal prices (*h* = 0.15)
Source: Personal elaborations on Datastream (2018)

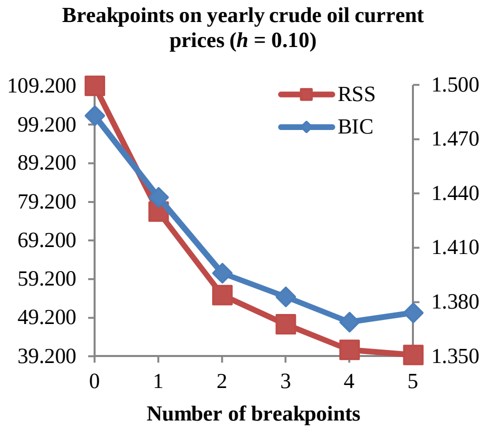

Fig. 3- Breakpoint detection within yearly WTI nominal prices (*h* = 0.10)
Source: Personal elaborations on Datastream (2018)

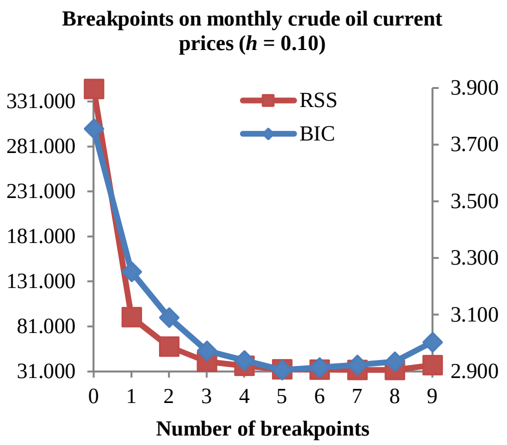

Fig. 4- Breakpoint detection within monthly WTI nominal prices (*h* = 0.10)
Source: Personal elaborations on Datastream (2018)

In the following Table 2 the exact identification of breakpoints is summarized, and in Fig. 5 to 8 are visually indicated by arrows.

Table 2- Identification of breakpoints

m (*h* = 0.15)	Yearly (1861-2017)	*m* (*h* = 0.15)	Monthly (1986:01-2018:05)
2	1970	3	1999 (11)
	1993		2005 (6)
			2013 (7)
m (*h* = 0.10)	Yearly (1861-2017)	*m* (*h* = 0.10)	Monthly (1986:01-2018:05)
4	1877	5	1999 (11)
	1972		2004 (7)
	1987		2007 (9)
	2002		2010 (12)
			2014 (11)

Source: Personal elaboration on Datastream (2018) and Quandl (2018)

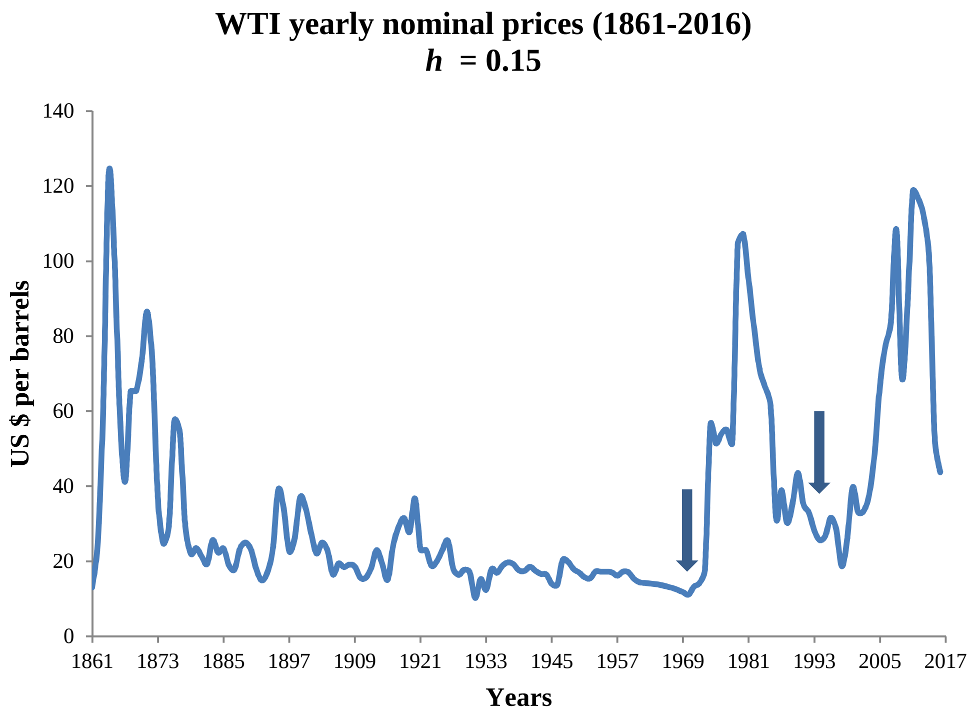

Fig. 5- Breakpoint visual identification within yearly WTI nominal prices (*h* = 0.15)
Source: Personal elaborations on Quandl (2018)

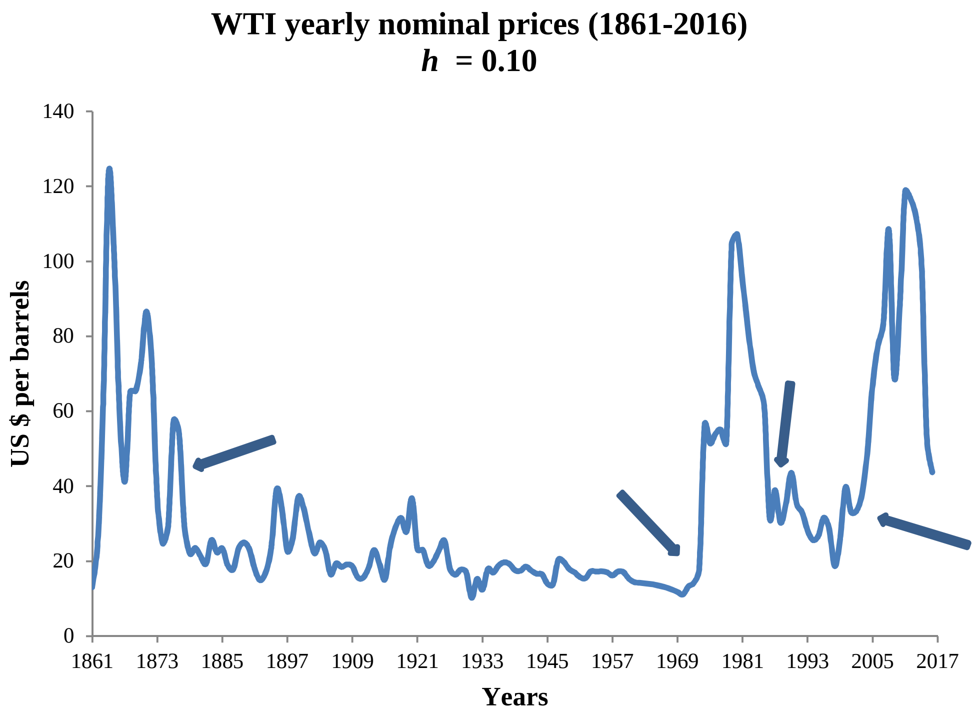

Fig. 6- Breakpoint visual identification within yearly WTI nominal prices (*h* = 0.10)
Source: Personal elaborations on Quandl (2018)

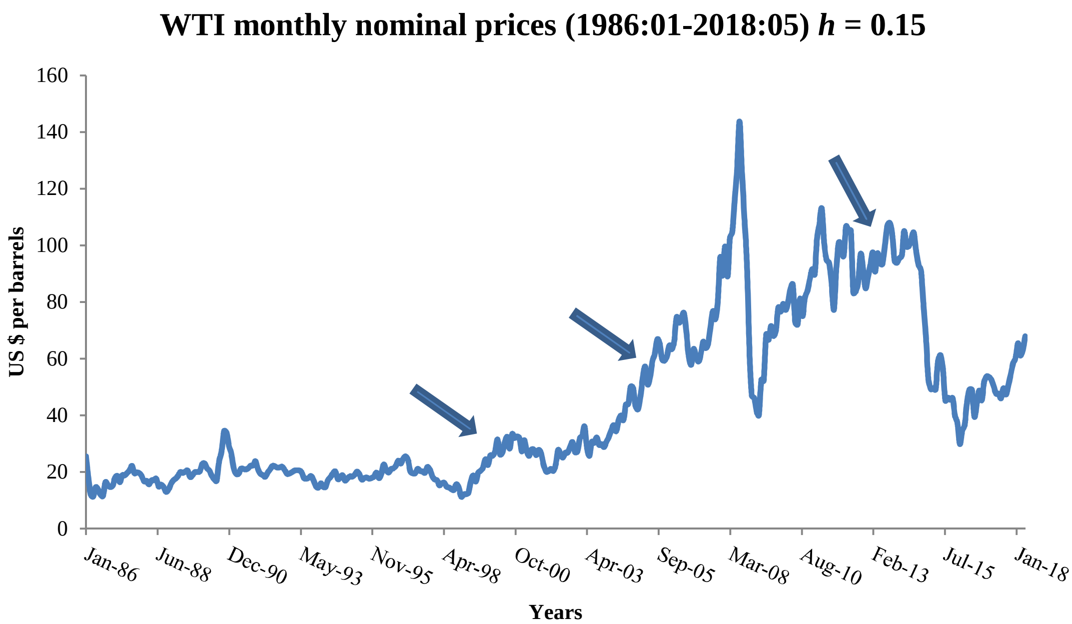

Fig. 7- Breakpoint visual identification within monthly WTI nominal prices (*h* = 0.15)
Source: Personal elaborations on Datastream (2018)

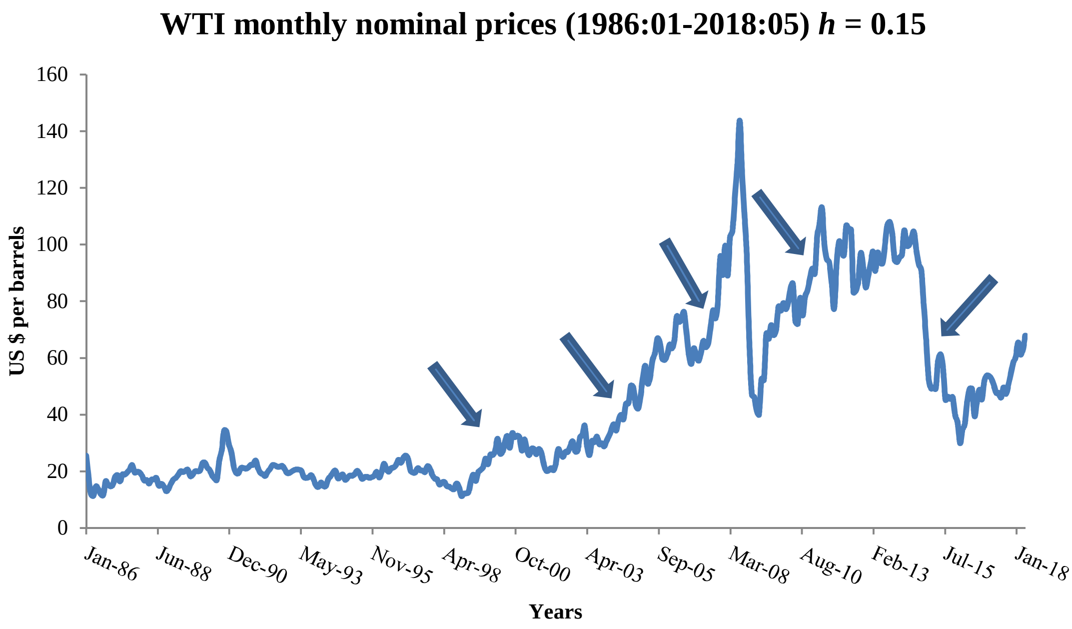

Fig. 8- Breakpoint visual identification within monthly WTI nominal prices (*h* = 0.10)
Source: Personal elaborations on Datastream (2018)

The first thing to note is that -as could be reasonable to expect- the lower the window trimmer *h* the higher the number of structural changes detected. Such an outcome is coherent with the fact that algorithm is forced to fine-tuning the process more times within its recursive procedure. This is resolved through a higher number of segments and partitions. Another feature to point out is that the longer the time series analyzed the lower is the overall precision of the whole calculation. As a matter of fact, only 2 and 4 statistical meaningful breakpoints are detected respectively with *h* = 0.15 and *h* = 0.10 in the 1861-2017 yearly time-frame. In the monthly series 3 (for *h* = 0.15) and 5 (for *h* = 0.10) breakpoints are present. Further to calculation, as previously stated, the main goal of the work is to understand the ability of the method to help researcher in highlighting statistical price movements coherent with historical facts exerting a relevant driving effect on recorded quotations. In pursuing such a task, we firstly analyze yearly elaborations. Chronological real oil facts to check are taken from BP (2017) and McGuire (2015). Interested readers can easily verify on their own.

The yearly analysis of breakpoints with *h* = 0.15 identifies only two relevant points. The first (1970) is not well-focused considering that the main event occurred in 1973 with the Yom Kippur war, as it well recognized also in economic literature. Also the second in 1993 is subsequent, and hence quite not well defined, to the 1990 Iraqi invasion of Kuwait. As far as the more fine-tuned yearly analysis with h = 0.10 is concerned, we found four points. The 1877 is coherent with Rockefeller's Standard Oil Company market dominance position (more than 95% of all refineries in the USA). The 1972 is just preceding the Yom Kippur war. The third point in 1987 is quite important considering that Saudi Arabia decides to regain its share of the global market by increasing production in the face of crashing prices. The OPEC leader went from 3.8 million barrel a day in 1985 to more than 10 million barrels a day in 1986. This behavior has surely affected crude quotations through market demand-supply balance interplay. The last point, identified in 2002, is located beyond the September 11st 2001 Twin Towers event that characterized a period with a great concern about the stability of Middle East's production because of subsequent invasion of Iraq.

For what concerns the medium-term analysis (1986-2018) analyzing monthly quotations, it is possible to note the followings. For the h = 0.15 derived values, the first identified change in statistical properties is dated in 1999:11. Obviously even if not on a monthly exact/corresponding basis, this is recorded by chronological sources as a perceived crucial moment in oil market due to the end of the 1997 financial crises for the Far East Tigers (Indonesia, South Korea and Thailand) and the inherent oil demand resurge. The second point located in 2004:7 is quite close to the mid-2000s, where the combination of declining production and soaring of Asian demand forced prices to peak. The subsequent 2007:9 point -also in this case not exactly centered- can be (widely) encompassed in the global financial international 2008 crisis period. The fourth point located in 2010:12 can be coupled with the riots and protests from the so called "Arab Spring" and the Libyan civil war. Finally, the last individuated break point in 2014:11 may be coupled with the oil prices crash due to the contemporary high crude production from USA and Russia jointly with OPEC's November decision to maintain the rate of production.

Overall, as it is reasonable to expect, a long-term analysis is more hard to compel with a general fitting statistical model. Considering the presence of unit roots in the series (even if not formally proved for brevity reasons, a visual inspection can be of easy help in the right perception), it is much better to adopt a more frequent trimming window. As a matter of fact, outcomes calculated by h = 0.10 are more significant than corresponding by h = 0.15. Also the monthly derived structural breakpoints follow such considerations crediting the more frequent parameter.

4. Conclusions

From previous discussion, we can get some insights about the proposed methodology implemented in the case of WTI oil prices. The applied method seem have good potential for further empirical investigations within (but not with limitation to) economics of commodity markets analysis. In the case of oil monthly data and selecting the more frequent trimming windows it can be possible to get a certain effectiveness in identifying periods where statistical properties of the series change in a meaningful manner. These points fit with an acceptable correspondence with real events. The main pros lie in the fact that intervention models techniques (usually) follow the inverse track. In fact in these cases the researcher must count on proper knowledge and sensibility to analyze data. A whatsoever degree of gained experience and judgement has to be put into practice. Such needs could be considered as issues in empirical econometric investigation of longitudinal data. Through the proposed method the very opposite holds, and a reverse path is to follow. Structural breaks are endogenously derived and, at this point, the research could feedback to the chronological events in order to understand their relevance in the analysis.. We do not affirm that this approach is necessarily the best track, but surely widening the opportunities, it should act in helping research work from a complementary perspective.

References

Adams, Z. and Glück, T., 2015. Financialization in commodity markets: a passing trend or the new normal ? Journal of Banking & Finance 60, 93-111.

Bai, J. (1997). Estimation of a change point in multiple regression models. The Review of Economic and Statistics 79 (4), 551-563.

Bai, J. and Perron, P., 1998. Estimating and testing linear models with multiple structural changes. Econometrica 66 (1), 47-78.

Bai, J. and Perron, P., 2003. Computation and analysis of multiple structural change models. Journal of Applied Econometrics 18 (1), 1-22.

Banerjee, A., Lumsdaine, R.L. and Stock, J.H., 1992. Recursive and sequential tests of the unit root and trend break hypothesis : theory and international evidence. Journal of Business and Economic Statistics 10 (3), 271-287.

Bellman, R., 1952. On the theory of dynamic programming. Proceedings of the National Academy of Science USA 38 (8), 716-719.

Box, G.E.P, Jenkins, G.M., Reinsel, G.C. and Ljung, G.M., 2016. Time Series Analysis-Forecasting and Control 5th ed. Wiley, Hoboken, USA.

BP, 2017. BP Statistical Review of World Energy June 2017, p.20.

Brown, R.L., Durbin, J. and Evans, J.M., 1975. Techniques for testing the constancy of regression relationships over time. Journal of the Royal Statistical Society, Series B (Methodological) 37 (2), 149-192.

Chevallier, J. and Ielpo, F., 2013. The economics of commodity markets. Wiley, Chichester.

Chow, G.C., 1960. Tests of equality between sets of coefficients in two linear regressions. Econometrica 28 (3), 591-605.

Clemente, J., Montañes, A. and Reyes, M., 1998. Testing for a unit root in variables with a double change in mean. Economic Letters 59 (2), 175-182.

Datastream, 2018. Accessed in May 2018.

Galeano, P. and Wied, D., 2014. Multiple break detection in the correlation structure of random variable.

Ghassan, H.B. and Alhajoj, H.R., 2016. Long run dynamic volatilities between OPEC and non-OPEC crude oil prices. Applied Energy 169, 384-394.

Kaufman, R.K. and Ullman, B., 2009. Oil price speculation, and fundamental: interpreting causal relations among spot and futures prices. Energy Economics 31 (4), 550-558.

Kuck, K. and Schweikert, K., 2017. A Markov regime-switching model of crude oil market integration. Journal of Commodity Markets 6, 16-31.

Lee, J. and Strazicich, M.C., 2003. Minimum Lagrange multiplier unit root test with two structural breaks. Review of Economics and Statistics 85 (4), 1082-1089.

Lumsdaine, R. L. and Papell, D.H., 1997. Multiple trend breaks and the unit root hypothesis. Review of Economics and Statistics 79 (2), 212-218.

Lütkepohl,H., Saikkonen, P. and Trenkler, C., 2004. Testing for the cointegrating rank of a VAR process with level shift at unknown time. Econometrica 72 (2), 647-662.

McGuire, A., 2015. 25 important events in crude oil price history since 1862. July 22, 2015. Wallstreetexaminer.com.

Mayer, H., Rathgeber, A. and Wanner, M., 2017. Financialization of metal markets:does futures trading influence spot prices and volatility ? Resources Policy 53, 300-316.

Ohara, H.I., 1999. A unit root test with multiple trend breaks: a theory and application to US and Japanese macroeconomic time series. The Japanese Economic Review 50 (3), 266-290.

Papell, D.H. and Prodan, R., 2003. The uncertain unit root in US real GDP: evidence with restricted and unrestricted structural change. Journal of Money, Credit and Banking 36 (3), 423-427.

Perron, P., 1997. Further evidence on breaking trend functions in macroeconomic variables. Journal of Econometrics 80 (2), 355-385.

Quandl, 2018. Accessed in May 2018.

Schwarz, G., 1978. Estimating the dimension of a model. The Annals of Statistics 6 (2), 461-464.

Sullivan, J.H., 2002. Estimating the locations of multiple change points in the mean. Computational Statistics 17 (2), 289-296.

Weiner, R.J., 1991. Is the world oil market “one great pool”? Energy Journal 12 (3), 95-107.

Zeileis, A., Leisch, F., Hornik, K. and Kleiber, C., 2002. Strucchange: an R package for testing structural change in linear regression models. Journal of Statistical Software 7 (2), 1-38.

Zeileis, A., Kleiber, C., Krämer, W. and Hornik, K., 2003. Testing and dating of structural changes in practice. Computational Statistics & Data Analysis 44 (1-2), 109-123.

Zivot, E. and Andrews, D.W.K., 1992. Further evidence on the great crash, the oil-price shock and the unit root hypothesis. Journal of Business and Economic Statistics 10 (3), 251-270.