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Decoupling and recoupling in the crude oil price benchmarks: An investigation of similarity patterns

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A B S T R A C T

COVID or Ukrainian War is a shock to detect decoupling and recoupling food prices

The aim of this paper is to investigate the decoupling and recoupling of WTI and Brent prices also with respect to the debate on the regionalisation-globalisation of the two oil markets.To this purpose, we employ the Dynamic Time Warping (DTW) algorithm to identify decoupling events between the two crude oil price series. DTW has been employed for classification and clustering aims in many fields, but in this paper we make a slightly different application of DTW with respect to those provided by the literature, demonstrating how DTW can be employed also to investigate the decoupling between the two oil benchmarks. Our analysis reveals that the two oil benchmarks decouple and recouple according to WTI local market conditions. Therefore, we found evidence that WTI-Brent market is not fully integrated at all times. We also propose two DTW-based indexes: Relative-Alignment Index (RAI) and Warping Index. The first confirms that the greatest decoupling between WTI and Brent occurs because of WTI local market conditions and is useful in highlighting the main decoupling between our crude oil series over time, while the second provides information on the time window of crude oil price decoupling. Lastly, we provide some policy implications based on our results.

1. Introduction

A growing interest in oil market literature focuses on the dynamics of the prices of the two oil benchmarks, West Texas Intermediate[1] (WTI) and Brent.[2] Some scholars studying the two oil price dynamics found evidence that they have been historically tracked very closely (see e.g. Chen et al. (2015), Caro et al. (2020), Klein (2018), Caporin et al. (2019) and Zhang et al. (2019)). Indeed, the equilibrium between the two benchmarks requires a premium for WTI over Brent to take into account the higher quality of WTI and the cost of shipping Brent across the Atlantic(see e.g. Kao and Wan (2012)). Most of the literature has argued that the two oil benchmarks have historically moved in tandem according to this equilibrium relationship.[3] However, as stated by Caporin et al. (2019) and by U.S. Energy Information Administration (2013), this equilibrium relationship has been broken in early 2011. Since then, the price trend has reversed and the WTI has started to be exchanged for a large discount at Brent. This price decoupling could be an indication that the two markets are not fully integrated at all times.

The proximity of prices and their convergence to their long term pattern is always associated with a globalised market. In a globalised (aka integrated) market, supply and demand shocks affecting the price of crude oil in one region shift to other markets, so the main consequence is that prices of crude oils of the same quality in different regions move together and this proximity hinders arbitrage opportunities. On the other hand, the regionalisation hypothesis is just the opposite. In a regionalised (aka fragmented) market, regional supply and demand shocks, together with changes in local market conditions, may affect the price of crude oil in one region, but do not necessarily lead to changes in oil prices in other markets. Therefore, prices of same quality

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[1] WTI is the crude oil price benchmark for oil extracted in the United States (Caporin et al. (2019)). WTI is delivered at Cushing (Oklahoma) which is also the most important supply hub, since it connects crude oils supplies to the refineries located in the Gulf Coast. It is traded on the New York Mercantile Exchange (NYMEX). WTI has an API gravity (measure of the density) of 39.6° and a sulphur content of 0.24% Fattouh (2010).

[2] Brent is the main crude oil price benchmark for Europe. It is extracted in the North Sea and made up of four blends (Brent, Forties, Oseberg and Ekofisk). Brent is traded on the Intercontinental Exchange (ICE) and it is delivered at Sullom Voe. Furthermore, two third of the world's global traded crude oils are priced-off Brent. Brent has an API gravity of 38.6° and a sulphur content of 0.37% Fattouh (2010).

[3] WTI traded at a premium over Brent with the price difference oscillating around ±3 USD per barrel, see e.g. Caporin et al. (2019).

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crudes may deviate substantially from each other (see e.g. Gülen (1997) and Fattouh (2010)).

In this paper we investigate the decoupling and recoupling between the two main crude oil reference prices, namely WTI and Brent. In particular, in our work we focus on the identification of decoupling and recoupling between the two oil benchmarks, arguing that when these events occur due to the impact of local conditions on prices, then this suggests that the two markets are not always fully integrated. However, since a globalised market can be compatible with some periods of decoupling and prices may temporarily diverge as long as they converge towards their long-term pattern over time, our findings fit into this debate, but do not provide conclusive evidence.

Decoupling and recoupling periods are identified by capturing the time-varying characteristics of the crude oil price series through the so-called Dynamic Time Warping (DTW).

DTW is the name of a class of algorithms used to measure similarity between two time series which may vary in time or speed. The rationale behind DTW is to stretch or compress two time series locally in order to make their shape as similar as possible, see e.g. Tormene et al. (2009); Lawrence Rabiner and Juang (1993); Giorgino (2009); Keogh and Pazzani (2000); Keogh and Ratanamahatana (2011).

DTW has been used for classification and clustering objectives in many sectors, (see e.g. Giorgino (2009)), but in our paper we show that DTW can also be successfully used to investigate the decoupling between the two oil benchmarks, Brent and WTI. This problem is not really part of the classification/clustering tasks, but actually represents a slightly different application of DTW compared to the ones provided by the literature. See Section 4 for further details.

Despite the advantages of DTW, there is no literature, to the best of our knowledge, in the analysis of crude oil price decoupling exploiting this mathematical tool. In our work we make use of DTW since this method can contribute to the existing literature by providing new evidence regarding the dynamics of Brent and WTI prices. Compared to the related literature on the dynamics of WTI and Brent prices, our work is the first and above all different from a methodological point of view. In fact, most studies have sought a long-term relationship using vector autoregression analysis on the WTI-Brent spread, while our work is directly based on prices. To make the relationship with the methods used in literature clearer, Table 1 summarises and organises the related literature, indicating both the methodological approach used in each paper and the differences with our approach.

Furthermore, in our paper, we propose two DTW-based indexes, that we call respectively Relative-Alignment Index (RAI) and Warping Index. The first confirms that the greatest decoupling between WTI and Brent occurs because of WTI local market conditions and is useful in highlighting the main decoupling between our crude oil series over time. On the other hand, the second index provides information on the time window of crude oil price decoupling.

Our aim is to contribute to the existing literature on WTI and Brent prices by analysing their decoupling over time.

More precisely, using the DTW algorithm we investigate:

1. whether the two oil benchmarks have been decoupled in response to both geopolitical tensions and local WTI market conditions;
2. whether local WTI market conditions play a decisive role in decoupling from the Brent price;
3. whether the frequent decoupling of WTI price from Brent price makes the WTI an unreliable benchmark;
4. which crude oil drives the decoupling during the time frame considered.

In particular, we identify, through the DTW, the main decoupling between the two price series over time and this allows us to identify the associated historical events. The most relevant contributions of our research are the following:

- the greatest decoupling between the two crude oil benchmarks corresponds to the increase in shale oil production at the beginning of 2011. In fact, problems in US oil transportation infrastructure have led to difficulties in moving crude oil from Cushing (Oklahoma)[4] to the refineries in the Gulf Coast, generating an oil glut that depreciated WTI compared to Brent (see e.g. Büyükşahin et al. (2013));
- The decoupling of WTI from Brent depends on local WTI market conditions and, as local conditions have become prevailing, we have found evidence that the two oil markets are not fully integrated at all times;
- the recoupling of the two crude oil benchmarks is in the period 2014–2017, when infrastructure problems in the WTI market are starting to decrease, thus providing further evidence that the impact of WTI's local market conditions is primarily responsible for decoupling from Brent;
- the stronger impact of local WTI market conditions led us to conclude that WTI cannot be considered a reliable benchmark, as it reflects a more local than global supply condition;
- the warping path associated with WTI and Brent shows that WTI precedes Brent in the period of the greatest decoupling, thus confirming that the impact of local market conditions on the price of WTI determines decoupling from Brent. On the other hand, Brent precedes WTI in the last part of the sample, with the exception of recoupling period.

The remainder of this article is structured as follows. Section 2 introduces the related literature review on the dynamics of WTI and Brent prices. Section 3 presents the data and the summary statistics for the daily WTI and Brent prices. Section 4 is devoted to the description of the tools we employ in our analysis, while Section 5 discusses the results. In addition, Section 6 provides conclusions and some policy implications based on our results.

2. Literature review

In this section we review the main literature about the dynamics of WTI and Brent prices also with respect to the debate on the globalisation-regionalisation of the oil market.

As we have already said, there are no papers that have applied the DTW algorithm in the study of crude oil price decoupling. We use this algorithm in our work as it can provide new insights into the dynamics of WTI and Brent prices.

Furthermore, our work focuses on prices, arguing that price decoupling is an indication that the WTI and Brent markets are not fully integrated (globalised) at all times. In fact, a globalised oil market is admitted if the prices of crudes of similar quality from different regions do not deviate from each other, whereas a regionalised oil market is exactly the opposite. We note that for the market to be regionalised, price decoupling have to take place because of specific local market conditions (see e.g. Weiner (1991) and Gülen (1997)). However, it is important to recall that a globalised oil market can be compatible with some periods of decoupling and that prices can diverge as long as over time they converge to their long term pattern.

In the context of WTI and Brent price dynamics, Chen et al. (2015) have focused their attention on the detection of a structural change in the persistence of WTI-Brent spread and define this structural change as a shift from a stationary to a non stationary process. They have found evidence of this structural change in 2010, i.e. in the period of the surge in shale oil production. Also, Büyükşahin et al. (2013) have focused on the dynamics of WTI and Brent prices. More in detail, the authors tried to identify the set of variables with a predictive power on the behaviour of the WTI-Brent spread. Their results showed that the

[4] Cushing is a storage location and also the delivery point for the Nymex light sweet crude oil contract (U.S. Energy Information Administration (2013))

Table 1
Broad classification of the considered related literature concerning the dynamics of WTI and Brent prices also with respect to the debate on the globalisation-regionalisation of the oil market.

Authors	Data	Methods	Main findings	Differences
Bravo et al. (2020)	Weekly prices of WTI and Brent	FCVAR	Globalisation	Parametric model
Chen et al. (2015)	Monthly and Daily prices of WTI and Brent	Persistence change test	Change in persistence in 2010	
Caporin et al. (2019)	Monthly prices of WTI and Brent	VECM	Long-run relationship until 2011	Parametric model. Indicated for linear dependencies
Fattouh (2010)	Weekly prices of Nigerian light, Algerian Blend, Mexican Maya, Canadian Blend, WTI, Brent and Dubai's Fateh	TAR model	Globalisation	Parametric model
Ji and Fan (2015)	Daily prices of WTI, Brent, Dubai, Tapis and Bonny	VECM	Long-run relationship in the period 2000–2010. After 2010, WTI lost the role of price setter	Parametric model. Indicated for linear dependencies
Büyükşahin et al. (2013)	Daily prices of WTI,Brent and LLS	Chow test and ARDL model	Structural break in 2008 and in 2010. Predictive power of physical variables and financial variables on WTI-Brent spread	
Liao et al. (2014)	Weekly prices of WTI and Brent	QUR-SB	Structural break in 2010	Parametric model
Zhang et al. (2019)	Weekly prices of WTI,Brent,Tapis, Bonny,Daqing and Minas	SVAR	Globalisation	Parametric model. Indicated for linear dependencies.
Klein (2018)	Daily and futures prices of WTI and Brent	BEKK framework	Influence of OPEC meetings on WTI and Brent price correlation	Parametric model

physical variables, such as storage condition in Cushing, Oklahoma, and long positions of Commodity Index Traders (CITs) in WTI and Brent futures helped to predict the WTI-Brent spread.

Fattouh (2010) analysed the dynamics of crude oil price spreads by means of a Two-regime Autoregressive Threshold (TAR) process and unit root tests. In particular, the author analysed the dynamics of crude oils price spreads for crudes of same quality (both light crude oils) and different quality (light and sour crude oils) and also for crudes for which an oil paper market does exist. He found evidence for a globalised oil market but in a wide sense. Actually, the results of the unit root tests suggested that the oil market is globalised since the spreads are found to be stationary. However, the TAR results suggested the presence of a threshold in the adjustment process to the long-run equilibrium. More in detail, the price spread for crudes which have a paper contract have no threshold effect and the process is stationary, but the other price spreads show an adjustment towards a stationary process when a certain threshold is exceeded.

In this regard, Liao et al. (2014) analysed the dynamics of the price spread between WTI and Brent by means of a Quantile Unit Root with Structural Breaks (QUR-SB) approach. The authors used the monthly price spread and found evidence of structural break in the spread around 2010. Besides, their main results suggest that the oil market is globalised.

Another paper that investigated the dynamic of WTI and Brent prices is the one by Caporin et al. (2019). To this purpose, the authors analysed the presence of a long-run relationship between WTI and Brent after the shale oil supply shock using a Vector Error Correction Model (VECM) and generalised impulse response functions. Their findings showed the presence of a long run relationship until 2011, then the long-run relationship between the two prices broke down. Klein (2018) employed a multivariate BEKK framework in the analysis of WTI and Brent price dynamics and found that OPEC meetings increase the correlation between WTI and Brent in the short-run. Furthermore, he found that the dynamics of long-term trends between WTI and Brent are similar and this suggests a globalised oil market.

Ji and Fan (2015) studied the dynamics of crude oil price spread using daily prices of WTI, Brent, Tapis and Dubai collected from Thomson Reuters Datastream. These crude oil prices are representative benchmarks for America, Europe, Middle East, Africa and Asia Pacific. The analysis was carried out using a Vector Error Correction Model (VECM) combined with a Direct Acyclic Graph (DAG) technique. Their results support the evidence of a long-run relationship between the crude oil markets in the period 2000–2010. At the end of 2010, the dynamic of WTI price started to be separated from that of other crude oil prices.

According to Ji and Fan (2015), the WTI was the leader in pricing until 2010, while Brent took over the role of WTI starting from 2011.

The dynamics of WTI and Brent prices has once again been addressed by Caro et al. (2020) who exploited a Fractionally Cointegrated Vector Autoregressive (FCVAR) approach to allow different degree of globalisation in the WTI-Brent market. The authors used weekly prices of Brent and WTI. They found evidence for a high globalised oil market, where Brent drives the price instead of WTI. The globalisation hypothesis was also supported by the study of Zhang et al. (2019). He used a Structural Vector Autoregression Model (SVAR) and connectedness measures based on the Forecast Error Variance Decomposition (FEVD) and found evidence that regional oil prices are highly integrated.

As far as our work is concerned, we analyse this issue from another perspective, i.e. analysing the decoupling of the price series using DTW algorithm.

3. Data and preliminary statistics

3.1. Data

In this paper, we exploit the daily closing price of WTI and Brent crude oils, downloaded from the Energy Information Administration (EIA) website.[5] The sample period of daily prices of Brent and WTI spans over 12 years, from May 2007 to September 2019 for a total of 3085 observations.

3.2. Descriptive statistics

Before proceeding with the results of descriptive statistics, let us have a graphical inspection of the time series plot over the sample period. Fig. 1 shows the time series plot of daily prices of WTI and Brent. The daily Brent price series is higher than the daily WTI series during the period 2010–2014, thus denoting an increase in the daily price of Brent with respect to WTI. In addition, both Brent and WTI experienced a decline in the price level in 2014. After 2014, the levels of both prices

[5] www.eia.gov

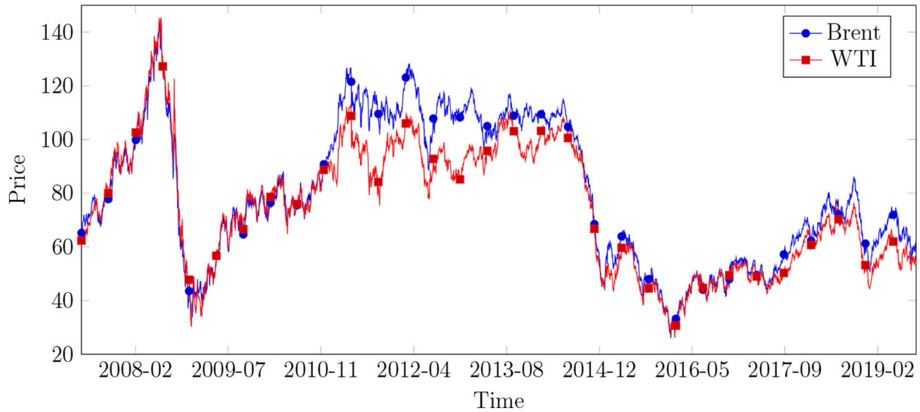

Fig. 1. Time series plot of WTI and Brent daily prices.

are lower than the one of pre-2014. The reasons for this drop in prices are to be found in Saudi Arabia's decision not to cut crude oil production in the presence of oversupply, Mănescu and Nuño (2015). The highest daily price was reached for both series in 2008 and then both fell sharply in 2009. The sharp drop in oil prices in 2009 was caused by a drop in demand that that exceeded the drop in supply (see e.g. U.S. Energy Information Administration (2011)).

In Table 2 the descriptive statistics of WTI and Brent daily prices are shown. The series of daily prices are positively skewed, platokurtic and clearly non-normal according to the value of the Jarque-Bera test statistic. The mean and the standard deviation of daily Brent price are higher than those of daily WTI price.

In order to test the stationarity of our series, we execute some standard unit root tests on our data. The first test employed is the Augmented Dickey Fuller (ADF) test. The ADF test was proposed by Dickey and Fuller (1979) and it is able to investigate the presence of a unit root allowing for an higher degree of autocorrelation. The second test is a non-parametric test (PP) proposed by Phillips and Perron in Phillips and Perron (1988). The null hypothesis for both the ADF test and the PP test is that the series contains a unit root against the alternative hypothesis of stationarity. As a third test, we execute the Kwiatkowsky, Phillips, Schmidt and Shin (KPSS) test proposed by Kwiatkowski et al. (1992). In the KPSS test the system of hypothesis is inverted. Actually the null hypothesis is that the series is stationary against the alternative hypothesis that the series contains a unit root.The results of the ADF test, the PP test and the KPSS test for the WTI and Brent daily prices show that our data do not provide sufficient evidences against the rejection of the hypothesis of a unit root in the series. The stationarity tests reported in this section are not necessary for the DTW algorithm to work. We report stationarity tests in order to have a complete picture, through the descriptive statistics, of the two series of oil prices. Indeed, the DTW technique is not an estimate but a deterministic algorithm, so it does not require the series to be stationary. Stationarity of the series is often required to have a reliable estimate of the parameters in the time series model. On the other hand, DTW is a data mining technique based on distance calculation that reveals how one time series is connected to another. The rationale behind DTW is to lengthen or compress two time series locally in order to make their shape as similar as possible.

Besides we evaluated the Ljung-Box portamanteau statistics which indicate that there is temporal dependence in the daily series of WTI and Brent prices. All this results are reported in Table 3.

4. Methodology

In our paper we show that DTW can be successfully used to investigate the decoupling between the two oil benchmarks, Brent and WTI. It represents a slightly different application of DTW compared to the ones provided by the literature.

The ability to successfully apply this algorithm to our problem derives from two considerations: (a) we have two time series (the ones of WTI and Brent) that are fully comparable because the data are recorded on the same days; (b) it is stated in most of the literature that the two prices have historically moved in tandem, therefore the decoupling events are very few compared to the entire time span of the data set. This translates into an a priori knowledge that the time distortion is limited. On the other hand, as highlighted e.g. Klein (2018) and as will be clearer in what follows, there may be some delay between WTI and Brent markets, which results in these small time distortions. Thanks to considerations (a) and (b), DTW:

- can be considered a method to detect the misalignment points between the two time series corresponding to the desired decoupling points;
- is suitable for investigating whether a pattern appears first in one time series rather than the other, thus it can provide a measure of the latency difference between two time series. In our case this is suitable to understand which series is leading the decoupling from the other one. if latency is found, how to leverage in prediction
- is a non-parametric technique that works directly on price data;
- is able to detect misalignment points also in the presence of non-linear variations between the two series.

There is a small number of papers that use DTW algorithms in financial applications. One of this is the paper by Wang et al. (2012), where DTW is used to analyse the topology of similarity networks among 35 major currencies in international foreign exchange (FX) markets using the minimal spanning tree approach. They list the advantages of the

Table 2
Descriptive statistics of WTI and Brent daily prices.

	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	Jarque-Bera
DBrent	80.27001	26.20717	26.01	143.95	0.09205417	−1.212356	189.42***
DWTI	79.92385	23.25983	26.19	145.31	0.1439574	−0.813607	93.72***

*,** and *** denote the rejections of null hypothesis at 10%, 5% and 1% significance level. The result of the Jarque-Bera test highlights that the null hypothesis of normal distribution is rejected at 1% significance level.

Table 3
Descriptive statistics of WTI and Brent daily prices.

	ADF constant	ADF trend	PP constant	PP trend	KPSS constant	KPSS Trend	Ljung-Box
DBrent	−1.6498	−2.0526	−1.66	−2.06866	7.8042	2.966	3021***
DWTI	−1.7819	−2.4389	−1.8087	−2.4672	9.5776	2.0837	3015.4***

*,** and *** denote the rejections of null hypothesis at 10%, 5% and 1% significance level. The results of the unit root tests highlight that there are no sufficient evidences to reject the null hypothesis of a unit root in the series. The result of the Ljung-Box test highlights that the null hypothesis of no serial correlation is rejected at 1% significance level.

DTW algorithm over the Pearson's correlation coefficient, i.e., non-linearity, time series of different lengths, robustness to outliers, out of phase series.

Another work is by Tsinaslanidis and Kugiumtzis (2014), which used DTW to find similar historical subsequences of the series and made predictions through the mappings of the most similar subsequences. The latter are assessed on simulated paths, and these paths are the composition of stochastic trend and chaotic deterministic time series. Let us remark that the existence of both paradigm "stochastic and chaotic" in commodity prices has been advocated also in some recent papers, see e.g. Mastroeni et al. (2019, 2018); Mastroeni and Vellucci (2020).

Juszczuk et al. (2019) and Tsinaslanidis et al. (2014) remarked the importance of using the DTW as a similarity measure. In particular, Tsinaslanidis et al. (2014) stated the helpfulness of this method when the series differ in lengths. In addition, they integrated the DTW measure into Spearman's and Pearson's coefficient in order to highlight the importance of DTW in giving a non-linear similarity measure. The authors also emphasised the importance of the DTW algorithm for similarity comparison between months with different trading days allowing a method for establishing the existence of a calendar effect. Moreover, they evidenced the benefit of DTW algorithm in the study of market seasonalities.

Other applications of DTW in economics and finance include the following: Berndt and Clifford (1994) used DTW technique for pattern detection; Raihan (2017) proposed an application of DTW to the prediction of recessions of both 1999 and 2007 in U.S. using Treasury term spread data.

4.1. Rationale and motivations

Dynamic time warping (DTW) is the name of a class of algorithms to reveal how much a time series is connected with another one. The rationale behind DTW is to stretch or compress two time series locally, in order to make their shape as similar as possible, Tormene et al. (2009); Lawrence Rabiner and Juang (1993); Giorgino (2009); Keogh and Pazzani (2000); Keogh and Ratanamahatana (2011). The distance between them is computed by summing the distances of individual aligned elements, Fig. 2.

After being introduced around 1970 in the context of speech recognition, it has been employed for classification and clustering aims in a plenty domains, Giorgino (2009). In this paper we have a slightly different situation, and in the discussion below we will see how DTW can be successfully employed also to investigate the decoupling between the two oil benchmarks, Brent and WTI.

First of all, we have two time series that are fully comparable because we collected the data in the same days. Since the days of the two time series correspond, why not simply calculate an Euclidean distance between them? As recalled by Keogh and Pazzani (2000), the reason why Euclidean distance may fail to produce an intuitively correct measure of similarity between the two oil benchmarks under investigation, is because it is very sensitive to small distortions in the time axis. Let us consider Fig. 2. The two simulated times series have approximately the same overall shape, but the shapes are not aligned in the time axis. The nonlinear alignment (shown in red on the same picture) would allow a more sophisticated distance measure to be calculated. Since, as highlighted e.g. by Klein (2018), there could be some delay between WTI and Brent markets, DTW can therefore be considered a method for achieving such alignments.

Let us consider two times series $\mathbf{x} = (x_1,\ldots,x_N)$ and $\mathbf{y} = (y_1,\ldots,y_M)$, respectively, where N and M are their respective lengths (by the way, in our problem $N = M$). They are defined as the "query" and the "reference" series in the DTW jargon. The total distance between $\mathbf{x}$ and $\mathbf{y}$ is computed through the so called "warping path", which ensures that each data point of the query is compared to the "closest" data point of the reference. As we will see below, in the subsection containing the technical details of the method, alignment is a global property of the time series, that is, it does not depend only on the value at a particular time t but also on those in the subsequent and previous ones. Because it is, obviously, the global optimum on all possible paths.

Moreover, as far as the algorithm is concerned, and as introduced in the Introduction and Section 2, it is assumed that the decoupling events are very few compared to the entire time span of the data set and this results in the a priori knowledge that the time distortion is limited.

When, as in our framework, DTW works with two time series that (almost) perfectly overlap for long periods of time, in these areas they substantially do not contribute to the alignment (i.e. to the cumulative

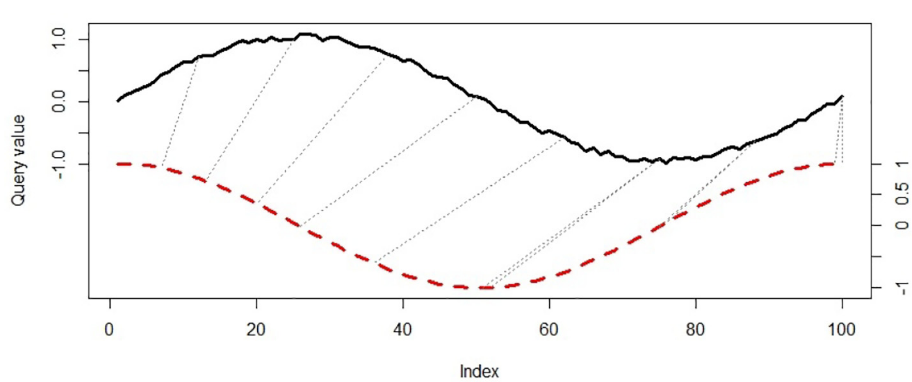

Fig. 2. Dynamic time warping distance. A simple example of aligning two time series. A query (solid) and a reference (dashed).

distance). Since there is a one-to-one correspondence in the sampling times of both time series, the DTW algorithm search the time of the series **x** optimally matching to the time of the series **y**. That is, if it finds that day 10 of **x** matches to day 10 of **y**, day 11 of **x** matches to day 11 of **y** and so on, this results in a diagonal warping path. So this time correspondence makes the warping path very close to the true diagonal, unless we are in a decoupling point.

On the other hand, since we know that for much of the time span, the difference between the price levels of the two benchmarks is low and that only in a few regions decoupling occurs, the DTW algorithm will stretch and compress the patterns locally in those regions, so that they are as similar to each other as possible.

Based on the process that produces the warping path, Zoumpoulaki et al. (2015) suggest that its distance from the diagonal provides a reliable measure of the direction of latency differences between two time series. A positive distance, which results from the warping path being below the diagonal, indicates that the reference time series (WTI in our case), used for alignment, precedes the query time series (Brent in our case), while a negative one indicates that the reference time series follows the query. This simple fact measures whether a pattern appears earlier in reference than in query and can be interpreted as a measure of causality (e.g. if reference precedes query, then it also drives query). Let us remark that, as recalled by Li et al. (2015), if two series are not similar in shape, it is not correct to use this concept to indicate causality. But this is not the case addressed in our paper, just see Fig. 1.

4.2. The warping path area

Let

$$
\begin{aligned}
&p_t = \left(p_{t,x}, p_{t,y}\right)\\
&p_{t,x} \in \{1, \ldots, N\}\\
&p_{t,y} \in \{1, \ldots, M\}
\end{aligned}
\tag{1}
$$

be the optimal warping path and let $p_{t,\,x}$, $p_{t,\,y}$ their components along x and y-axes.

A *window* is a global constraint which explicitly forbids warping curves to enter some region of the (i,j) plane. For example, according to the well-known Sakoe-Chiba band (Sakoe and Chiba (1978)), the displacement between warping path components is bounded above by a maximum permitted time deviation i.e.

$$
\left|p_{t,x} - p_{t,y}\right| \leq R \tag{2}
$$

where R is the window size. It results in an a-priori knowledge that time distortion is limited, see e.g. Giorgino (2009).

Let us introduce a new index, that we call *Warping Index*, based on the fact that Sakoe-Chiba band works well when $N \sim M$ and our problem fits this requirement.

The measurement proposed in this subsection is based on the area between the warping path and the main diagonal of the Distance Matrix D, under a Sakoe-Chiba additional constraint (2). Let us denote this area by $\mathcal{A}$. Let $N = M$ be the lengths of both time series. Then the maximum Sakoe-Chiba area (see Fig. 3) is given by the formula $R(2N - R)$. Hence, we can define the Warping Index as follows:

$$
i_w := \frac{\mathcal{A}}{R(2N-R)}. \tag{3}
$$

Index i_w gives us the maximum measure of the deviation of the warping path, so that we could quantify the area outside the diagonal in relation to the lawful band R. It explains how much it was necessary for the DTW algorithm to warp the times, in order to make one time series as similar to the other as possible.

In Section 5 we will see that, for $R = 10$, the value of i_w is equal to 0.234, which we will deemed under the light of decoupling events.

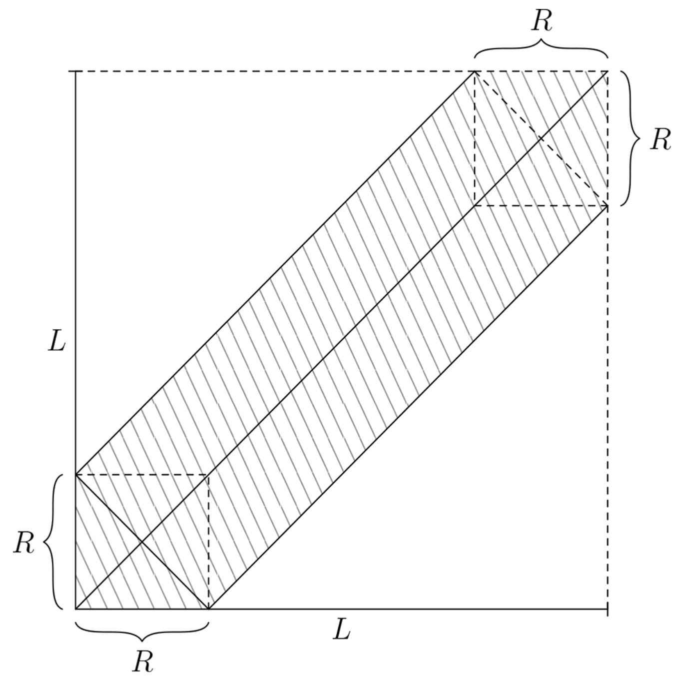

Fig. 3. Maximum possible area under warping curve for a Sakoe-Chiba constraint of width R.

4.3. DTW relative-alignment index

Following the study of Tsinaslanidis et al. (2014), in this section we propose a new Index, that we call Relative-Alignment Index (RAI), to evaluate the alignment per year between the time series. It takes values in the interval $[0, 1]$, where 0 means that the two series are perfectly aligned and 1 means that the series are perfectly misaligned.

In order to explain RAI, we need to define some previous notions. Let P be the optimal warping path and $\Delta(P)$ be the length of the segment obtained intersecting a line parallel to the column of the distance matrix with the warping path P and the diagonal of the distance matrix.

We define T the total sample period for our observations, i.e. the period spanning from 2007 to 2019 and with T_i the sub-sample for the observations in the i-th year. For example $T_1 = [2008, 2009]$, $T_2 = [2009, 2010]$ and so on. Now, we call P_T the warping path referred to the total sample period and P_{T_i} the warping path referred to the sub-sample for i-th year observations. Therefore we can define the Relative-Alignment Index (RAI) in the following way:

YH: Δ(P) will be calculated at each time point; T_i defines the sub-sample window, including a set of time points.

$$
\mathbb{I}_{P_{T_i}} = \mathbb{E}\left[\frac{\Delta(P_{T_i})}{\max(\Delta(P_T))}\right] \tag{4}
$$

I_{P_{T_i}} is an average of Δ(P) over time T_i

Let us introduce now a threshold $\mathbb{I}_{P_T}$ that will play a crucial role to our aims. The threshold is defined as the Relative-Alignment Index evaluated over the total sample period. If it happens that

$$
\mathbb{I}_{P_{T_i}} < \mathbb{I}_{P_T} \tag{5}
$$

then it follows that the time series are aligned in the i-th year, otherwise they are not.

It can be noted that this type of alignment measure is relative in the sense that it depends on the threshold that is strongly related by the type of series considered. The value of the threshold in the interval $[0, 1]$ can be seen as a measure of the goodness of our series, which means a good alignment between time series. A high value of the threshold $\mathbb{I}_{P_T}$ indicates that overall the series are misaligned. This happens when the $\mathbb{I}_{P_{T_i}}$ is greater than the threshold and the series are more misaligned in the i-th year than their overall misalignment.

5. Results

In this section our aim is to give economic meaning to our findings by taking into account the relationship between the two oil benchmarks and the historical period. Figs. 5 and 6 show the results of this section. They have been built as follows.

We considered two time series x, for Brent, and y, for WTI. As a general rule, we assume the convention that the first argument and indices refer to Brent time series (the query), and the second to WTI (the reference). DTW starts aligning the oil series by building the Distance matrix D, whose dimension is $N \times N$ (N is the length of both oil series) and the (i^{th}, j^{th}) component contains the Euclidean distance between the two points x_i (i-th Brent observation) and y_j (j-th WTI observation), defined by Eq. (A.1).

In particular, each element (i,j) of the Distance matrix D corresponds to the alignment between the two points considered. The Warping Path (WP), depicted in Fig. 5 (on the left), is a contiguous set of the entries of the Distance matrix D that defines the alignment between Brent and WTI series. More precisely, a valid path is a sequence of elements $P = \{p_1, \ldots, p_T\}$ with $p_t = (i,j)_t$, $t \in \{1, \ldots, T\}$ and $T \in [N, 2N+1]$, denoting the positions in the distance matrix D that satisfies the conditions outlined in Section 4. There are several WPs that satisfy these conditions, but our interest is on the path which minimizes warping costs, as described by Eq. (A.2). The resulting WP is the blue line in Fig. 5 (on the left), which may be above or below the red line representing the highest achievable similarity. Fig. 5 (on the right) and Fig. 6 show instead the distance between the WP thus obtained and the diagonal line, for time. More formally, if $p_t = (t, p_{t,y})$ is the optimal warping path and t represents the time, then this distance is represented by $p_{t,y} - t$.

Fig. 5 shows the main decoupling periods between WTI and Brent prices. The right hand picture of Fig.5 has been enlarged and annotated in Fig. 6, to focus attention on the links between decoupling points and the most relevant events in energy markets. It is important to specify that the decoupling of prices shown in Fig. 6 have different magnitude. The magnitude for any price decoupling is represented by the warping path that is far from the diagonal. Therefore, the greater the distance from the diagonal, the greater the decoupling between the two prices. A formal hypothesis could be the absence of a decoupling between the prices when the warping path is very close to the diagonal, as for example the recoupling of prices shown in Fig. 6 in the period 2014–2017. Moreover, we also applied the DTW algorithm on a longer dataset from January 1996 to September 2019. Applying DTW on a longer dataset shows that the two series are close to the diagonal until 2007. This confirms the evidence that, before 2007, the decoupling periods were few and had a smaller magnitude. More in detail, the greatest

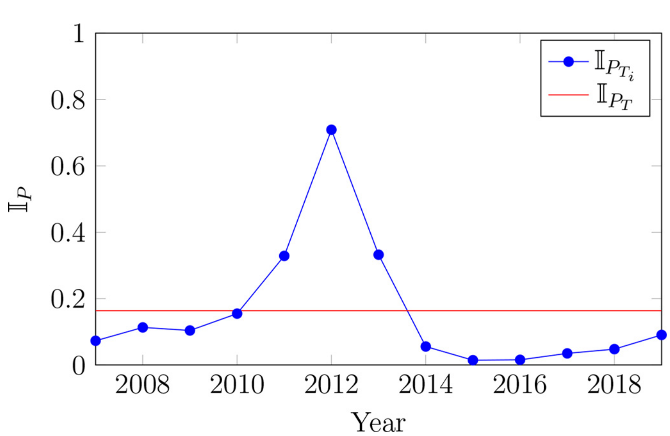

Fig. 4. Relative similarity index $\mathbb{I}_{P_{T_i}}$ during the period 2007–2019 (threshold =0.163).

decoupling occurred between 11/05/11–11/05/13. This evidence is also supported by the value and the graphical representation of the Relative-Alignment Index, shown in Fig. 4 respectively. The others decoupling are observed in the following periods:

- 11/05/07–11/05/08;
- 11/05/09–11/05/10;
- 11/05/13–11/05/14;
- 11/05/2017–11/05/2018;
- 11/05/2018–11/05/2019.

The daily prices recouple in the period 11/05/14–11/05/17. As we discussed earlier, DTW stretches and compresses the time series locally to make them as similar as possible. Therefore, if the series were aligned on the diagonal (which means there's a great similarity between the crude oil prices), there would be evidence of two highly integrated markets at all times. The position of the misalignment on the diagonal is also informative about which series is conducting the decoupling. Decoupling may be below or above the diagonal depending on which series is considered as the reference series. In our case, the reference series is WTI while the query series is Brent, therefore the decoupling below (above) the diagonal is driven by WTI (Brent).

Let us now give our explanation for the events that led to the decoupling of the two benchmarks. Most of these events are linked to the local conditions in the WTI market, but also the geopolitical and the financial conditions have to be taken into account. The first decoupling, in Fig.6(a), is observed in the period 11/05/07–11/05/08. It was related to problems in WTI crude oil infrastructures. Indeed, difficulties arose in moving crude oil from to the refineries in the Gulf Coast, generating an oil glut that depreciated WTI compared to Brent (see e.g. Büyükşahin et al., 2013).

The other decoupling, in Fig. 6(b)-(c), happened in the periods 11/05/09–11/05/10 and 11/05/11–11/05/13. These decouplings have several explanations but the most relevant is the impact of shale production on the WTI market.

As it is well known, the type of shale oil is light, has a low sulphur content and is contained in formations known as shales. The extraction of shale oil is not an easy task, but the increase in the oil prices in 1970s has contributed to the research on horizontal drilling and fracking techniques to facilitate its extraction (see e.g. Mănescu and Nuño (2015)). The growth in shale oil production has had a huge impact on the entire oil market and led to a widening in the spread between WTI and the other international crude oil price benchmarks. The oil flow from North Dakota, Texas and Canada was moved to Cushing (Oklahoma) where the reduced pipelines' capacity hindered the transportation of crude oil to the refineries in the Gulf Coast (see e.g. Liu et al. (2015)). This event generated an excess of oil that depreciated the WTI compared to Brent, in fact the former started to be traded at a discount of 16 dollars on the latter, Mănescu and Nuño (2015).

In fact, there was a logistical problem in the pipeline positions because they were able to transport crude oil production from the Gulf Coast refineries inland, but not vice versa, Kilian (2016). The reason for this logistical problem was that, prior to the increase in shale oil production, the United States was a net importer of crude oil and the refineries were located near the import regions.

In addition to the surge in shale oil, the Tunisian revolution in December 2010, the Libyan crisis in February 2011 and the Fukushima nuclear disaster led to an increase in the price of Brent and other seaborne crudes (see e.g. Büyükşahin et al. (2013)).

Bahgat (2012) highlights how the Arab Spring has created uncertainty in the global crude oil supply. Indeed, it is a fact that the global economy depends on crude oil and gas supplies from the Middle East.

These geopolitical tensions have generated an upward trend in the price of Brent, Büyükşahin et al. (2013).

Fig.6(d) shows also that in the period of the greatest decoupling, i.e. 2011–2013, the prices recoupled temporarily because of the announcement of the reversal of the Seaway pipeline in May 2012. This

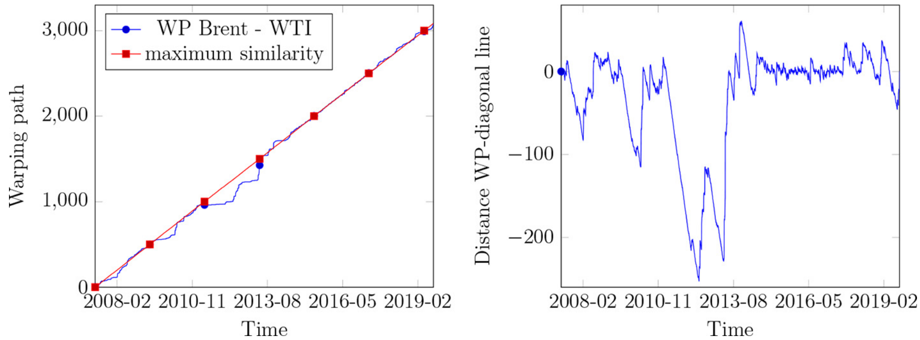

Fig. 5. Optimal path for daily prices of WTI and Brent and optimal path vs the perfect similarity path in red.

infrastructure operation should have relieved the oil glut by facilitating the transportation of crude oil to the refineries. However, due the fact that the reversal would have taken months longer than previously established, WTI price, compared to Brent, was again depressed (U.S. Energy Information Administration (2012)). As can be seen in Fig.6(e), the planning of new pipelines constructions recoupled the prices in the period 2014–2017.

The improvement of the oil infrastructure and the increase in Cushing's capacity have put upward pressure on the price of the WTI. In addition, the completion of other oil pipelines and rail projects has allowed the shipment of oil from North Dakota to the Gulf Coast refineries. Thus the replacement of Brent crude oil has turned into downward pressure on its price. The mitigating effect of the transport difficulties was twofold: upward pressure on the WTI price and downward pressure on Brent due to the replacement of this crude oil by WTI (U.S. Energy Information Administration (2013)).

Moreover, the abolition of export restrictions in 2015 contributed to an increase in US crude oil exports and a decrease in Brent imports. In particular, the US increased exports of refined products to Europe and Latin America, leading to a recoupling of WTI and Brent prices (see e.g. Kilian (2016)).

It is important to recall that, as argued by Kilian (2016), the abolition of export restrictions in the early years of the surge in oil shale production would not have been able to increase the price of WTI and recouple

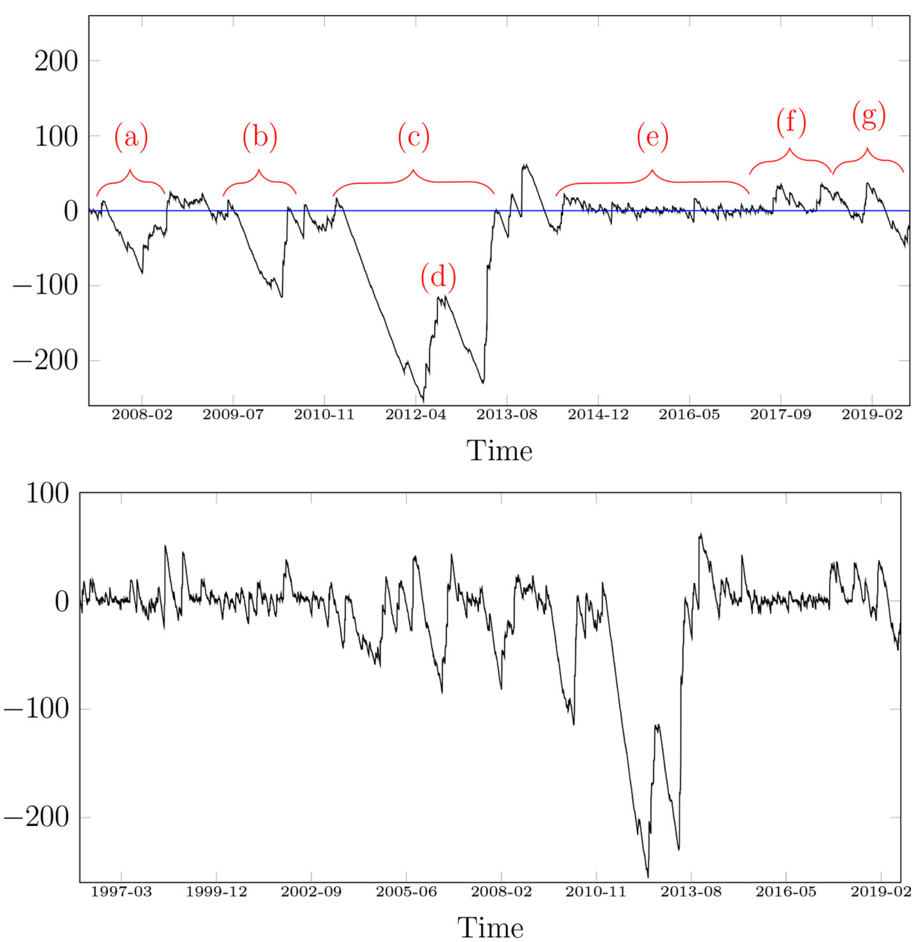

Fig. 6. Distance between WP and diagonal line with reference to the most relevant events (up); same distance referred to an extended sample (down).

WTI and Brent, as the lack of transport capacity was a problem to manage large crude oil exports. Thus, the improvement of the crude oil infrastructure started in 2014 and the abolition of export restrictions in 2015 allowed the two prices to recouple in the years 2014–2017.

From a financial point of view, some events contributed to the decoupling of the two crude oil prices. Particular attention should be paid to changes in the weight of WTI and Brent in the S & P GSCI commodity index. In January 2011, in fact, the weight of Brent increased compared to that of WTI. In addition, the weight of WTI was subsequently reduced in January 2012 and, during the same period, Brent was also included for the first time in the Dow-Jones DJ-USB commodity index (see e.g. Büyükşahin et al. (2013)).

From a practical point of view, the GSCI and DJ-UBS are key indicators for investments in commodity index funds (see e.g. Büyükşahin et al. (2013)). According to Singleton (2014), changes in the weight of the commodity index funds may have contributed to the increase in the price difference of crude oil.

Finally, it can be said that the pipeline problems in the WTI market, the change in the weight of the commodity index funds in favour of Brent crude oil and the Arab Spring contributed to the decoupling of the two benchmarks in the years 2010–2013. However, since the decoupling shown by the warping path is below the diagonal, the local WTI market condition is primarily responsible for decoupling from Brent.

Fig. 6(f)-(g) shows also that the two prices decouple in the following periods: 11/05/2017–11/05/2018 and 11/05/2018–11/05/2019. These decoupling are mainly due to upward trends in the price of Brent. Indeed, a pipeline outage in the North Sea, during December 2017, generated an increase in the price of Brent (U.S. Energy Information Administration (2018)).

Furthermore, the increase in the price of Brent has also been caused by the cut in crude oil production by OPEC and non-OPEC countries together with growing global demand. OPEC and non-OPEC countries have also decided to continue production cuts in 2018, and Saudi Arabia (OPEC) and Russia (non-OPEC) will also monitor actual compliance with production targets, see e.g. U.S. Energy Information Administration (2018).

Indeed, these decisions have created a tightening of international crude oil supply conditions with the exception of the United States and have contributed to the upward trend in the price of Brent crude. The price of Brent also benefits from supply cuts in OPEC countries, Iran and Venezuela. In addition, the contamination of the Druzhba crude oil pipeline in Russia has also led to an increase in the price of Brent due to its substitutability with disrupted Russian crude oil barrels, U.S. Energy Information Administration (2019). However, although the downward trend in the WTI price is present due to oversupply, these decouplings are above the diagonal, so the query series precedes the reference series and therefore the Brent price drives decoupling from the WTI.

Since WTI and Brent are reference prices for the other crudes traded on the market, we expect that changes between these crude prices appear in a time window of few days. In support of this evidence, Klein (2018) found equal trends between WTI and Brent in a time window of three trading days. This allows us to apply the Warping Index, defined by Eq. (3), with a Sakoe-Chiba band around 10 days, i.e. by setting $R = 10$. We computed this index obtaining the value $i_w = 0.234$. This explains that, in order to make both shapes of oils prices as similar as possible, it was necessary to warp the times for 23.4% of the maximum what we had expected. In other words, it provides information on the time window of crude oil price decoupling, which corresponds to approximately 2 days.

interesting explanation when window restriction is used in DTW

6. Conclusions and policy implications

This paper investigates the decoupling and recoupling of WTI and Brent prices also with respect to the debate on the globalisation-regionalisation of the two oil markets using the Dynamic Time Warping algorithm. In particular, we identify, through the DTW, the main decoupling between the two price series over time and this allows us to identify the associated historical events.

We also propose two DTW-based indexes: Relative-Alignment Index (RAI) and Warping Index. The first, that helps us to understand how the alignment per year of our series changes over time, confirms that the greatest decoupling between WTI and Brent occurs because of WTI local market conditions. It is useful in highlighting the main decoupling between our crude oil series over time. On the other hand, the second index provides information on the time window of crude oil price decoupling.

Our findings suggest that the main decoupling between the two price series is due to WTI local market conditions and thus our results provide evidence of a temporary decoupling between WTI and Brent prices which may suggest that the oil market is not fully integrated at all times. In fact, local conditions in the WTI market have a negative impact on its price. Moreover, since the largest decoupling is found during the surge in shale oil production and is below the diagonal, the WTI price is the driver of decoupling from Brent. In the last part of the sample, the price of Brent is increasing due to cuts in oil production by OPEC and non-OPEC countries and Brent precedes WTI. The strict response of the WTI price to local conditions provides evidence that the two markets are not fully integrated at all times. More specifically, these local conditions are the main reasons why most of the literature argues that WTI can no longer be considered an efficient oil price benchmark in the United States of America (see e.g. Kao and Wan (2012)- Fattouh (2007)- Fattouh (2011)). We point out that our results fit into the debate on globalisation-regionalisation, but we do not provide any reliable evidence of this since a globalised market may be compatible with some periods of decoupling and prices may temporarily diverge, provided that over time they converge towards their long-term pattern. Unfortunately, on the basis of the proposed methodology, it is not possible to carry out a statistical test to deduce with a degree of confidence whether or not the oil market is globalised for a sufficiently long period of time, since DTW is a deterministic algorithm and evaluates how much the series are aligned from time to time by working on distances.

The usefulness of our method derives from the ability to understand short-term movements in oil prices. In fact, one of the greatest advantages of the method is the understanding of which series is driving the decoupling from the other one. In addition, another advantage of our study is the use of daily data. Indeed, as can be seen from Table 1, most studies of crude oil price dynamics have used monthly or weekly data, and only a few of them use sample data on a daily basis. The use of daily observations is an advantage because it provides more information on price dynamics.

Some policy implications can be derived from our results. A first one is that our results may be useful for short term policy decisions. Indeed, as supply conditions are the main responsible for the decoupling of WTI from Brent, one could argue that in a condition of excess of supply (excess of demand), governments should favour exports (imports) in order to eliminate the excess of supply (excess of demand) and drive up (lower) prices. This policy would be able to recouple crude oil prices if prices are flexible enough and if there are no export barriers. A second policy implication can be derived from the method's ability to understand which series is driving the decoupling from the other. As can be seen in Fig. 6, the main decoupling between the two oil benchmarks is mainly due to the bottlenecks in the Cushing infrastructure and driven by the WTI price, since the warping path lies below the diagonal. Therefore, the fact that the WTI price suffers a Brent discount due to local supply conditions implies its unreliability as a benchmark for the United States, as also argued by Fattouh (2011). Indeed, as highlighted by Kaufmann and Ullman (2009), an oil benchmark is the first to react to changes in global supply and towards which other crude oils' prices are balanced. Therefore, the weight of local conditions on the price of the WTI hinders its reliability as a benchmark.

However, in the last part of the sample it is Brent that drives the decoupling from the WTI. Since the latency difference between two time series is a measure of the fact that a pattern appears first in one series compared to the other, then the fact that a pattern appears first in

Brent compared to WTI suggests that it is the Brent price dynamics that deviates from WTI.

The need for a global oil benchmark is discussed also by Brigida (2014). According to Brigida (2014), the correct definition of a global oil benchmark, which has the ability to represent the global demand and supply conditions, has important implications for firms related to the oil business and for policy makers to define energy policies.

Moreover, the depreciation trend of the WTI compared to Brent is a measure of how competitive the US is in the market. This means that US refiners' profits are positively influenced by the lower price of WTI, as they can buy crude oil benchmarked off WTI and sell refined products that are benchmarked to Brent, Scheitrum et al. (2018).

In addition, Janzen and Nye (2013) underlines how a lower price of WTI is important for those countries exporting crude oil into the United States. Indeed, since the reference price for these crude oil exports is the WTI, the countries concerned have a negative impact on their investments.

A third policy implication concerns the possibility of arbitrage between the two crudes because the markets are not fully integrated at all times. However, since the difference between prices should be greater than transaction costs, due to the fact that crude oils are located in different regions, then arbitrage opportunities may not be exploited and the market would be inefficient and unable to recover prices (see e.g. Gülen (1997)).

A fourth policy implication concerns the role of Brent as a global oil benchmark, since two thirds of the world's traded crude oil is priced-off Brent. We have found that only a decoupling is due to a pipeline disruption in the Brent market, so Brent crude oil is less affected by the dislocation problem in the WTI market. In 2013, the stability of the Brent price led the U.S. Energy Information Administration to consider Brent instead of WTI as the reference spot price. This decision was motivated by WTI dislocation problems, Scheitrum et al. (2018). However, although Brent has proven to be a more stable benchmark than WTI, the problems of declining production in the North Sea and the inclusion of lower grades crudes in the definition of Brent undermine its role as a benchmark (see e.g. Scheitrum et al. (2018)).

The results of the DTW algorithm in Fig. 6 helps us to answer to an open question left by Ji and Fan (2015). The question is whether the decoupling of the two benchmark is transitory or permanent. According to the economic interpretation of the results in Fig.6, we found that the greatest decoupling between the two oil benchmarks depends on WTI local conditions. For instance, the oil gluts at Cushing in 2008 and 2010 caused the WTI to be treated at a large discount to Brent. Furthermore, in the last part of the sample, geopolitical tensions due to the production cuts of OPEC and non-OPEC countries generated an upward trend in the price of Brent. These decisions have created a tightening of international crude oil supply conditions, with the exception of the United States, and have contributed to the upward trend in the price of Brent crude. We can theorise that these events, which have occurred since 2011, have set the conditions for the decoupling of the two oil benchmarks that will occur in subsequent years. However, we have not taken the predictive aspect into account in our framework, as the prediction of price decoupling is very complex. Its complexity also derives from the evidence that the dynamics of oil prices strongly depends on the geopolitical situation. Prediction on price decoupling could be the topic of future research.

Appendix A: The Dynamic Time Warping

This section is devoted to the detailed description of the dynamic time warping. Let us consider two time series $\mathbf{x} = (x_1,\ldots,x_N)$ and $\mathbf{y} = (y_1,\ldots,y_M)$ where the lengths N and M are not necessarily equal. As a general rule, we assume the convention that the first argument and indices refer to the query time series, and the second to the reference. DTW starts aligning these two series by building the Distance matrix D, whose dimension is $N \times M$ and the (i^{th}, j^{th}) component contains the Euclidean distance between the two points x_i and y_j, defined as follows

$$d\left(x_i, y_j\right) = \left(x_i - y_j\right)^2, \quad i \in \{1,\ldots,N\} \quad \text{and} \quad j \in \{1,\ldots,M\}. \tag{A.1}$$

In particular, each element (i,j) of the Distance matrix D corresponds to the alignment between the two points considered. The warping path (WP) is a contiguous set of the entries of the Distance matrix D that defines the alignment between the time series $\mathbf{x}$ and $\mathbf{y}$. More precisely, a valid path is a sequence of elements $P = \{p_1,\ldots,p_T\}$ with $p_t = (i,j)_t$, $t \in \{1,\ldots,T\}$ and $T \in [\max(N,M),\ N+M+1]$, denoting the positions in the distance matrix D that satisfies the following conditions:

- *boundary conditions*: the first index of the time series $\mathbf{x}$ must be matched with the first index from the time series $\mathbf{y}$, ensuring that $p_1 = (1,1)$ and $p_T = (N,M)$;
- *continuity*: the path advance one step at a time, both i and j can only increase by one on each step along the path;
- *monotonicity*: the path will not turn back on itself, both i and j indexes either stay the same or increase, they never decrease.

The last two conditions ensure that the path can move along three different directions: up, right, up and right with respect the current position in D. That is $p_t - p_{t-1} \in \{(1,0),(0,1),(1,1)\}$. There are several WPs that satisfy these conditions, but our interest is on that path which minimise the warping cost

$$DTW(\mathbf{x},\mathbf{y}) = \min_P \left(\frac{1}{T}\sum_{t=1}^{T} d(p_t)\right) \tag{A.2}$$

The optimal path P is usually found using dynamic programming approach, see Giorgino (2009); Keogh and Pazzani (2000); Keogh and Ratanamahatana (2011).

The sequences are non-linearly aligned in time by DTW algorithm, in order to determine a measure of their similarity regardless of certain non-linear variations in the time dimension.

Before using DTW algorithm, time series involved in the process are usually z-normalised. Z-normalisation is used to adjust time series amplitude and mean (see Batista et al. (2011); Holt et al. (2007)). It consists in subtracting from the considered time series, $\mathbf{x}$ and $\mathbf{y}$, their mean and then in dividing them by their standard deviation, i.e.

$$\widehat{\mathbf{x}} = \frac{\mathbf{x} - \mathbb{E}(\mathbf{x})}{\sqrt{\mathbb{V}(\mathbf{x})}}, \quad \widehat{\mathbf{y}} = \frac{\mathbf{y} - \mathbb{E}(\mathbf{y})}{\sqrt{\mathbb{V}(\mathbf{y})}}. \tag{A.3}$$

Author contributions

All the authors provided an equal contribution to designing and carrying out the following roles: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Project administration; Resources; Software; Supervision; Validation; Visualization; Writing - original draft; Writing - review & editing.

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