Determinants of the WTI-Brent Price Spread Revisited*

Jerome Geyer-Klingeberg

(Corresponding Author)

Phone: +49 821 598 3046

Email: jerome.geyer-klingeberg@mrm.uni-augsburg.de

Andreas Rathgeber

Phone: +49 821 598 3040

Email: andreas.rathgeber@mrm.uni-augsburg.de

Authors' affiliation

Institute of Materials Resource Management
University of Augsburg
Werner-von-Siemens-Straße 6
86159 Augsburg, Germany

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Abstract

We apply autoregressive distributed lag regression (ARDL) and several methods of structural break analysis on a daily data set between 1995 and 2014 to explore various supply and demand factors as drivers of the price differential between WTI and Brent crude oil. In line with previous literature, we identify a major break in the WTI-Brent spread in December 2010. The ARDL regression reveals that the convenience yield, as a proxy for crude oil inventories, is the most important spread determinant. Moreover, also the trading activity in crude oil paper markets, shipping costs, as well as the stock market development in the US and Europe affect the size of the spread. Unlike other papers, we find that the impact of the spread determinants changed after the break in 2010. Especially, the impact of local WTI inventories as well as the influence of paper markets activity on physical trading in crude oil spot markets have gained in importance. In summary, the rising variability in the spread time series after 2010, which reflects a decoupling process of WTI and Brent, can be explained by an absolute increase in several economic determinants.

Keywords: Crude Oil, West Texas Intermediate, Brent, Convenience Yield, Structural Break

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1 Introduction

Due to its paramount importance for the global economy, crude oil is the world's most actively exchanged commodity. However, not all traded crude oil barrels are alike. There are multitudes of varieties and blends from hundreds of different oil production spots located all over the world.[1] The wide heterogeneity of crude oil grades is a challenge for a unique market price and hence also for its marketability. Thus, traders define a group of crude oil benchmarks as pricing reference. The most dominant global benchmarks for (light) crude oil are West Texas Intermediate (WTI) and North Sea Brent crude (Brent).[2] Although the quality characteristics of Brent and WTI are quite similar, WTI is a bit lighter making it more valuable for refining (Energy Intelligence Group, 2011).

The local market price of different crudes, as any other tradable good, is determined by supply and demand. If price differences between various local markets are large, demand and supply from one market may spill over to another market. This concept of market integration was first proposed by Adelman (1984) and the globalization hypothesis for global oil markets. The level of market integration depends on the interchangeability between regional markets and transaction costs (Kleit, 2001), capacities for transporting oil to the next steps in the supply chain, and the ability of suppliers to change the supply line (George and Breul, 2014). As an implication of integrated oil markets, the price of crudes with similar quality characteristics, like WTI and Brent, should manifest a co-movement, such that the price spread is more or less constant over time (Fattouh, 2010b). Fig. 1 depicts the WTI and Brent crude oil spot prices, as well as their price spread[3].

<<<INSERT FIGURE 1 HERE >>>

Until 2008, WTI and Brent prices moved closely together with a relatively constant average spread around \$1.3 per barrel. Accordingly, WTI's price historically traded at a premium against Brent, which approximately represents the transportation costs of moving oil form the North Sea to refineries along the U.S. Golf Coast (Kaminski, 2014). Between 2006 and 2010, the volatility of the WTI-Brent spread increased, which is illustrated by alternating periods with positive and negative price spreads. Since 2010, WTI and Brent decoupled resulting in an increasing discount of WTI against Brent that peaked at

[1] For example, the International Crude Oil Market Handbook (Energy Intelligence Group, 2011) lists more than 190 different crude oil streams.
[2] WTI is a blend of several American domestic crude streams with its major trading spot in Cushing, Oklahoma. Brent oil covers four crude streams pumped in the North Sea.
[3] In this paper, the WTI-Brent spread is defined as WTI spot (futures) price – Brent spot (futures) price.

a maximum spread of -$29.59 per barrel in September 2011. By the end of 2015, the disparity of the benchmark prices shrunk to about $1 per barrel. However, since the second half of 2017, WTI is again traded at a continuous discount and the spread re-widened again. Accordingly, the price gap between WTI and Brent has not yet found its equilibrium state.

The substantial volatility of the WTI-Brent spread has real economic and policy implications, as firms and governmental institutions rely on global oil benchmarks to define their business strategy and energy policy. When global markets are integrated, producers with the lowest costs provide the supply and consumers can rely on the signaling and allocation function of prices (Kleit, 2001). Otherwise, if local prices diverge and spreads are volatile, transaction costs increase and the balancing mechanism across markets diminishes (Gülen, 1999). Moreover, depending on whether oil markets are fragmented or unified, local policy interventions may have regional or global effects (Weiner, 1991). Moreover, different authors argue that the wide price spread illustrates that WTI no longer reflects the world oil supply-demand balance and thus loses its eligibility as global oil price benchmark (Bentzen, 2007; Fattouh, 2010a; Kaufmann and Ullman, 2009). In addition, abnormal WTI-Brent price differences result in revenue declines of U.S. oil producers and other oil-exporting countries, because oil imports to the U.S. are priced on the basis of WTI (Janzen and Nye, 2013). If, as a consequence, upstream oil producers lower their production levels, also the transport volumes and thus midstream sector's (esp., transport operators) earnings decrease as well. Additionally, the negative WTI-Brent price gap affects contractual agreements where WTI is the reference price and thus also the instruments used for financial risk management (Kaminski, 2014).

These implications make the examination of the WTI-Brent spread evolution to an intensively discussed topic in academic research, media, and political debates. The academic literature's focus is on the analysis of structural breaks in the WTI and Brent price time series and the cointegration among both prices (e.g., Chen et al., 2015; Fattouh, 2010b; Hammoudeh et al., 2008; Kao and Wan, 2012). In contrast, only few authors, like Büyüksahin et al. (2013) as well as Milonas and Henker (2001), examine the driving forces of crude oil price differentials, but without analyzing the impact of structural breaks on the spread determinants. This paper re-examines a broad set of supply and demand factors as drivers for the variation in the WTI-Brent price spread. Thereby, we combine the previous literature on structural break analysis and the determinants of price differentials. Based on a daily data set for the time period between 1995:01 and 2014:07, we identify structural breaks in the time series and estimate an autoregressive distributed lag (ARDL) model to analyze how the impact of the spread determinants changed. Our findings confirm a major structural breakpoint in December 2010. The most important spread determinant is the convenience yield, which is a proxy for local crude oil inventories. Also the trading activity in crude oil paper markets, shipping costs, as well as the stock market development in the US and Europe affect the size of the spread. Unlike other papers, we find that the impact of the spread determinants changed after the break in 2010. Especially, the importance of WTI inventories as explanatory factor and the influence of paper market trading on the physical spot market heavily increased after 2010. Moreover, weak evidence can be found that shipping costs are less relevant after the break. These outcomes underpin that, after 2010, the WTI-Brent spot spread is largely driven by WTI inventories and pressure from the paper markets. The increasing importance and differences in the spread determinants, as well as the amplified variability in the WTI-Brent price gap reflect the decoupling process of the two leading oil price benchmarks.

The remainder of this paper is organized as follows. In section 2, we present a brief overview of the literature. Section 3 explains the data set and the determining factors of the WTI-Brent spread, followed by the methodology outlined in Section 4. The results of the empirical analysis are presented in section 5, followed by a discussion in Section 6. Section 7 concludes.

2 Literature review

There is a wide range of literature on the integration of global crude oil markets (e.g., Gülen, 1997; Gülen, 1999; Kleit, 2001; Weiner, 1991). Especially two research streams are related to this work, which are summarized in Tab. 1.

<<<INSERT TABLE 1 HERE >>>

The first stream analyzes structural breaks in the time series of major oil price differentials. Bentzen (2007) apply Bai and Perron (1998, 2003)'s test for multiple structural breaks and document a disruption in the WTI-Brent price spread in November 1999, which is approximately the time of OPEC's policy intervention to bring prices into a target zone of $22–$28 per barrel. In contrast, Büyüksahin et al. (2013) use the Chow (1960) structural break test and identify two major structural changes in the WTI and Brent price differential in November 2008 and December 2010. Moreover, they disentangle the WTI-

Brent spread in a landlock and a transatlantic spread. Through this approach, they prove that the structural break in 2008 is due to a change in the landlock spread, while a second break in 2010 appears specific to Brent crude. The structural break in late 2010 is confirmed by several authors like Chen et al. (2015), Leybourne et al. (2007), Liu et al. (2016), as well as Ye and Karali (2016). In addition, when employing the rolling Chow test by Hansen (1997), Li et al. (2015) find a breakpoint in early 2010.

The second stream explores the determining factors of crude oil price differentials. Milonas and Henker (2001) use the convenience yield as proxy for the local availability of crude oil. Within an OLS regression framework and daily observations for the period between 1991:02 and 1996:01, the authors show that the convenience yield is a statistically significant factor for the magnitude of the price spread between WTI and Brent futures contracts with two and three months to maturity. In a further study, Bacon and Tordo (2004) conclude from an OLS regression over the period from 2003:01 through 2004:06, that price differentials among 56 different crudes can be explained by quality characteristics (gravity, sulfur content, and acidity), as well as by transport costs. Moreover, Büyüksahin et al. (2013) adopt an ARDL model to explore the predictive power of three variable groups (macroeconomic fundamentals, physical-market conditions, and financial factors) on the observed spread between nearby futures on WTI and Brent crude oil. Based on daily futures prices, but monthly macroeconomic and oil production data between 2004:04 and 2011:12, they find that the climate of the U.S. economy impacts the WTI-Brent spread level. However, the negative sign of the coefficients is often counterintuitive. Among the physical factors, storage problems in Cushing are a significant factor indicating a decreasing WTI-Brent spread when storage bottlenecks occur. Moreover, there is some evidence that greater Canadian oil shipments to the Midwest lower the spread. The spread is also driven by financial variables like the open interest, long positions of index traders, and financial crises variables. More recently, Li et al. (2015) use monthly data between 2004:01 and 2013:12 to investigate physical determinants of the WTI-Brent spread. The results of their Granger causality test reveal that Cushing's as well as Midwest's inventories drive the spread before 2010. After 2010, the Chinese demand for crude oil remains the only driving force. Overall, their explanation is strongly concentrated on the U.S. market, without providing explanation of the changes occurring in the Brent price.

Taken together, the previous literature provides evidence that the price gap between WTI and Brent is alternating over time with a major structural break in 2010. Moreover, recent publications document that several factors beyond quality differences are drivers of crude oil price differences. In this study, we extend both aforementioned streams by (i) analyzing the change in the spread determinants before and after structural break(s), (ii) investigating the transmission channel between physical and paper markets for crude oil, (iii) combining a wide set of spread determinants including new variables, which have not been examined before (e.g., extreme weather conditions in the Atlantic Ocean and North Sea), and variables that have been investigated separately (e.g. the convenience yield in Milonas and Henker (2001) and other supply and demand factors in Büyüksahin et al. (2013)).

3 Data

For the variables used in this study, we obtain daily data for the time period between January 01, 1995 and July 23, 2014. This observation period extends previous studies, like Milonas and Henker (2001), and includes more recent events in global oil markets. In contrast to previous studies, for example Büyüksahin et al. (2013), we only consider spread determinants with data available on a daily basis. Hence, we match daily observations of the WTI-Brent spread with daily data of the explanatory variables. Tab. 2 provides an overview of the variables used in this study.

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3.1 WTI-Brent price spread

We use opening spot prices for WTI crude (from Datastream) and closing spot prices of Brent oil (from Bloomberg). Through this approach, we account for the time lag of trading hours between U.S. and European markets (analogously to Milonas and Henker, 2001). We define the WTI-Brent spot spread as the WTI crude oil price P_t^{WTI} minus the Brent price P_t^{Brent}.[4] For the further analysis, we use the normalized spread SPR_t, which smooths the time series and reduces heteroscedasticity:

$$SPR_t^{Spot} = (P_t^{WTI} - P_t^{Brent})/P_t^{Brent}. \quad (1)$$

3.2 Convenience yield

Following Milonas and Henker (2001), we investigate the convenience yield as proxy for crude oil availability. This interrelation is derived from the theory of storage (among many others, Kaldor, 1939;

[4] We calculate the spread only for days with price data available for both WTI and Brent crude oil. Consequently, we remove all days that are public holidays either in the U.S. or Europe.

Working, 1927, 1949), which implies that the convenience yield is inversely related to inventories.[5] A high convenience yield indicates low storage volumes and thus a high level of supply risk. Consequently, we assume that an increase in WTI's convenience yield widens the price spread between WTI and Brent (and vice versa for Brent).

For daily estimates of the convenience yield, we follow the cost-of-carry hypothesis (Brennan, 1958). Accordingly, commodity futures prices are equal to the spot price plus the convenience yield and the cost-of-carry represented by the storage costs (e.g., tanker rates, pipeline costs, and insurance fees). In its continuous form, the cost-of-carry pricing formula of a WTI or Brent future $F_{t,T}^{\bullet}$ is given by:

$$F_{t,T}^{\bullet} = P_t^{\bullet} e^{\left(RF_{t,T} + SC_{t,T}^{\bullet} - CY_{t,T}^{\bullet}\right)(T-t)}, \tag{2}$$

where $P_t^{\bullet}$ denotes the corresponding spot price of WTI or Brent, $RF_{t,T}$ represents the risk-free interest rate from t to T, $SC_{t,T}^{\bullet}$ denotes the storage costs of WTI or Brent, and $CY_{t,T}^{\bullet}$ is the convenience yield of WTI or Brent. $T - t$ is the time to the contract's maturity. By rearranging Eq. (2), we receive the convenience yield:

$$CY_{t,T}^{\bullet} = RF_{t,T} + SC_{t,T}^{\bullet} - \frac{1}{T-t}\left\{\ln\left(F_{t,T}^{\bullet}\right) - \ln\left(P_t^{\bullet}\right)\right\}. \tag{3}$$

Convenience yields are derived from WTI and Brent crude oil futures with three months to maturity. In addition, futures contracts with six and twelve months to maturity are used for robustness analysis. Futures price data is obtained from the New York Mercantile Exchange (NYMEX) for WTI and the Intercontinental Exchange (ICE) for Brent. As risk-free rate of return, we use three months U.S. Treasury bill yields from the Federal Reserve System's website. For better comparability, discrete interest rates are transformed into continuous rates. For the storage costs, we follow Ederington et al. (2012) and assume the 'fairly common rough estimate' of \$0.40 per barrel per month. In line with Stepanek et al. (2013), storage costs are measured as logarithmic difference between the storage fee and daily spot prices. For robustness analysis, we also test inventory-dependent storage costs.

Due to the non-existence of a continuous three months futures contract, we construct a contract or respectively a convenience yield with the desired maturity. Our preferred method is an approach applied in term structure estimation of yield curves (e.g., Martellini, 2003). In the first step, we calculate the

[5] Many authors find empirical evidence for this inverse relationship for various commodities (Fama and French, 1987; Geman and Ohana, 2009; Geman and Smith, 2013; Stepanek et al., 2013).

convenience yield from the observed future prices according to Eq. (3). In the second step, we interpolate all data points (maturity and convenience yield) with the help of a cubic spline function. In the last step, we evaluate the spline function at the respective maturity. This is our preferred methodology due to the nonlinear construction of the futures price for the required maturity. As robustness test, we define and test alternative roll-over strategies.

3.3 Trading volume and open interest

As liquidity in derivatives markets might affect spot market segmentation, we follow Büyüksahin et al. (2013) and include the aggregate open interest (OI^{WTI}, OI^{Brent}) for all crude oil futures traded at NYMEX (for WTI) and ICE (for Brent). We also add the aggregate trading volume in WTI and Brent paper markets (VL^{WTI}, VL^{Brent}). Since increased futures trading amplifies the pressure from paper markets on physical trading in the spot markets, we hypothesize a positive impact of WTI (Brent) open interest and trading volume on the respective spot price, which therefore increases (decreases) the WTI-Brent spread.

3.4 Freight rates

The transportation costs of crude oil determine its interchangeability between physical markets and thus also its price gap. Transportation costs are mainly driven by the freight rate for shipping. Freight rates increase with declining shipping space and port capacities. Thus, when freight rates are high, it is more costly to ship crude oil from Europe to North America[6] (Lanza et al., 2005), which negatively affects liquidity of intercontinental crude oil markets. As a consequence, the balancing mechanism between regional physical markets are hampered if transportation costs are high. Thus, we expect an increasing absolute price spread between WTI and Brent when freight rates rise. As proxy variable for the crude oil freight rates, we define BD as the Baltic Dry Index, which is a broad index for different goods, vessel types, and routes. The data for the freight rate index is retrieved from Bloomberg. As fright rates influence the absolute spread, they are pre-multiplied by the sign of the spread. In addition, we also use the Baltic Dry Dirty Tanker index (BDT), which is a dedicated index for shipping of crude oil and thus a more precise measure of the transportation costs for crude oil. For the empirical analyses,

[6] Exports of WTI crude oil from North America to Europe can rather be neglected due to rigid export restrictions for over 40 years by the U.S. government until January 2016.

we report results for both indices, since the time series for the BDT is only available since 2002, whereas BD is available for the entire sample period.

3.5 Economic conditions

On the demand side, we consider the economic situation in North America and Europe as drivers of the WTI-Brent spread. A growing economy is accompanied by increasing industrial demand for essential commodities, which causes rising prices in local crude oil markets. Accordingly, we expect an increasing (decreasing or even negative) price difference when the U.S. (European) economy grows. As a proxy for the industrial crude oil demand, we construct an aggregated oil-consuming industry stock index for the U.S. and Europe. We use performance index time series for different (super)sectors from the Industry Classification Benchmark (ICB), which were chosen with regard to their high crude oil consumption. In particular, we consider the following sectors: chemicals (ICB-1300), construction & materials (ICB-2300), automobiles & parts (ICB-3300), as well as the supersectors utilities (ICB-7000) and industrial goods (ICB-2700). Data for the different indices is retrieved from STOXX. We then construct ST^{US} and ST^{EU} as arithmetic mean of the five aforementioned indices for the U.S. and Europe. Both time series are normalized with a value of one at the starting point of our sample on January 01, 1995.

3.6 Heating and cooling

Besides crude oil consumption for production purposes, crude oil demand is also affected by households and their crude oil needs for heating and cooling. While directly used for heating, crude oil is indirectly connected to cooling through electricity production. As heating and cooling both increase crude oil demand, we expect them to widen the price gap between the two local oil prices. To account for crude oil consumption for heating and cooling, we create two temperature indices. For the U.S. (TP^{US}), we take the arithmetic mean of the daily temperature in the following cities across the continent: Chicago, Dallas, Kansas City, Los Angeles, Miami, New York, and Seattle.[7] Weather data is retrieved from the National Climatic Data Center. For Europe (TP^{EU}), we proceed analogously using daily temperature of the following cities: Berlin, Central England, Madrid, Nancy, Rotterdam, and Vienna. The data is retrieved from the European Climate Assessment & Dataset, which is in line with Klein

[7] For each city, we took weather stations close to the city center.

Tank et al. (2002). Crude oil demand from heating HT is measured by $(TP^{US} - TP^{EU})_{TP^{US} < 18.3°C}$ and cooling CL is approximated by $(TP^{US} - TP^{EU})_{TP^{US} > 18.3°C}$, which equals the difference between the mean temperature in North America and Europe if the difference is below (above) the threshold value of 18.3°C and zero otherwise. The threshold of 18.3°C is commonly used for the identification of heating and cooling degree days (Hall Jr. and Basara, 2006).

3.7 Extreme weather conditions

Beyond inventories, crude oil supply might be affected by weather anomalies hampering oil production and transportation. In the case of WTI, weather anomalies are tornados in the Cushing area. For Brent, hurricanes in the North Sea might change crude oil supply. Weather data for tornados is collected from the 'homefacts' website[8]. Data for hurricanes in the North Sea production areas is provided by the database of the University of Siegen[9]. We define two dummy variables for extreme weather conditions. Three days before and after a tornado occurs in the Cushing area, TR is equal to one. Equivalently, HR is equal to one if hurricanes appear in the North Sea. Both weather anomalies are expected to have a negative influence on the supply situation, thus leading to an increase of the respective crude oil price. Thus, we expect the WTI-Brent spread to increase if a Tornado occurs and to decrease for hurricanes. As weather effects are not affected by the other endogenous variables, we classify TR and HR as exogenous variables for the further analysis.

4 Methodology

We apply the ARDL methodology developed by Pesaran and Shin (1999) to explore the long-run relationship between the WTI-Brent spread and its determinants. The ARDL model has been frequently employed in empirical research due to several preferable aspects (among many others, Ahmad and Du, 2017; Büyüksahin and Robe, 2014; Ozturk and Acaravci, 2013). First, it allows to disentangle the short-run and long-run dynamics of the regressors. Second, the ARDL model generates unbiased estimates for the long-run effects even if some of the model regressors are endogenous (Narayan, 2005). Third, the ARDL bounds test by Pesaran et al. (2001) is more flexible compared to other traditional cointegration techniques, like Johansen and Juselius (1990), as it does not require the input variables to

[8] http://www.homefacts.com/tornadoes/Oklahoma/Payne-County/Cushing.html
[9] http://www.bau.uni-siegen.de/fwu/wb/forschung/sturmflutarchiv/

be integrated of the same order. Indeed, the ARDL bounds test can deal with mixed order of integration. Thus, it can even be employed if some variables are stationary in levels, i.e. they are $I(0)$, and others are stationary in first differences, i.e. $I(1)$. Finally, the ARDL procedure allows that the variables in the model may have different length of optimal lags, which is not possible for conventional cointegration approaches.

In the ARDL model, the normalized WTI-Brent price spread SPR_t is regressed over its own lags, as well as present and lagged values of the spread determinants. The ARDL$(p, q_1, \ldots, q_n)$ model with optimal lags is estimated via ordinary least squares and can be described by an unrestricted error correction representation:

$$\Delta SPR_t = a_0 + a_1 t + \sum_{i=1}^{p-1} \psi_{1,i} \Delta SPR_{t-i} + \sum_{j=1}^{n} \sum_{i=0}^{q_j-1} \psi_{j+1,i} \Delta X_{j,t-i} + \lambda_1 SPR_{t-1} + \sum_{j=1}^{n} \lambda_{j+1} X_{j,t-1} + \sum_{k=1}^{m} \delta_k Z_{k,t} + u_t, \tag{4}$$

where a_0 is the drift component, $t = \max(p, q_1, \ldots, q_n), \ldots, T$ is the time trend component, $X = [CY^{WTI}, CY^{Brent}, VL^{WTI}, VL^{Brent}, OI^{WTI}, OI^{Brent}, BD, ST^{US}, ST^{EU}, HT, CL]$ represents the $n = 11$ spread determinants described in section 3, $Z = [TR, HR]$ captures the $m = 2$ exogenous dummy regressors for weather anomalies, u_t is the white noise error term. $\psi_1, \ldots, \psi_n$ symbolize the error correction dynamics, and $\lambda_1, \ldots, \lambda_n$ represent the long-run relationship among the variables.

Whether there exists a long-run cointegration relation among SPR_t and the spread determinants X is examined by the ARDL bounds test. In this test, the null hypothesis of no cointegration, $H_0^F: \lambda_1 = \cdots = \lambda_{n+1} = 0$, is evaluated via a joint F-statistic. As the distribution of the test statistic is nonstandard under the null hypothesis, critical values must be obtained by stochastic simulation. Pesaran et al. (2001) present asymptotic lower and upper bound critical values for large sample sizes. The lower bound critical values consider that the variables are $I(0)$, whereas the upper bounds assume that the variables are $I(1)$. When the estimated F-statistic exceeds the upper bound, the null hypothesis is rejected, and we can conclude a cointegration relation among the variables. In contrast, if the test statistic falls under the lower bound, we cannot reject the null and thus can also not infer the existence of a cointegration relation. A drawback of the bounds in Pesaran et al. (2001) is that they are only available for a range of $k \in [0,10]$ long-run forcing variables. Kripfganz and Schneider (2018) present asymptotic critical values for the lower and upper bounds, which are independent of the number of long-run variables. As the number of spread determinants exceeds the range available from Pesaran et al. (2001), we use the critical values by Kripfganz and Schneider (2018).

If a long-run relationship exists, the error correction model can be re-formularized as follows:

$$\Delta SPR_t = a_0 + a_1 t + \sum_{i=1}^{p-1} \psi_{1,i} \Delta SPR_{t-i} + \sum_{j=1}^{n} \sum_{i=0}^{q_j-1} \psi_{j+1,i} \Delta X_{j,t-i} + \sum_{k=1}^{m} \delta_k Z_{k,t} + \phi ECT_{t-1} + u_t, \quad (5)$$

where ECT_{t-1} is the correction term and ϕ indicates the speed of adjustment to the long-run equilibrium after a shock in the system. If the value of the bounds test falls in between the two critical bounds, the results for cointegration are inconclusive and the decision depends on the error correction term ECT_{t-1} (Banerjee et al., 1998; Kremers et al., 1992). When ECT_{t-1} is significant with a negative sign, it implies a long-run cointegration among the estimated variables. Otherwise, cointegration must be neglected.

5 Empirical analysis

5.1 Summary statistics and unit root test

Tab. 3 presents summary statistics for the WTI-Brent spread and the spread determinants.

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Although ARDL deals with a mixed order of integration, it is necessary to ensure that none of the variables is integrated with an order greater than one. Otherwise, the critical bounds by Kripfganz and Schneider (2018) are not valid. Tab. 4 reports the results from the Augmented Dickey-Fuller (Dickey and Fuller, 1981) and the Philipps and Perron (Phillips and Perron, 1988) test for non-stationarity in the time series. For both tests, we include a constant and time trend in the regression. Optimal lag length is selected by the Schwartz-Bayesian Information Criterion (SBC).

<<<INSERT TABLE 4 HERE >>>

According to the unit root tests, we can infer that the time series of VL^{Brent}, OI^{WTI}, BD, ST^{US} and ST^{EU} have a unit root at levels, whereas the null hypothesis for VL^{Brent} can only be rejected in the PP test. When taking first differences, all variables appear to be stationary. Accordingly, the series for VL^{Brent}, OI^{WTI}, BD, ST^{US}, and ST^{EU} are $I(1)$. As mentioned above, the ARDL model allows estimation with both $I(0)$ and $I(1)$. Since none of the variables is $I(2)$, the requirements for the ARDL model can be confirmed.

5.2 Structural break identification

For the structural break identification, we (i) determine the number of potential breakpoints, (ii) detect the dates when the time series changes abruptly, and (iii) analyze the robustness of the breakpoints while controlling for the WTI-Brent spread determinants.

In the first step, we perform Hansen (2000)'s test for breakpoint detection, as it accounts for heteroscedasticity through conditional distributions and, compared to other approaches like the Chow test, does not foster the identification of an excessive number of breaks. This method identifies three potential breakpoints: two are significant at the 1% level, a third breakpoint is significant at the 5% level.

In the second step, we apply several parametric tests to locate the position of the three breakpoints (Bai and Perron, 2003; Busetti and Harvey, 2001; Harvey and Mills, 2003; Lee and Strazicich, 2001; Perron, 1997; Zivot and Andrews, 1992). Comparing the results of all tests, we find a clustering around three dates in the WTI-Brent spread series. Nearly all tests detect a first break point in 2010. Some tests determine additional break points in 2012 and 2005. In the following, we concentrate on four methods from the autoregressive process literature (Lee and Strazicich, 2001; Perron, 1997; Zivot and Andrews, 1992). The general idea is to include a crash dummy[10], a shift dummy, or a trend in the autoregressive equation of the inspected variable, which is in our case the WTI-Brent spread. In the Zivot and Andrews (1992)'s test, the minimum *t*-statistic of the regression coefficient of the lagged variable is the relevant test statistic. Perron (1997) suggests the maximum absolute *t*-statistic of the regression coefficient of the breakpoint dummy variable. Lee and Strazicich (2001) use the Schwarz Bayesian criterion to identify the optimal breakpoint. In addition, we also conduct a minimum BIC search to find the optimal break. All models show the similar three breakpoints.[11] However, our favorite model by Lee and Strazicich (2001) uncovers a major break in December 2010. This finding is in line with previous literature (Chen et al., 2015; Leybourne et al., 2007; Liu et al., 2016; Ye and Karali, 2016). Two other, but minor breaks are in November 2012 and February 2005.

In the third step, we include the determinants of the WTI Brent spread as controls in the autoregressive equation. Hence, we receive a time series of residuals, which are tested for the structural breaks. Again, we find a major breakpoint in December 2010.

[10] Due to the large number of observations in our daily time series, we define the crash dummy to be one in a period of 10 days.
[11] Results of the structural break analysis are reported in Appendix A in the online supplement.

5.3 Cointegration analysis

After the breakpoint detection, we analyze the WTI-Brent price time series via cointegration techniques. To find the optimal lag length, we follow Toda and Yamamoto (1995). For the cointegration analysis, we set up a VAR model as follows:

$$(1-L)y_t = Cy_{t-1} + B_1(1-L)y_{t-1} + \cdots + B_q(1-L)y_{t-q} + c_0 + c_1 t + e_t, \qquad (6)$$

where $y_t = (Brent_t, WTI_t)^T$. To test for the long-run relationship among WTI and Brent crude oil prices, we apply the cointegration tests by Engle and Granger (1987) as well as Johansen and Juselius (1990). Within the Engle-Granger framework, we apply two implementation strategies. First, we use an exogenous WTI-Brent spread at the delivery spread of $0.30 (CME Group, 2009). Second, we estimate the spread within the cointegration test. Consequently, in the second case, the test statistics have to be changed to the Engle-Granger statistics with constant and trend.

Due to the structural break discovered in the previous section, we extend both cointegration tests by a structural break dummy. For the Engle-Granger test, we follow Gregory and Hansen (1996) and introduce a shift variable in the cointegrating relation. Hence, the time series for the fixed delivery spread is adjusted by the dummy variable multiplied by the regression coefficient. This time series serves as basis for the standard ADF-testing. In the second case, the spread is estimated within the Engle-Granger test. Here, we can include the dummy in the estimation equation and apply the test statistic proposed by Gregory and Hansen (1996). For the Johansen-test with structural break, Johansen et al. (2000) present a methodology to include structural breaks in the rank-tests. Thus, they introduce a shift dummy in their VEC-framework and estimate the rank statistics. To derive the critical values, they apply a gamma-distribution, whereby their first two moments are estimated by a rational function of fourth degree. Tab. 5 reports the corresponding results of the cointegration tests.

<<<INSERT TABLE 5 HERE >>>

All three tests lead to similar results. For the time series ending in 2010, both tests indicate cointegration. The same holds for the full sample. Thus, we can conclude that there is a common stochastic trend in both oil price time series before the structural break. This changes if we look at the time series beginning in 2010. Here, Johansen as well as Engle-Granger with endogenous spread show significant results, whereas the Engle-Granger version with the delivery spread implies no significant cointegration. Altogether, we can conclude that there is a slight tendency for both crude oil prices to decouple after 2010. This finding is supported by the results from impulse response function analysis. We estimate the stable and invertible VAR model in Eq. (6) in differences and generate impulse response functions with a Cholesky one standard deviation shock in the Brent (WTI) innovations.

<<<INSERT FIGURE 2 HERE >>>

From Fig. 2, it can be seen that a shock in the Brent price before 2010 causes a response in the WTI price. The same conclusion can be derived for the impact of a WTI price shock on Brent prices, although the response is more pronounced. After the break in 2010, the findings change. A shock in Brent has no impact on the WTI price. In the opposite direction, a shock in the WTI market still affects the Brent price. However, after the equilibrium price is achieved, the confidence interval widens stronger in the post-2010 period. The fact that WTI does not react to Brent shocks after 2010 emphasizes the discussion if WTI still reflects the international oil supply-demand balance as a global benchmark or whether WTI is strongly driven by local factors, such as the inventories in Cushing (Bentzen, 2007; Fattouh, 2010a; Kaufmann and Ullman, 2009).

After the structural break identification and cointegration analysis, we update the vector of exogenous variables from Eq. (4) to $Z = [TR, HR, D_{2010}]$ for the baseline models with the major break and $Z = [TR, HR, D_{2010}, D_{2005}, D_{2012}]$ for the models including the minor breakpoints as well.

5.4 ARDL model: Bounds test

The first step of the ARDL estimation is the selection of the lag order. Pesaran and Shin (1999) show via Monte Carlo experiments that SBC performs better than other lag selection criteria. Thus, we use the SBC to choose the appropriate lag orders of p and q for the ARDL model. Next, the regression parameters of Eq. (4) are estimated via ordinary least squares with an unrestricted intercept and unrestricted trend. Tab. 6 reports the estimates of F-statistics of the ARDL bounds test, the t-statistics of the error correction term in the ARDL model, and the Kripfganz and Schneider (2018) critical values for the significance levels. Again, results are reported for the full sample and the time before/after the break in 2010.

<<<INSERT TABLE 6 HERE >>>

According to the results, we can reject the null hypothesis of no cointegration at the 1% level for the full sample and the pre-break period, as the F-statistics lie above the upper bound critical value. For the time after the break, the F-statistic does not exceed the common levels of significance for the $I(1)$ upper bound. Accordingly, we can infer that there is strong evidence for a long-run economic relationship among the regressors and the WTI-Brent price spread in the full sample period and in the period before the break in 2010. In contrast, the evidence for cointegration is weaker after the break, as both the estimate of the F-test and the t-test fall in between the critical bounds of $I(0)$ and $I(1)$. This finding indicates that the relationship between the determinants and the spread changed after 2010.

5.5 ARDL model: Long-run elasticities

Tab. 7 presents the long-run elasticities of the ARDL model. As model diagnostics indicate that we cannot reject the null hypothesis of no serial correlation from Durbin's test and also not the null hypothesis of a constant variance in the residuals from Breusch-Pagan test for heteroscedasticity, we apply Newey-West procedure for robust standard errors (Newey and West, 1987). We also report the interaction terms of the spread determinants and the 2010 break dummy for all variables driving the balancing mechanisms between the physical spot market and the paper markets (VL^{WTI}, VL^{Brent}, OI^{WTI}, OI^{Brent}, BD and BDT).

<<<INSERT TABLE 7 HERE >>>

In Model (1), we see a strong and statistically significant impact of the WTI and Brent convenience yield on the spread values, whereas the coefficient is positive for WTI and negative for Brent. Hence, high levels of the WTI (Brent) convenience yield increase (lower) the size of the spread. As the convenience yield is an indicator for inventories, our findings imply that the storage levels of the two crudes are strong drivers of the spread. In addition, we can see that the trading volume in Brent paper markets explains variation of the spread. Due to the negative sign of the long-run coefficient, extended trading of Brent futures lowers the price differential between WTI and Brent. Moreover, the elasticity estimates for the economic condition reveal that an increase in the U.S. stock index widens the spread, while a surge in the European stock markets decreases the size of the price gap. Finally, there is also evidence that heating periods in the U.S., as a proxy for increased energy demand for cooling, influence the size of the price spread. However, the sign is contrary to the expected positive impact.

Regarding the impact of the structural breakpoints, we observe in Models (1) and (2) that the major break in 2010 is highly significant with a negative sign revealing a decrease in the spread after 2010. For the other two (minor) breakpoints, a significant change in the spread can be found after 2012. However, no significant impact can be confirmed for the break in 2005. In terms of statistical significance and the size of the economic effect represented by the reported long-run elasticities, the break in 2010 is the most dominant breakpoint.

When interacting the spread determinants with the major break dummy, it becomes apparent that the impact of two variables changes tremendously after 2010. First, the convenience yield of WTI becomes more important after the break, whereas we find no change in the case of Brent (Model 3). Second, when splitting the trading volume in WTI and Brent futures markets, the results uncover a significant positive impact of WTI trading on the spread before 2010 (Model 5). However, after 2010 the impact decreases significantly and becomes negative. For the open interest, there is no statistically relevant evidence for a change in the strength or direction of its impact, even after the break (Model 4). In addition, we can also see that transportation costs measured by the Baltic Dry index (BD) have no explanatory power. In contrast, when using the Baltic Dirty Tanker index (BDT) in Model 6, which is the better proxy for the transportation costs of crude oil, we find that increasing shipping costs enlarge the spread. This might be due to the fact that when shipping from Brent oil to the U.S. coast becomes more expensive, it will be more difficult to reduce price differentials between both crudes by transporting it from one physical market to the other. However, as discussed in Section 3, a disadvantage of this alternative measure is that the time series shortens as BDT data is not available for the entire sample period. Summing up, we confirm the results from the bounds test and find evidence for a change in the underlying dynamics of the spread determinants after 2010.

Model (7) directly tests the interactions among the physical market (spot) and the paper markets (futures) by including the WTI-Brent futures price spread as an explanatory factor in the ARDL model. The results imply a positive impact from the paper markets on the spot markets. This effect reinforces strongly after the break in 2010, which indicate pressure from the paper market on the physical spot market.

Tab. 7 also reports the coefficients of the error-correction term ECT_{t-1} from Eq. (5), which measures how quickly variables converge to the equilibrium. As the coefficient is statistically significant with a negative sign in all models, we can confirm the presence of an established long-run relationship in the full sample. The significant speed of adjustment suggests convergence of the model dynamics from short-run to a long-run equilibrium. Deviations from the equilibrium are corrected by 2.93% per day in Model 1 up to 10.63% in Model 7.

5.6 Robustness analysis

In addition to the ARDL results presented in the previous section, we performed various tests for the robustness of our results with alternative variable definitions and model specifications. The results are reported in Appendix B and C of the online supplement.

First, we extend the estimation of the convenience yield by two alternative methods. First, we construct a futures contract with three months to maturity by the weighted average of the two futures prices with lower and higher maturity. The weights are defined linearly as difference between three months and the maturity of the respective future divided by the maturity difference between both (higher – lower maturity). This implies a daily roll-over from the short-term future to the long-term future (Hammerschmid, 2018; Szymanowska et al., 2014). Second, we simply use the future with the closet maturity to three months to calculate the convenience yield (Geman and Nguyen, 2005; Gibson and Schwartz, 1990; Milonas and Henker, 2001). When applying these alternative methods, the ARDL results remain stable and we can confirm the previous findings from Tab. 7.

Second, we include the term spread (defined as difference between the futures and the spot price) as an alternative proxy for the convenience yield. The findings confirm the outcomes from the direct examination of the convenience yield, with a significant impact of the Brent and WTI term spread, whereas the latter increases after 2010.

Third, we calculate the convenience yields for contracts with 6 and 12 months to maturity. Here, the size of the long-run elasticity increases for both WTI ($\lambda_{CY(6M)^{WTI}} = 0.5872^{***}$; $\lambda_{CY(12M)^{WTI}} = 0.9237^{***}$) and Brent ($\lambda_{CY(6M)^{Brent}} = -0.6534^{***}$; $\lambda_{CY(12M)^{Brent}} = -1.0005^{***}$). However, in the case of a 12 months contract, which is a proxy for the expected long-term storage (Weymar, 1966), the interaction term of WTI including the break dummy (CY^{WTI} x D_{2010}) shows no significant change after 2010.

Fourth, as extension of Model (7) in Tab. 7, we include the futures price spread (3, 6, and 12 months to maturity) instead of the spot price spread as dependent variable and treat the spot price spread as explanatory factor. This analysis shows that the impact of the physical market on the paper market ($\lambda_{SPR^{Spot}} = 1.0388^{***}$) is stronger than vice versa ($\lambda_{SPR^{Future}} = 0.6792^{***}$), which coincide with previous evidence, for example, by Lautier et al. (2018).

6 Discussion

Consolidating the different regression models leads to the conclusion that the WTI-Brent spread is positively correlated with the convenience yield obtained from the three months WTI futures contracts and negatively correlated with the convenience yield of the Brent futures contracts, both to a strong significant extent. This finding is in line with the theory of storage according to Working (1927, 1949) and Brennan (1958). Accordingly, the convenience yield is a surrogate for the availability of a commodity and a high convenience yield implies a critical supply situation, which leads to higher spot prices and thus to a larger spread. Although this finding in line with Milonas and Henker (2001), who find a significant impact of WTI convenience yield at the 10% or 5% level (depending on the maturity of the futures used for the spread calculation), we obtain higher effects in terms of significance levels (all at the 1% level and even lower) as well as economic significance as shown by the long-run elasticities from the ARDL estimation. This could be reasoned by the differences in the data sample. Milonas and Henker (2001) examine the period of 1991 – 1995, a time when the WTI-Brent spread was more or less negligible. Another difference is that we apply an alternative method for the computation of the convenience yield and also include other supply and demand factors as controls in the ARDL model.

Moreover, we can conclude from the interaction terms with the break dummy that the relevance of the convenience yield for WTI strongly increases after 2010. Accordingly, the spread reacts more intensively to changes in the WTI inventory levels, which is not surprising due to the extreme storage conditions arising from a glut of crude oil in Cushing. This oversupply of U.S. crude oil was also stimulated by the shale oil revolution (Kilian, 2016). As a consequence of increased fracking, the U.S. oil production rates reversed and started to increase in 2008 after a long-standing decline (EIA, 2017). However, pipeline systems in the U.S. were originally designed to transport imported crude oil from the Gulf Coast to the interior of the country, and not the other way around to transport shale oil from the interior, where fracking sites are located, to the Gulf Coast (Kilian, 2016).

Comparing the findings for the other spread determinants with the previous literature shows some interesting differences. Similar to Büyüksahin et al. (2013), we find a significant effect of the U.S. economy on the WTI-Brent spread. However, the sign of the effect is different. The positive effect resulting from the ARDL model in Tab. 8 is in line with the predicted sign, but in contrast to the negative sign reported in Büyüksahin et al. (2013). An explanation could be the difference in the variable definition, as Büyüksahin et al. (2013) use an U.S. Business Climate index, whereas we create a dedicated stock index for oil-dependent industries. In addition, we also measure the impact of the European economy on the spread, which was included in previous studies. For the variables measuring the extent of paper markets trading, Büyüksahin et al. (2013) document a significant effect for the open interest in both WTI and Brent markets. This result cannot be confirmed by our results. Instead, we find explanatory power for the trading volume as proxy for paper market activity. In addition to that, we analyze the forces driving the crude oil market segmentation. To proxy the trade barrier, we use the Baltic Dry and the Baltic Dry Tanker index. While Büyüksahin et al. (2013) find no effect of shipping rates, we find indeed a positive impact of the tanker index. This implies that high freight rates cause higher barriers to transport oil and consequently higher WTI-Brent spreads. This underpins the importance of low transportation costs to balance the supply and demand across regional markets. On the other hand, higher freight rates coincide often with situations of economic prosperity leading to higher economic scarcity of crude oil, causing oligopolistic local structures and higher price differences.

7 Conclusion

This study investigates the determinants of the price differential between Western Texas Intermediate and North Sea Brent crude oil for the time period between January 01, 1995 and July 23, 2014. Our analysis consists of three steps: (i) Structural break analysis of the WTI-Brent time series, (ii) examination of the cointegration relation among WTI and Brent, and (iii) exploration of the spread determinants within an ARDL model.

For the structural break analysis, we apply several methods and detect a major break in December 2010, which is strongly in line with previous literature. From the cointegration analysis, we find that the strong long-run relationship between WTI and Brent becomes weaker after 2010. The results from impulse response analysis suggest that Brent reacts stronger to WTI shocks than vice versa. However, after 2010 there is no more response of WTI to a Brent price shock illustrating the decoupling of the two major crude oil variants. The results from the ARDL model imply that the convenience yield, as proxy for crude oil inventories, is the most important spread determinant. Moreover, we find a strong positive influence of the WTI convenience yield, which is an indicator for the crude oil supply situation in the U.S., on the WTI-Brent spread. There is also a strong negative influence of the Brent convenience yield. Both results are in line with the theory of storage, i.e. low storage volumes and thus high convenience yield strongly influence the size of the price gap between WTI and Brent. Moreover, also the trading activity in crude oil paper markets, transportation costs for crude oil shipping, as well as the stock market development in the U.S. and Europe determine the size of the spread. Unlike other papers, we find that the impact of the spread determinants changed after the major break in 2010. Especially, the importance of WTI inventories as explanatory factor for the WTI-Brent and also the influence of the paper market on the physical spot market heavily increased after 2010. As the convenience yield is by nature a function of the future prices, our findings underpin the hypothesis by Fattouh (2010b) that derivatives foster a 'great pool' oil market. In a similar vein, we find evidence that the balancing mechanism between both crudes changed over time and paper markets became more important for equalizing price differentials between WTI and Brent.

While we focus on WTI and Brent as crude oil classifications, an interesting subject for future research would be the examination of the determinants of alternative crude oil spreads like the price gap between WTI or Brent and Dubai crude. In addition, it would be interesting to add further spread determinants, as for example, a measure for the shale oil production volume. However, this requires the availability of daily production data to match them with the daily observations of the spread and the determinants examined in this study. Another possible direction for further research is whether the same variables, which drive the WTI-Brent spread, also affect other commodities (e.g., cacao or wheat).

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Table 1. Overview of existing studies on the WTI-Brent price spread

Authors	Sample period	Methodology	Findings
Panel A: Structural breaks			
Bentzen (2007)	1987:04 – 2004:12	Bai-Perron test for multiple structural breaks	SB: 1999:11
Büyüksahin et al. (2013)	2006:06 – 2012:07	Chow test	SB: 2008:11, 2010:12
Argua (2015)	2001:01 – 2014:05	Bai-Perron test for multiple structural breaks	SB: 2003:01, 2005:01, 2007:01, 2009:02, 2011:02
Chen et al. (2015)	1988:01 – 2014:12	CUSUM of squares-based test	SB: 2010:12
Li et al. (2015)	2004:01 – 2013:12	Rolling Chow test	SB: 2010:01
Liu et al. (2016)	2004:01 – 2010:12	Bai-Perron test for multiple structural breaks	SB: 2010:12
Ye and Karali (2016)	1993:12 – 2016:04	Bai-Perron test for multiple structural breaks	SB: 2005:05, 2010:12, 2013:04
Panel B: Spread determinants			
Milonas and Henker (2001)	1991:02 – 1996:01	OLS regression	Convenience yield explains WTI-Brent futures price spread
Bacon and Tordo (2004)	2003:01 – 2004:06	OLS regression	Quality differences and transport costs influence WTI-Brent oil price differences
Büyüksahin et al. (2013)	2004:04 – 2012:04	ARDL	Several factors drive the WTI-Brent futures price spread, especially U.S. business climate, storage problems in Cushing, open interest, position of futures traders
Li et al. (2015)	2004:01 – 2013:12	Granger causality	Cushing and Midwest's inventories drive WTI-Brent spread before 2010, after 2010 Chinese crude oil demand is the main force

Notes: This table presents a review of existing studies on crude oil price differentials. SB = Structural break.

Table 2. Variable description and data sources

Variable	Definition	Source
P^{WTI}	Western Texas Intermediate opening spot price (U.S. dollars per barrel)	Datastream
P^{Brent}	UK Brent nominal closing spot price (U.S. dollars per barrel)	Bloomberg
F^{WTI}	WTI opening futures crude oil price (U.S. dollars), 3 months to maturity	NYMEX
F^{Brent}	Brent closing futures crude oil price (U.S. dollars), 3 months to maturity	ICE
RF	Three months U.S. treasury yield on actively traded non-inflation-indexed issues, adjusted to constant maturity	Federal Reserve
SC^{WTI}	Logarithmic difference between storage fee (\$0.40 per barrel) and P^{WTI}	Ederington et al. (2012)
SC^{Brent}	Logarithmic difference between storage fee (\$0.40 per barrel) and P^{Brent}	Ederington et al. (2012)
SPR^{Spot}	Normalized spot price spread	Own calculation
SPR^{Future}	Normalized futures price spread	Own calculation
CY^{WTI}	Convenience yield of WTI futures	Own calculation
CY^{Brent}	Convenience yield of Brent futures	Own calculation
VL^{WTI}	Logarithm of aggregate trading volume for WTI futures contracts	NYMEX
VL^{Brent}	Logarithm of aggregate trading volume for Brent futures contracts	ICE
OI^{WTI}	Logarithm of aggregate open interest for WTI futures contracts	NYMEX
OI^{Brent}	Logarithm of aggregate open interest for Brent futures contracts	ICE
BD	Baltic dry index divided by 1000 and pre-multiplied by the sign of the WTI-Brent spread	Baltic Exchange
BDT	Baltic dry dirty tanker index divided by 1000 and pre-multiplied by the sign of the WTI-Brent spread	Baltic Exchange
ST^{US}	Arithmetic mean of five sector indices for chemicals, construction & materials, automobiles & parts, utilities and industrial goods, normalized to an index value of one starting on January 01, 1995	STOXX
ST^{EU}	Arithmetic mean of five sector indices for chemicals, construction & materials, automobiles & parts, utilities and industrial goods, normalized to an index value of one on January 01, 1995	STOXX
TP^{US}	Arithmetic mean temperature for Chicago, Dallas, Kansas City, Los Angeles, Miami, New York and Seattle	National Climatic Data Center
TP^{EU}	Arithmetic mean temperature for Berlin, Central England, Madrid, Nancy, Rotterdam and Vienna	European Climate Assessment
HT	Heating day, defined as $(TP^{US} - TP^{EU})_{\text{Temperature(US)}>18.3°C}$	Own calculation
CL	Cooling day, defined as $(TP^{US} - TP^{EU})_{\text{Temperature(US)}<18.3°C}$	Own calculation
TR	= 1 for the three days before and after a tornado occurred in the Cushing area, 0 otherwise	Homefacts[a]
HR	= 1 for the three days before and after a hurricane occurred in the North Sea, 0 otherwise	University of Siegen[b]

Notes: This table presents the variables used in the analysis.

[a] Source: http://www.homefacts.com/tornadoes/Oklahoma/Payne-County/Cushing.html
[b] Source: http://www.bau.uni-siegen.de/fwu/wb/forschung/sturmflutarchiv/

Table 3. Summary statistics

	Mean	Median	Std. Dev.	Min.	Max.	N
SPR^{Spot}	0.0160	0.0272	0.0852	-0.2498	0.3470	4708
SPR^{Future}	0.0167	0.0307	0.0800	-0.2413	0.2284	4708
CY^{WTI}	0.1615	0.1374	0.2288	-1.3395	1.2963	4708
CY^{Brent}	0.1791	0.1406	0.1847	-0.4825	1.1224	4708
VL^{WTI}	11.5632	11.5427	1.3381	5.1120	14.1915	4708
VL^{Brent}	12.4249	12.3400	0.7687	9.7730	14.2560	4708
OI^{WTI}	12.9290	12.7242	0.6839	11.7484	14.2958	4708
OI^{Brent}	13.5635	13.4734	0.5497	12.6411	14.4952	4708
BD	2.4274	1.6155	2.0309	0.6470	11.7930	4708
BDT	0.2318	0.5030	1.1394	-2.3470	3.1940	3019
ST^{US}	1.7335	1.7315	0.3550	0.7925	2.5429	4708
ST^{EU}	1.5530	1.5317	0.3453	0.8799	2.5600	4708
HT	0.5346	0	1.4160	-3.9125	7.5875	4708
CL	1.2797	0	3.1998	-12.225	15.4896	4708
TR	0.0227	0	0.1490	0	1	4708
HR	0.0042	0	0.0650	0	1	4708

Notes: This table presents summary statistics for the full sample period from January 01, 1995 through July 23, 2014. Variable definitions can be obtained from Table 2.

Table 4. Unit root test

	ADF test		PP test	
	Levels	First differences	Levels	First differences
SPR^{Spot}	-9.51***	-29.41***	-10.83***	-82.25***
SPR^{Future}	-5.69***	-36.50***	-19.05***	-159.83***
CY^{WTI}	-5.59***	-31.83***	-7.91***	-77.58***
CY^{Brent}	-6.41***	-31.73***	-7.21***	-76.80***
VL^{WTI}	-4.50***	-31.72***	-40.70***	-199.26***
VL^{Brent}	-2.93	-15.42***	-10.97***	-161.50***
OI^{WTI}	-3.26	-12.58***	-3.02	-82.56***
OI^{Brent}	-3.90***	-25.32***	-5.02***	-99.93***
BD	-2.80	-10.84***	-2.47	-24.07***
BDT	-20.09***	-15.35***	-29.18***	-31.04***
TR	-20.00***	-24.68***	-23.59***	-96.00***
HR	-19.51***	-30.37***	-22.14***	-75.26***
ST^{US}	-2.33	-50.65***	-2.39	-72.84***
ST^{EU}	-1.97	-47.27***	-1.95	-67.17***
HT	-10.72***	-27.88***	-29.56***	-134.03***
CL	-21.28***	-18.93***	-21.71***	-88.56***

Notes: ADF is the Augmented Dickey Fuller test (Dickey and Fuller, 1981) and PP is the Phillips and Perron (1988) unit root test. The lag order for the tests are select using the Schwartz-Bayesian Information Criterion. All unit root tests regressions include an intercept and drift. The tests for the spot and futures spread also include a structural break component.

***, **, * denote statistical significance at the 1%, 5% or 10% level.

Table 5. Cointegration test between WTI and Brent spot price

	Before structural break in 2010	After structural break in 2010	Full period with structural break
Engle-Granger test			
Fixed spread ($0.30)	-5.73***	-0.91	-6.52***
Endogenous spread	-9.42***	-4.11**	-6.65***
Johanson-Juselius test			
Trace test with $r = 0$	95.82***	29.43**	48.46**
λ Max test with $r = 0$	89.96***	20.46**	46.99**
Trace test with $r \leq 1$	5.86	8.97	1.46
λ Max test with $r \leq 1$	5.86	8.97	1.46
Lags	2	1	1

Notes: This table shows the results from Engle and Granger (1987) and Johansen and Juselius (1990) test for cointegration. Number of lags are selected by Schwartz-Bayesian Information Criterion. The number of conintegrating vectors is indicated by *r*.

***, **, * denote rejection of the null hypothesis at the 1%, 5% or 10% level.

Table 6. Bounds test for cointegration in ARDL model

Model: $F(SPR^{Spot} \mid CY^{WTI},\ CY^{Brent},\ VL^{WTI},\ VL^{Brent}, OI^{WTI},\ OI^{Brent}, BD, ST^{US},\ ST^{EU}, HT, CL)$				
	Optimal lag structure	F	t	Inference
Before structural break in 2010	(1,1,1,0,0,0,0,0,1,0,0,0)	7.39^{***}	-8.57^{***}	Cointegration
After structural break in 2010	(1,1,1,0,0,0,0,0,1,0,0,0)	2.99	-4.60	Weak cointegration
Full sample	(4,4,4,0,0,1,0,1,1,0,0,0)	5.41^{***}	-7.49^{***}	Cointegration

Critical value bounds	F		t	
Significance level	$I(0)$	$I(1)$	$I(0)$	$I(1)$
1%	2.67	3.90	-3.96	-5.99
5%	2.22	3.35	-3.41	-5.39
10%	1.99	3.08	-3.13	-5.06

Notes: The ARDL models are estimated according to Eq. (4) with unrestricted intercept and unrestricted trend. The *F*-statistics refer to a joint test of the long-run coefficients from Eq. (4) ($H_0^F: \lambda_1 = \cdots = \lambda_{n+1}$). The *t*-statistics refer to the test of the error correction term from Eq. (5) ($H_0^t: \phi = 0$). The rejection of both null hypotheses indicates a long-run relationship. Critical values for the lower $I(0)$ and upper $I(1)$ bounds are taken from Kripfganz and Schneider (2018).

***, **, * denotes rejection of the null of no cointegration for $I(1)$ at the 1%, 5% or 10% level.

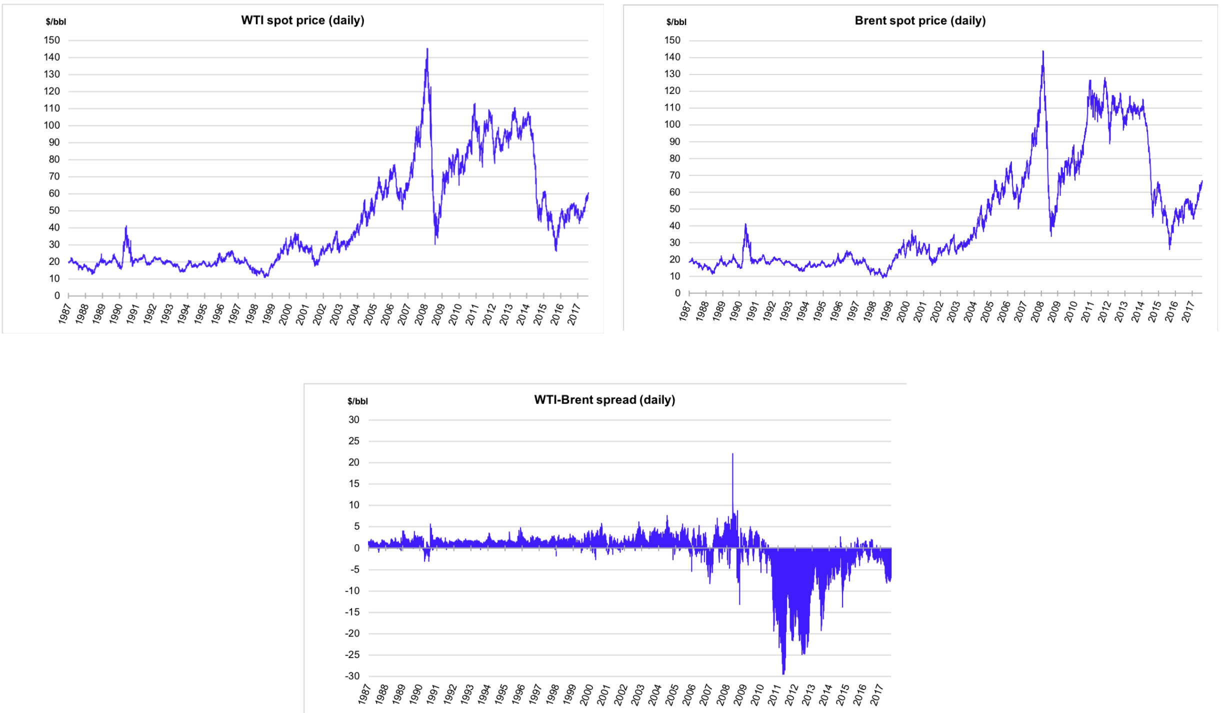
Table 7. Long-run elasticities from ARDL model

Variables		(1) One break	(2) Three breaks	(3) CY with break	(4) OI with break	(5) VL with break	(6) BDT with break	(7) SPR^{Fut} w. break
Constant		-0.0155 (-1.36)	-0.017 (-1.40)	-0.0156 (-1.36)	-0.0086 (-0.74)	-0.0016 (-0.44)	-0.0212 (-1.05)	-0.0260** (-2.37)
Trend		-0.0001*** (-3.13)	-0.0001*** (-3.18)	-0.0001*** (-3.47)	-0.0001*** (-2.23)	-0.0001*** (-3.74)	-0.0001 (-1.09)	-0.0001*** (-5.00)
CY^{WTI}	+	0.4079*** (6.69)	0.3929*** (6.85)	0.3793*** (6.08)	0.3835*** (5.11)	0.3820*** (5.73)	0.3112*** (3.49)	0.2513*** (11.69)
CY^{WTI} x D_{2010}				0.3403** (2.57)	0.3065* (1.65)	0.4100*** (2.91)	0.3622** (2.18)	-0.1304*** (-4.38)
CY^{Brent}	−	-0.4537*** (-5.95)	-0.4410*** (-6.60)	-0.4243*** (-5.74)	-0.4170*** (-4.74)	-0.4225*** (-5.40)	-0.2443* (-1.81)	-0.2621*** (-10.34)
CY^{Brent} x D_{2010}				-0.1164 (-0.38)	-0.1262 (-0.34)	-0.0185 (-0.06)	-0.3789 (-1.15)	0.1494** (2.47)
SPR^{Future}	+							0.4858*** (7.95)
SPR^{Future} x D_{2010}								0.4979*** (7.34)
VL^{WTI}	+	0.0121 (1.07)	0.0168 (1.60)	0.0170* (1.65)		0.0253** (2.28)	0.0017 (0.13)	0.0046* (1.68)
VL^{WTI} x D_{2010}						-0.0734** (-2.20)		
VL^{Brent}	−	-0.0124*** (-3.53)	-0.0106*** (-2.92)	-0.0127*** (-4.01)		-0.0108*** (-3.25)	-0.0070** (-2.04)	-0.0053*** (-4.67)
VL^{Brent} x D_{2010}						-0.0065 (-0.15)		
OI^{WTI}	+	0.0009 (0.03)	0.0323 (0.85)	0.0088 (0.27)	0.0395 (1.01)		0.0094 (0.23)	0.0126 (1.30)
OI^{WTI} x D_{2010}					-0.1527 (-0.95)			
OI^{Brent}	−	0.0533* (1.80)	0.0122 (0.43)	0.0366 (1.37)	-0.0046 (-0.14)		0.0488 (1.25)	0.0129* (1.79)
OI^{Brent} x D_{2010}					0.0916 (1.07)			
BD	+	0.0012 (1.07)	0.0009 (0.91)	0.0013 (1.23)	0.0021* (1.76)	0.0012 (1.09)		0.0006* (1.72)
BDT	+						0.0116** (2.23)	
BDT x D_{2010}							-0.1159* (-1.67)	
ST^{US}	+	0.0390** (2.34)	0.0288* (1.90)	0.0331** (2.22)	0.0397** (2.26)	0.0346*** (2.63)	0.0219 (0.60)	0.0168*** (3.48)
ST^{EU}	−	-0.0611** (-2.28)	-0.0535** (-2.31)	-0.0559** (-2.34)	-0.0718*** (-2.59)	-0.0523*** (-3.02)	-0.0485 (-1.37)	-0.0309*** (-3.92)
HT	+	-0.0054** (-2.53)	-0.0043** (-2.38)	-0.0051*** (-2.61)	-0.0059*** (-2.59)	-0.0052** (-2.47)	-0.0028 (-1.40)	-0.0013*** (-2.98)
CL	+	0.0003 (0.30)	0.0005 (0.46)	0.0004 (0.40)	0.0005 (0.38)	0.0006 (0.56)	-0.0001 (-0.10)	0.0003 (1.09)
Exogenous variables								
TR	+	-0.0003 (-0.63)	-0.0003 (-0.65)	-0.0003 (-0.53)	-0.0002 (-0.41)	-0.0003 (-0.57)	-0.0003 (-0.51)	-0.0001 (-0.14)
HR	−	0.0028* (-1.80)	0.0026* (1.79)	0.0027* (1.80)	0.0026* (1.73)	0.0029* (1.87)	0.0033* (1.91)	0.0007 (1.04)
D_{2005}			-0.0006 (-0.91)					
D_{2010}		-0.0028*** (-4.47)	-0.0035*** (-5.07)	-0.0028*** (-3.11)	0.0222 (0.49)	0.0298** (2.13)	-0.0060*** (-2.65)	0.0006 (0.87)
D_{2012}			0.0017*** (3.07)					
ECT_{t-1}		-0.0293*** (-7.49)	-0.0338*** (-8.46)	-0.0328*** (-7.99)	-0.0274*** (-6.96)	-0.0309*** (-7.84)	-0.0346*** (-7.08)	-0.1063*** (-11.67)
N		4704	4705	4705	4705	4705	3017	4704
$Adj. R^2$		0.8282	0.8379	0.8395	0.8381	0.8386	0.7838	0.8710

Notes: This table reports the long-run coefficients estimated from the ARDL model. Variables are defined in Tab. 2. *t*-statistics (in parentheses) are based on Newey and West (1987) adjusted standard errors to account for serial correlation and heteroscedasticity.

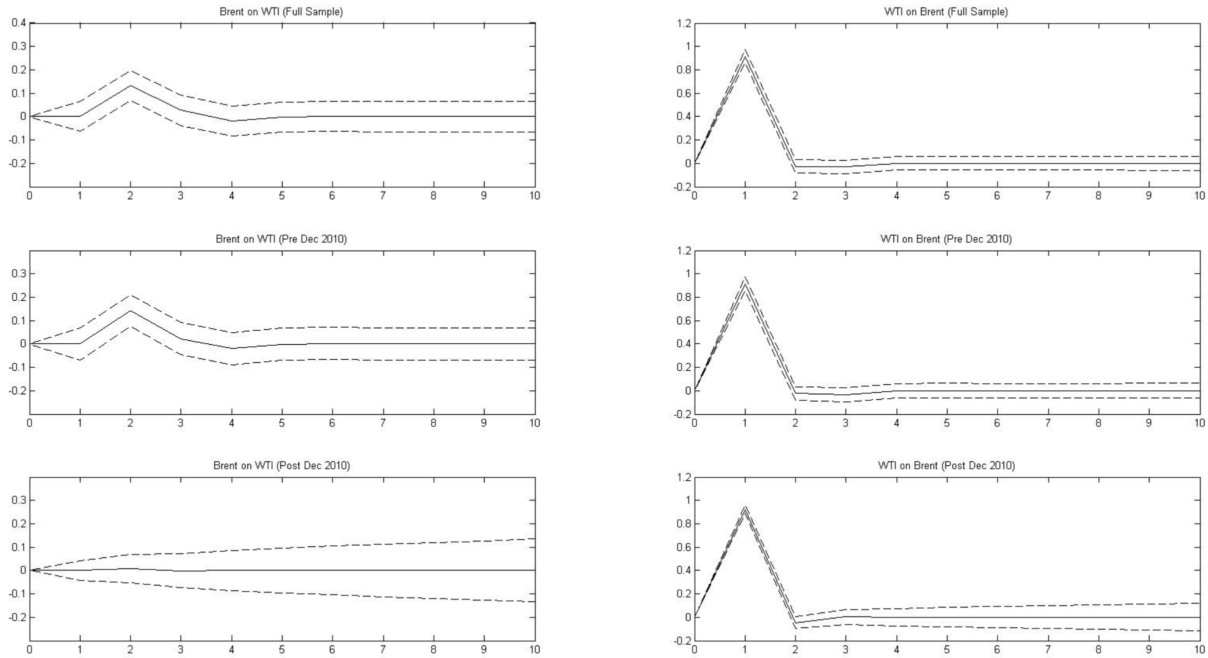
***, **, * denote statistical significance at the 1%, 5% or 10% level.

Figure 1. WTI and Brent spot prices and price spread



Source: U.S. Energy Information Administration.

Figure 2. Impulse response functions



The figure depicts the orthogonalized impulse response function of Brent on WTI (left column) and WTI on Brent (right column) for the first 10 days after a one standard deviation shock in WTI (Brent) spot price. The first row refers to the entire time period (January 01, 1995 - July 23, 2014), the second row refers to the time period before the structural break (January 01, 1995 – December 08, 2010), and the third row refers to the time period after the structural break (December 09, 2010 - July 23, 2014). Dashed lines represent 99% confidence bands.