Are carbon futures prices stable? New evidence during negative oil

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Abstract

We investigate volatility spillovers from West Texas Intermediate (WTI) crude oil to carbon emission allowance futures, focusing on the period surrounding the WTI negative pricing event of April 2020. Results evidence, pre-negative WTI, a doubling of directional spillover from WTI oil to carbon allowance futures upon the global spread of COVID-19, with a sharp elevation of directional spillover from WTI oil to carbon allowances during the specific period of negative WTI. This extraordinary rise in directional spillover continued past the near-term contract through several ensuing contracts. Results suggest that carbon futures markets are highly sensitive to periods of fragility.

Keywords: Supply Shocks; Negative Pricing; WTI; Crude Oil; Carbon Emissions; COVID-19.
1. Introduction and motivation


As understanding the co-movements between carbon emissions trading markets and crude oil markets is important for designing effective policies for reducing greenhouse gas emissions [Tol, 1999, Fankhauser and Tol, 2005, Tol, 2005, Böhringer et al., 2009, Tol, 2018], we are motivated to investigate spillovers in the volatility of West Texas Intermediate crude oil (WTI) on the volatility of carbon emission allowance futures products during times of great fragility.

We focus on the effects of the April 2020 dropping of WTI prices to negative values, applying a generalised version of the spillover index proposed by Diebold and Yilmaz [2012], based on the vector autoregressive (VAR) models of Sims [1980]. To identify the transmission mechanism of volatility stock among oil prices and carbon credits, we build on the dynamic correlation model of Engle [2002], focusing on the estimation of traditional dynamic conditional correlation of the energy sector with that of WTI. The magnitude of volatility spillovers and co-movements of EUAs during a time of both the COVID-19 pandemic and negative oil prices presents valuable information regarding carbon futures markets during times of great financial distress. By examining spillovers around the unprecedented extreme event of COVID-19 overlapping with negative oil prices, we add to our understanding of how spillover relationships manifest during extreme circumstances.

We consider a risk premium channel of volatility spillover, in which a shock in one capital market affects the willingness of participants in another market to hold risk, [Khalfaoui et al., 2015, Du and He, 2015, Wang and Wu, 2018, Xu et al., 2019]. We apply the generalized spillover index of Diebold and Yilmaz [2009] and DCC-GARCH approach of Engle [2002] to investigate the possible transmission mechanism of volatility shocks across WTI and 12 different Thomson Reuters Eikon classified energy future products. By incorporating both high-frequency and daily time series from March 2019 through May 2020, we compare volatility spillovers among different periods: i) pre-pandemic, defined to be the period 1 March 2019 through 31 December 2019; ii) during the occurrence of pneumonia caused by unknown aetiology initially in Wuhan, but by 1 January 2020 identified as a pandemic, defined by us as Q1 2020 to represent the COVID-19 development phase; and iii) the official occurrence of the significant period of oil price disruption and negative oil prices during and after 20 April 2020, when the prices turned negative.

Our results evidence for the first period a doubling of directional spillover from WTI oil to carbon allowance futures as COVID-19 initially manifested in western economies. Results for the
subsequent periods are most striking, with an enormous spiking of directional spillover from WTI oil to carbon allowances during the period surrounding negative WTI prices. This extraordinary rise in directional spillover continues from the near-term contract through several ensuing contracts. We interpret our results as consistent with COVID-19 establishing a platform for the fragility concerning the interaction of WTI oil and carbon allowances. Subsequently, when an extraordinary movement in WTI price occurred, the impact of this injection of uncertainty on carbon allowances was enormous.\footnote{Why WTI oil prices suddenly dropped negative in April 2020 is not the focus of this study but was likely caused by a combination of COVID-19 and other geopolitical factors, as detailed by Corbet et al. [2020].}

To investigate the transmission mechanism of volatility shocks of oil prices to carbon credits, we focus on the carbon future products traded under European Union Allowance or European Union Aviation Allowance. The EU ETS, as with other carbon credit market systems, is designed to encourage companies and individuals to reduce their greenhouse gas emissions and select greener energy options. Previous evidence suggests that the most important determinants for carbon prices are energy prices. Given this, it is important to consider the role of negative crude oil prices concerning transitioning the world from fossil fuels to green energy. The EU ETS is a key component of the European Union’s climate policy. Currently, the EU ETS is the single largest carbon pricing item in the world, with the system encompassing about 45% of the EU’s greenhouse gas emissions.

We provide new evidence regarding how markets behave during times of heightened fragility. We evidence that directional spillover from WTI oil to carbon-allowance futures extends well beyond near-term contracts to subsequent contracts. Our findings complement recent work that investigates how markets, in general, are prone to manifesting spikes of disruption during periods of downturn and fragility [Anand and Venkataraman, 2016].

\section{Data}

We investigate the sample period March 2019 to May 2020, at both daily and hourly frequencies. Overall, we have 868 daily observations\footnote{We also note that similar analyses carried out on a variety of higher frequency data produced qualitatively similar results. For brevity, these results are not presented in this analysis but are available from the authors upon request.}, as shown in Table 1. Data are from Thomas Reuters Eikon. Descriptive statistics for hourly WTI prices and prices of the carbon future products are shown in Table 1. Following Antonakakis et al. [2018] and Corbet et al. [2020], we define the price of stock $i$ as its absolute return, $V_{it} = |\ln P_{it} - \ln P_{it-1}|$, where $P_{it}$ is the daily closing value of the stock oil price on day $t$. The price of WIT is denoted by $j$.

Insert Table 1 and Figure 1 about here

Figure 1 presents the daily volatilities of the carbon future products, evidencing that each of the carbon future products shared similar patterns in their price volatility through the sample...
period, with similar peaks and troughs. For example, there were peaks in volatility during the third quarter in 2018 for every carbon future except for RPC Fuel Switching EUA TTF Monthly Continuation (FSEUATTFMc1). There was another peak in the price volatility for all future products at the beginning of the second quarter of 2020. This pattern is consistent with a connection between crude oil prices and carbon future prices.

3. Methodology

Initially, we focus on estimating dynamic conditional correlations. We select the use of FIGARCH, because, as highlighted by Cont [2001], long memory is a stylised fact of financial time series. Therefore, a hyperbolic decay in the autocorrelation of absolute returns may suggest persistence in return volatilities. Ding et al. [1993] posit that absolute returns are found to display higher autocorrelations than log returns. Consequently, initially, we employ Hurst exponent tests to check for long memory in the return series. The results of these tests, presented in Table 2, suggest persistence of return volatility. Consequently, we consider that the FIGARCH model, incorporating fractional differencing to account for long memory, is preferred.

To establish a FIGARCH model, we employ the dynamic conditional correlation methodology (DCC-GARCH) of Engle [2002], decomposing the conditional covariance matrix:

\[ H_t = D_t R_t D_t \]  

\[ R_t = \text{diag}(Q_t)^{-\frac{1}{2}} Q_t \text{diag}(Q_t)^{-\frac{1}{2}} \quad \text{and} \quad Q_t = \Omega + \alpha \epsilon_{t-1} \epsilon_{t-1}' + \beta Q_{t-1} \]  

where \( R_t \) is defined as the conditional correlation matrix, and \( D_t \) is a diagonal matrix with time-varying standard deviations \( \sqrt{h_{i,t}} \) on the main diagonal. Additionally, \( Q_t \) denotes the approximation of the conditional correlation matrix, displayed above in Eqs.1 & 2 as \( R_t \). The positive semi-definiteness of \( Q_t \) is guaranteed if both \( \alpha \) and \( \beta \) are both positive, and the sum of both \( \alpha \) and \( \beta \) is less than one, with the initial matrix \( (Q_1) \) being positive. \( \Omega = (1 - \alpha - \beta) \bar{R} \), where \( \bar{R} \) representing the unconditional average correlation. Next, we estimate \( D_t \), which denotes the conditional volatility. We use the \( \epsilon_t = D_t^{-1} r_t \) to estimate the quasi-conditional correlation matrix \( Q_t \). \( Q_t \) is re-scaled to obtain the conditional correlation matrix described in Eq.2 [Harris and Nguyen, 2013]. Additionally, the conditional volatility \( D_t \) and the conditional correlations \( R_t \) are then employed to generate the conditional correlation matrix \( H_t \). The h-step-ahead conditional covariance matrix is:

\[ H_{t+h} = D_{t+h} R_{t+h} D_{t+h} \]
We note that the forecast of each volatility in \( D_{t+h} \) can be estimated for the univariate case using the function 
\[
H_{t+1} = h \sum_{i=0}^{T} \lambda(h,i) r_{t-i} \frac{r_{t-i}}{r_{t-i}}.
\]
Since \( R_t \) is described as a non-linear process, the h-step-ahead forecast of \( R_t \) cannot be computed using the recursive procedure, however, the forecasts of \( Q_{t+h} \) and \( R_{t+h} \) are calculated as:

\[
Q_{t+h} = \sum_{j=0}^{h-2} (1 - \alpha - \beta) Q(\alpha + \beta)^j + (\alpha + \beta)^{h-1} Q_{t+1} \tag{4}
\]

\[
R_{t+h} = \text{diag}(Q_t)^{-\frac{1}{2}} Q_{t+h} \text{diag}(Q_t)^{-\frac{1}{2}} \tag{5}
\]

We extend this structure with a fractionally-integrated GARCH methodology (FIGARCH). The FIGARCH model offers adaptability to modelling conditional variance, as it allows for the covariance stationary GARCH model when \( d = 0 \), along with that of the IGARCH model when \( d = 1 \). For our FIGARCH modelling, the persistence of conditional variance shock is estimated by the parameter \( d \), also referred to as the fractional differencing parameter. This denotes a long-memory process imposed through a fractional-difference operator. Therefore, for \( 0 < d < 1 \), the FIGARCH methodology is sufficiently adaptable to accommodating an intermediate range of persistence [Baillie et al., 1996]. The conditional volatility of the FIGARCH(1,d,1) model is shown as:

\[
h_t = \omega + \left[ 1 - \beta L - (1 - \phi L)(1 - L)^d \right] r_t^2 + \beta h_{t-1} \tag{6}
\]

where \( L \) is a lag operator. The FIGARCH process defaults to a GARCH process when \( d = 0 \), while the h-step forward prognosis of the FIGARCH(1,d,1) model is:

\[
h_{t+h} = \omega (1 - \beta)^{-1} + \left[ 1 - (1 - \beta L)^{-1} (1 - \phi L)(1 - L)^d \right] r_{t+h-1}^2 \tag{7}
\]

When in a multivariate context, the same DCC approach is re-deployed with the same forecast functions for \( Q_{t+h} \) and \( R_{t+h} \). The multivariate Student t distribution is employed since the assumption of normality is rejected for each of the volatility series.

To investigate spillovers in the volatility of WTI during the COVID-19 pandemic, along with subsequent impacts of negative oil prices on carbon pricing, we apply the spillover index of Diebold and Yilmaz [2009]. This builds on the vector autoregressive (VAR) models developed by Sims [1980]. The methodology culminates in the following net pairwise volatility spillover index:

\[
\text{NPS}_{ij}(H) = \left( \hat{\phi}_{ij}(H) \sum_{i,m=1}^{N} \hat{\phi}_{i,m}(H) - \hat{\phi}_{ij}(H) \sum_{j,m=1}^{N} \hat{\phi}_{j,m}(H) \right) \times 100 = \left( \frac{\hat{\phi}_{ij}(H) - \hat{\phi}_{ij}(H)}{N} \right) \times 100 \tag{8}
\]

where the net pairwise volatility spillovers (NPS) between markets i and j are consequently determined as the difference between gross volatility shocks received by variable j from variable i,
while concomitantly acknowledging shocks transmitted from \( j \) to \( i \) (Eq.8).

4. Results

We analyse the co-movements and connectedness of WTI and selected carbon markets during the period May 2019 to May 2020. To investigate co-movements, we apply the generalized spillover index by Diebold and Yilmaz [2012]. We then investigate net-pairwise directional volatility spillovers of WTI on stated carbon markets. Figure 2 highlights results of DCC-GARCH volatility co-movement analysis, showing total directional volatility spillovers from WTI onto each carbon market product before and after the outbreak of the COVID-19 pandemic. These results are obtained by applying the generalised spillover index by Diebold and Yilmaz [2012], which is built on the VAR approach developed by Sims [1980]. Figure 2 highlights the impact of the outbreak of the COVID-19 pandemic and negative oil prices on carbon products. There was subsequent direct volatility spillover from WTI prices to each carbon market product around the beginning of the second quarter in 2020. Spillovers from the negative price shock on WTI correlated more than 20 with the price movements of each carbon market product. For some carbon price products, the sharp increase in dynamic correlation with WTI increased over five-fold in the period between January 2020 and May 2020, and eight-fold based on the twelve months prior. Before 2020, the directional spillovers from WTI to carbon markets were significantly lower, with the estimated directional correlation coefficient estimate averaging 1.58.

Initial results suggest that during the outbreak of COVID-19 and negative oil prices, a large part of the volatility fluctuations of carbon markets were driven by crude oil prices\(^3\). Sharp interactions were perhaps due to concerns of traders regarding the sharp effects that negative oil price valuations might present on the supply and demand for carbon futures products.\(^4\) Further evidence of the directional volatility spillovers from WTI to the carbon market products during the COVID-19 pandemic is presented and analysed in the next subsection.

\(^3\)On the other hand, fluctuations in carbon pricing might have been due to the reduced energy demand. According to Corbet et al. [2020], renewable energy markets reacted to the drop in global energy demand during the pandemic, while renewable energy output was increased. One particular view pertaining from such research is based upon the possible scenario where businesses and firms re-evaluated to a view that renewables would be more likely to meet future energy demand, and so, the threshold investment in fossils would be less likely to be needed, therefore, we would expect a decline in carbon offsets.

\(^4\)For example, the International Energy Agency (IEA) has reported that global carbon dioxide emissions fell 8% at the beginning of the pandemic. In total, the annual energy demand has been estimated to decline by 1.5%. Previous research has also shown that crude oil markets and carbon markets are connected. For example, Yu et al. [2015] find strong spillover effects between EUA carbon and Brent crude oil markets on the medium-time scale. Similarly, Ji et al. [2018] and Wang and Guo [2018] found that oil markets affect carbon price changes and risks.
Our analysis next continues by investigating the volatility spillover relationship of WTI crude oil prices to each carbon product used in our study. Having investigated total volatility spillovers from the oil market to the carbon market, it is interesting to examine which of the carbon market products received more spillover effects from WTI compared to other future products. Figure 3 illustrates our estimation of net pairwise direct volatility spillovers from WTI crude oil price to selected carbon market products for the period October 2017 through May 2020. This period includes observations from both before and during the COVID-19 crises, as well during the negative oil pricing event, in order to assess how such markets behaved under fragility versus ’normal’ periods.

**Figure 3 highlights that net directional volatility spillover effects from WTI to each carbon market product were respectively very similar, indicating that the efficiency of carbon futures markets remained intact during this incredibly difficult period. While nominal differentials exist, the differentials between the identified spillovers remain modest\(^5\). The net spillover effects from WTI to the carbon markets were negative for all other carbon products during the period throughout Q3 and Q4 2019, through Q1 and Q2 2020, despite a short positive peak at the beginning of Q2 2020. These results indicate that WTI received more spillover effects than transmitted during the COVID-19 pandemic. Furthermore, Figure 3 suggests that before 2020, the net volatility spillover effects have been bi-directional. These findings are consistent with previous research, which has identified bi-directional net volatility spillovers of oil markets to various stock markets before the COVID-19 pandemic and unexpected negative prices [Arouri et al., 2011, 2012, Antonakakis et al., 2018, Khalfaoui et al., 2015, Maghyereh et al., 2009].**

**Further evidence on the connectedness of WTI and the selected carbon market products is presented in Table 3. These results illustrate the net directional spillovers between the two markets for the period March 2019 through May 2020, which includes the time of relative calm before, and the significant period of market panic during the escalation and development of the COVID-19 pandemic, and the resulting negative oil price event. Examining Table 3, we can observe further evidence of market correlations between oil and carbon markets. The results support our previous finding that crude oil markets acted as source, rather than recipients, of net spillovers. Oil markets dominate each respective carbon market, with the source of net directional connectedness in each**

\(^5\)Interestingly, there is one carbon market product, based on RPC Fuel Switching EUA TTF Monthly Continuation (FSEUATT), for which the net directional spillover effects of WTI appears to be quite different to for rest of the selected carbon products, however, this can be explained through differentials of holdings and the creation of the fuel-switching series when compared to the other analysed products.
case over 93% from WTI to each carbon market product. However, the dynamic and time-varying changes of such spillovers, Table 4, are of much interest. When presenting the average, intra-period estimates of directional spillovers, pairwise spillovers and net directional connectedness, we observe the differential behaviour between three distinct periods. We observe clear evidence of differential behaviour between the pre-crisis and COVID-19 periods, however with again distinctly differential behaviour evident in the period surrounding negative WTI prices. This indicates that although financial market participants evaluated the effects of COVID-19 upon both WTI and carbon futures markets, the event of negative WTI prices also catalyzed extreme market effects.

Our results suggest that the WTI and EUA carbon markets shared substantial ‘confusion’ proximate to the early evolution of the COVID-19 pandemic\(^6\) and during the period surrounding negative WTI prices. We infer more generally that carbon markets are vulnerable to extreme macroeconomic and commodity market conditions.

5. Conclusions

We investigate spillovers in the volatility of West Texas Intermediate crude oil (WTI) on the volatility of carbon emission allowance futures, specifically for the time when WTI prices became negative during the onset of COVID-19. Applying a generalized spillover index, and employing dynamic correlation modelling, we identify transmission of volatility between oil prices and carbon credits during this extraordinary period. Results evidence, for the period preceding negative WTI, a doubling of directional spillover from WTI oil to carbon allowance futures upon the global spread of COVID-19. Subsequently, there is a spiking of directional spillover from WTI oil to carbon allowances during the specific period of negative WTI, with this extraordinary rise in directional spillover continuing from the near-term contract through several ensuing contracts. Our results are consistent with COVID-19 establishing a fragile platform for other external conditions to affect sudden spikes in directional volatility.

Results are consistent with the extreme fall in WTI prices catalysing a market reassessment of the appropriate future cost of polluting, as has been suggested by recent studies [Corbet et al., 2020, 2021, 2022]. Our results also suggest that carbon futures are simply vulnerable to volatility contagion from energy markets, without an attributable cause. More broadly, our findings complement recent research highlighting how markets are prone to manifesting spikes of disruption during periods of downturn and fragility. We contribute both to an understanding of energy markets during

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\(^6\)Considered as a ‘black-swan’ event of financial markets [Conlon et al., 2020, Corbet et al., 2020, 2021, Goodell, 2020, Yarovaya et al., 2020].
COVID-19, as well as to understanding the vulnerability of carbon futures markets during periods of heightened fragility.

References


Figure 1: Carbon market price volatility

i) EAAc1  
ii) CF12Z0  
iii) FEUA1

iv) FEUAZ0  
v) NEUAZ0  
vii) FEUAZ2 
vi) FEUAZ1  

viii) FEUAZ3 
ix) FEUAZ4

x) FEAAC1  
xi) FSEUATTFMc1 

Note: The data sample used for the estimation covers the period from March 2019 through May 2020 and it includes both daily and hourly observations.
Figure 2: Total Directional Volatility Spillovers from WTI onto each Analysed Sector

i) EAAc1  

ii) CFIZZ0  

iii) FEUAC1

iv) FEUAZ0  

v) NEUAZ0  

vi) FEUAZ1

vii) FEUAZ2  

viii) FEUAZ3  

ix) FEUAZ4

x) FEAAC1  

xi) FSEUATTFMc1  

xii) EAAC0

Note: The above table represents the total directional volatility spillovers from WTI upon each carbon market product. To examine spillovers of the volatility of WTI during COVID-19, we apply the generalized version of the spillover index proposed by Diebold and Yilmaz [2009], and which builds on the vector autoregressive (VAR) models of Sims [1980].
Note: The above table represents the net pairwise directional volatility spillovers by carbon market. To examine spillovers of the volatility of WTI during the COVID-19 pandemic, we apply the generalized version of the spillover index proposed by Diebold and Yilmaz [2009], and which builds on the vector autoregressive (VAR) models developed by Sims [1980].
Table 1: Descriptive Statistics

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<th>NEUAZ0</th>
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Note: The above data presents the carbon futures products used in this analysis for the period March 2019 through May 2020. Data was obtained from Thomson Reuters Eikon.
### Table 2: Hurst Exponents

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Note: The above data presents the carbon futures products used in this analysis for the period March 2019 through May 2020. Data was obtained from Thomson Reuters Eikon.

### Table 3: Net Directional Connectedness

<table>
<thead>
<tr>
<th></th>
<th>WTI Carbon</th>
<th>WTI Carbon</th>
<th>WTI Carbon</th>
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<tr>
<td></td>
<td>CLc1 CFIZZ0</td>
<td>CLc1 EAAc1</td>
<td>CLc1 EAAZ0</td>
</tr>
<tr>
<td>WTI</td>
<td>94.30 5.70</td>
<td>94.36 5.64</td>
<td>94.17 5.83</td>
</tr>
<tr>
<td>Carbon Product</td>
<td>1.80 98.2</td>
<td>1.95 98.05</td>
<td>2.06 97.94</td>
</tr>
<tr>
<td>Directional TO Others</td>
<td>1.80 5.70</td>
<td>1.95 5.64</td>
<td>2.06 5.83</td>
</tr>
<tr>
<td>Directional Including Own</td>
<td>96.10 103.90</td>
<td>96.31 103.69</td>
<td>96.23 103.77</td>
</tr>
<tr>
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<td>-3.9 3.90</td>
<td>-3.69 3.69</td>
<td>-3.77 3.77</td>
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<tr>
<td>WTI</td>
<td>94.70 5.43</td>
<td>94.35 5.66</td>
<td>94.18 5.82</td>
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<tr>
<td>Carbon Product</td>
<td>1.64 98.36</td>
<td>1.72 98.28</td>
<td>1.73 98.27</td>
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<tr>
<td>Directional TO Others</td>
<td>1.64 5.43</td>
<td>1.72 5.65</td>
<td>1.73 5.82</td>
</tr>
<tr>
<td>Directional Including Own</td>
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<td>96.06 103.94</td>
<td>95.91 104.09</td>
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<td>-3.94 3.94</td>
<td>-4.09 4.09</td>
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<tr>
<td>WTI</td>
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<td>94.23 5.77</td>
<td>94.18 5.82</td>
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<td>Carbon Product</td>
<td>1.79 98.21</td>
<td>1.88 98.12</td>
<td>1.94 98.06</td>
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<tr>
<td>Directional TO Others</td>
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<td>1.94 5.82</td>
</tr>
<tr>
<td>Directional Including Own</td>
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<td>96.12 103.88</td>
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<td>-3.89 3.89</td>
<td>-3.88 3.88</td>
</tr>
<tr>
<td>WTI</td>
<td>94.14 5.86</td>
<td>94.26 5.74</td>
<td>93.64 5.36</td>
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<tr>
<td>Carbon Product</td>
<td>1.91 98.09</td>
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<td>2.06 97.94</td>
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<tr>
<td>Directional TO Others</td>
<td>1.91 5.86</td>
<td>8.20 5.74</td>
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<tr>
<td>Directional Including Own</td>
<td>96.06 103.94</td>
<td>102.46 97.54</td>
<td>95.70 104.30</td>
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<tr>
<td>NET Directional Connectedness</td>
<td>-3.94 3.94</td>
<td>2.46 -2.46</td>
<td>-4.30 4.30</td>
</tr>
</tbody>
</table>

Note: The above data presents the carbon futures products used in this analysis for the period March 2019 through May 2020. Data was obtained from Thomson Reuters Eikon. Shown are estimates of net directional connectedness. For brevity, only significant results at the 1% level are presented. Further results at varying time-frequencies and variation of methodological structure are available from the authors on request.
Table 4: Differentials of market dynamics between WTI and carbon markets during the periods investigated

<table>
<thead>
<tr>
<th>Directional Spillover</th>
<th>Fairwise Spillover</th>
<th>Net Directional Connectedness</th>
</tr>
</thead>
<tbody>
<tr>
<td>CFPZ0</td>
<td>2.152 3.915 21.733</td>
<td>0.254 -1.732 -5.191</td>
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<tr>
<td>EEAcl</td>
<td>2.101 4.026 21.496</td>
<td>0.198 -1.770 -4.749</td>
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<tr>
<td>EEAc0</td>
<td>2.102 4.017 21.508</td>
<td>0.201 -1.819 -4.895</td>
</tr>
<tr>
<td>FEAa1</td>
<td>2.188 3.855 21.860</td>
<td>0.298 -1.848 -4.911</td>
</tr>
<tr>
<td>FEAa0</td>
<td>2.136 3.909 21.693</td>
<td>0.251 -1.851 -5.610</td>
</tr>
<tr>
<td>FEUa1</td>
<td>2.160 3.855 21.821</td>
<td>0.277 -2.145 -5.791</td>
</tr>
<tr>
<td>FEUa2</td>
<td>2.164 3.848 21.834</td>
<td>0.281 -2.178 -5.738</td>
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<tr>
<td>FSEUATT</td>
<td>1.391 8.499 11.424</td>
<td>-0.480 0.905 2.671</td>
</tr>
<tr>
<td>NEUAz0</td>
<td>1.993 4.181 19.692</td>
<td>0.113 -2.298 -4.831</td>
</tr>
</tbody>
</table>

Note: The above data presents evidence of the differential behaviour between metrics as calculated by the averages of the results in the periods inclusive of the entire sample between May 2019 and December 2019, that of January 2020 through March 2020, and finally, that of the sample inclusive of April and May 2020, representing the period in which WTI prices experienced negative pricing due to exceptional volatility associated with the COVID-19 pandemic financial market panic.