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

Carbon credit markets and cap-and-trade systems have received increasing attention from researchers after the implementation of the EU emission trading system (EU ETS) in 2005. with subsequent studies examining connections between European Union carbon allowances (EUA) and energy markets [Bunn and Fezzi, 2007, Hintermann, 2010, Keppler and Mansanet-Bataller, 2010, Koch, 2014, Ji et al., 2018, Wang and Guo, 2018, Zheng et al., 2015, Tan et al., 2020, Batten et al., 2021]. Studies suggest that macroeconomic conditions, supply and demand conditions, and new institutional information impact carbon credits [Chevallier, 2009, Alberola et al., 2008, Chesney and Taschini, 2009, Aatola et al., 2013, Oberndorfer, 2009, Sousa et al., 2014, Zhu et al., 2020]. 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.[1]

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].

2. Data

We investigate the sample period March 2019 to May 2020, at both daily and hourly frequencies. Overall, we have 868 daily observations[2], 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, $V_{it} = |lnP_{it} - lnP_{it-1}|$, 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

[1] 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].

[2] 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.

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 FI-GARCH, 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.

Insert Table 2 about here

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

$$H_t = D_t R_t D_t \tag{1}$$

$$R_t = \text{diag}(Q_t)^{-\frac{1}{2}}.Q_t.\text{diag}(Q_t)^{-\frac{1}{2}} \quad and \quad Q_t = \Omega + \alpha\varepsilon_{t-1}\varepsilon_{t-1}^{'} + \beta Q_{t-1} \tag{2}$$

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 α and β are both positive, and the sum of both α and β 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 $\varepsilon_t = D_t^{-1} r_t$ 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 :

$$H_{t+h} = D_{t+h} R_{t+h} D_{t+h} \tag{3}$$

We note that the forecast of each volatility in D_{t+h} can be estimated for the univariate case using the function $H_{t+1:t+h} = h\sum_{i=0}^{T}\lambda(h,i)r_{t-i}r_{t-i}^{'}$. 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:

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

$$R_{t+h} = \mathrm{diag}(Q_t)^{-\frac{1}{2}}.Q_{t+h}.\mathrm{diag}(Q_{t+h})^{-\frac{1}{2}} \tag{5}$$

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:

$$\mathrm{NPS}_{ij}(H) = \left(\frac{\tilde{\phi}_{ji}(H)}{\sum_{i,m=1}^{N}\tilde{\phi}_{i,m}(H)} - \frac{\tilde{\phi}_{ij}(H)}{\sum_{j,m=1}^{N}\tilde{\phi}_{j,m}(H)}\right) \mathrm{x}\,100 = \left(\frac{\tilde{\phi}_{ji}(H) - \tilde{\phi}_{ij}(H)}{N}\right) \mathrm{x}\,100 \tag{8}$$

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.

Insert Figure 2 about here

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.

Insert Figure 3 about here

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].

Insert Table 3 about here

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.

Insert Table 4 about here

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

[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

Aatola, P., M. Ollikainen, and A. Toppinen (2013). Price determination in the EU ETS market: Theory and econometric analysis with market fundamentals. *Energy Economics 36*, 380–395.

Alberola, E., J. Chevallier, and B. Chezè (2008). Price drivers and structural breaks in European carbon prices 2005–2007. *Energy Policy 36*(2), 789–797.

Anand, A. and K. Venkataraman (2016). Market conditions, fragility, and the economics of market making. *Journal of Financial Economics 121*(2), 327–349.

Antonakakis, N., J. Cunado, G. Filis, D. Gabauer, and F. Perez de Gracia (2018). Oil volatility, oil and gas firms and portfolio diversification. *Energy Economics 70*, 499–515.

Arouri, M. E. H., L. Amine, and D. K. Nguyen (2012). Return and volatility transmission between world oil prices and stock markets of the GCC countries. *Economic Modelling 28*(4), 1815–1825.

Arouri, M. E. H., J. Jouini, and D. K. Nguyen (2011). On the impacts of oil price fluctuations on European equity markets: Volatility spillover and hedging effectiveness. *Energy Economics 34*(2), 611–617.

Baillie, R. T., C.-F. Chung, and M. A. Tieslau (1996). Analysing inflation by the fractionally integrated ARFIMA–GARCH model. *Journal of applied econometrics 11*(1), 23–40.

Batten, J. A., G. E. Maddox, and M. R. Young (2021). Does weather, or energy prices, affect carbon prices? *Energy Economics 96*, 105016.

Bunn, D. W. and C. Fezzi (2007). Interaction of European Carbon Trading and Energy Prices. *FEEM Working Paper* (63).

Böhringer, C., T. Rutherford, and R. Tol (2009). THE EU 20/20/2020 targets: An overview of the EMF22 assessment. *Energy Economics 31*(SUPPL. 2), S268–S273.

Chesney, M. and L. Taschini (2009). The endogenous price dynamics of emission permits in the presence of technology change. *Grantham Research Institute, London School of Economics*.

Chevallier, J. (2009). Carbon futures and macroeconomic risk factors: A view from the EU ETS. *Energy Economics 31*(4), 614–625.

Conlon, T., S. Corbet, and R. J. McGee (2020). Are Cryptocurrencies a Safe Haven for Equity Markets? An International Perspective from the COVID-19 Pandemic. *Research in International Business and Finance*, 101248.

Cont, R. (2001). Empirical properties of asset returns: stylized facts and statistical issues. *Quantitative finance 1*(2), 223.

Corbet, S., J. W. Goodell, and S. Günay (2020). Co-movements and spillovers of oil and renewable firms under extreme conditions: New evidence from negative WTI prices during COVID-19. *Energy economics*, 104978.

Corbet, S., G. Hou, Y. Hu, C. J. Larkin, and L. Oxley (2020). Any Port in a Storm: Cryptocurrency Safe-Havens during the COVID-19 Pandemic. *Economics Letters 194*, 109377.

Corbet, S., G. Hou, Y. Hu, L. Oxley, and D. Xu (2021). Pandemic-related financial market volatility spillovers: Evidence from the Chinese COVID-19 epicentre. *International Review of Economics & Finance 71*, 55 – 81.

Corbet, S., Y. G. Hou, Y. Hu, and L. Oxley (2020). The influence of the COVID-19 pandemic on asset-price discovery: Testing the case of Chinese informational asymmetry. *International Review of Financial Analysis 72*, 101560.

Corbet, S., Y. G. Hou, Y. Hu, and L. Oxley (2021). An analysis of investor behaviour and information flows surrounding the negative WTI oil price futures event. *Energy Economics*, 105589.

Corbet, S., Y. G. Hou, Y. Hu, and L. Oxley (2022). The influence of the COVID-19 pandemic on the hedging functionality of Chinese financial markets. *Research in International Business and Finance 59*, 101510.

Diebold, F. X. and K. Yilmaz (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal 119*(534), 158–171.

Diebold, F. X. and K. Yilmaz (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting 28*(1), 57–66.

Ding, Z., C. W. Granger, and R. F. Engle (1993). A long memory property of stock market returns and a new model. *Journal of empirical finance 1*(1), 83–106.

Du, L. and Y. He (2015). Extreme risk spillovers between crude oil and stock markets. *Energy Economics 51*, 455–465.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics 20*(3), 339–350.

Fankhauser, S. and R. Tol (2005). On climate change and economic growth. *Resource and Energy Economics 27*(1), 1–17.

Goodell, J. W. (2020). COVID-19 and finance: Agendas for future research. *Finance Research Letters*, 101512.

Harris, R. D. and A. Nguyen (2013). Long memory conditional volatility and asset allocation. *International Journal of Forecasting 29*(2), 258–273.

Hintermann, B. (2010). Allowance price drivers in the first phase of the EU ETS. *Journal of environmental economics and management 59*(1), 43–56.

Ji, Q., D. Zhang, and J.-b. Geng (2018). Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets. *Journal of Cleaner Production 198*, 972–978.

Keppler, J. H. and M. Mansanet-Bataller (2010). Causalities between CO2, electricity, and other energy variables during phase I and phase II of the EU ETS. *Energy Policy 38*(7), 3329–3341.

Khalfaoui, R., M. Boutahar, and H. Boubaker (2015). Analyzing volatility spillovers and hedging between oil and stock markets: Evidence from wavelet analysis. *Energy Economics 49*, 540–549.

Koch, N. (2014). Dynamic linkages among carbon, energy and financial markets: a smooth transition approach. *Applied Economics 46*(7), 715–729.

Maghyereh, A. I., B. Awartani, and E. Bouri (2009). The directional volatility connectedness between crude oil and equity markets: new evidence from implied volatility indexes. *Energy Economics 57*, 78–93.

Oberndorfer, U. (2009). Energy prices, volatility, and the stock market: Evidence from the Eurozone. *Energy Policy 37*(2), 5787–5795.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: Journal of the Econometric Society*, 1–48.

Sousa, R., L. Aguiar-Conraria, and M. J. Soares (2014). Carbon financial markets: a time–frequency analysis of CO2 prices. *Physica A: Statistical Mechanics and Its Applications 414*, 118–127.

Tan, X., K. Sirichand, A. Vivian, and X. Wang (2020). How connected is the carbon market to energy and financial markets? A systematic analysis of spillovers and dynamics. *Energy Economics 90*(104870).

Tol, R. (1999). The marginal costs of greenhouse gas emissions. *Energy Journal 20*(1), 61–81.

Tol, R. (2005). The marginal damage costs of carbon dioxide emissions: An assessment of the uncertainties. *Energy Policy 33*(16), 2064–2074.

Tol, R. (2018). The economic impacts of climate change. *Review of Environmental Economics and Policy 12*(1), 4–25.

Wang, X. and C. Wu (2018). Asymmetric volatility spillovers between crude oil and international financial markets. *Energy Economics 74*, 592–604.

Wang, Y. and Z. Guo (2018). The dynamic spillover between carbon and energy markets: New evidence. *Energy 149*, 24–33.

Xu, W., F. Ma, W. Chen, and B. Zhang (2019). Asymmetric volatility spillovers between oil and stock markets: Evidence from China and the United States. *Energy Economics 80*, 310–320.

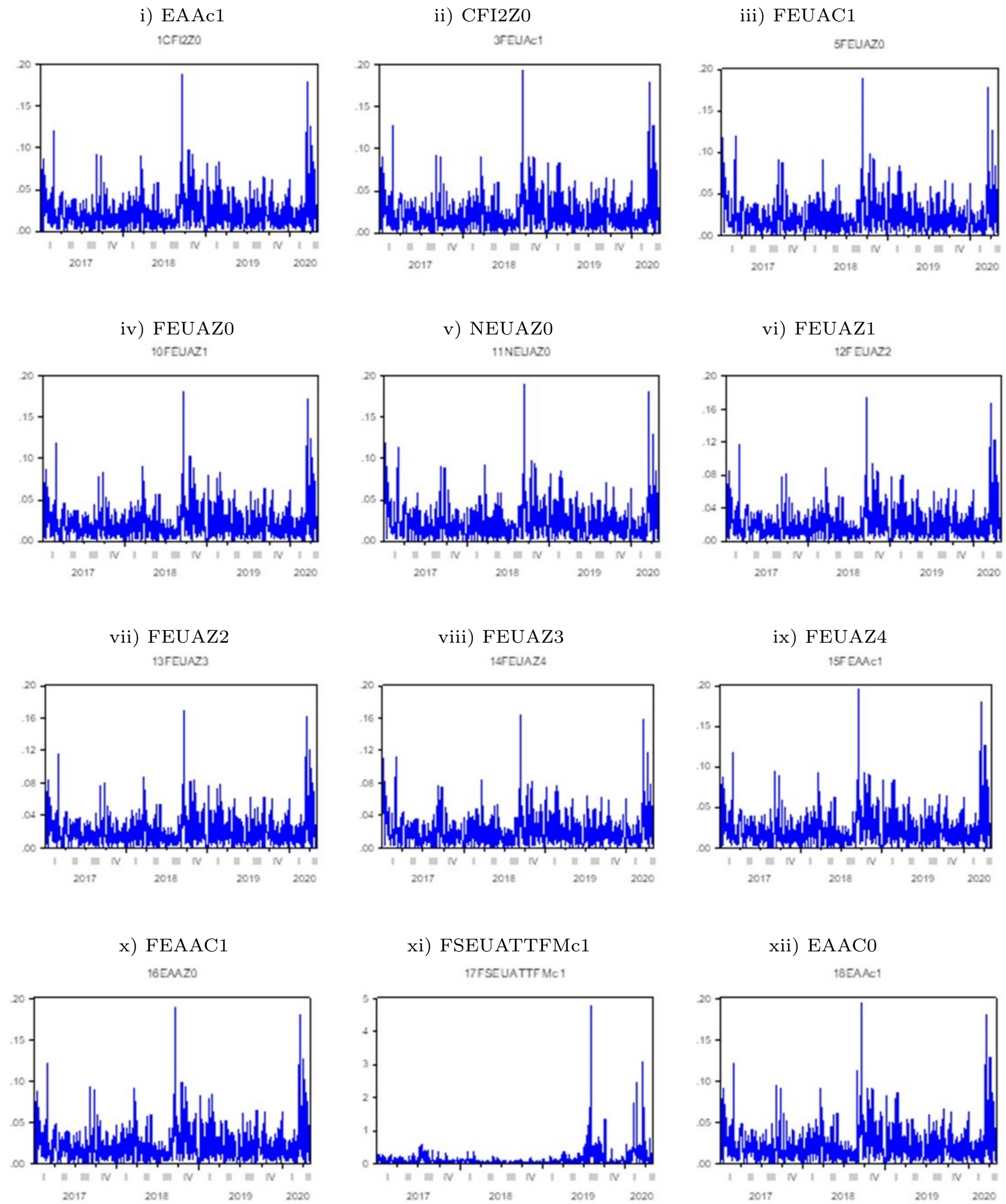
Yarovaya, L., R. Matkovskyy, and A. Jalan (2020). The Effects of a 'Black Swan' Event (COVID-19) on Herding Behavior in Cryptocurrency Markets: Evidence from Cryptocurrency USD, EUR, JPY and KRW Markets. *EUR, JPY and KRW Markets (April 27, 2020)*.

Yu, L., J. Li, L. Tang, and S. Wang (2015). Linear and nonlinear Granger causality investigation between carbon market and crude oil market: A multi-scale approach. *Energy Economics 51*, 300–311.

Zheng, Z., R. Xiao, H. Shi, G. Li, and X. Zhou (2015). Statistical regularities of Carbon emission trading market: Evidence from European Union allowances. *Physica A: Statistical Mechanics and its Applications 426*(7), 9–15.

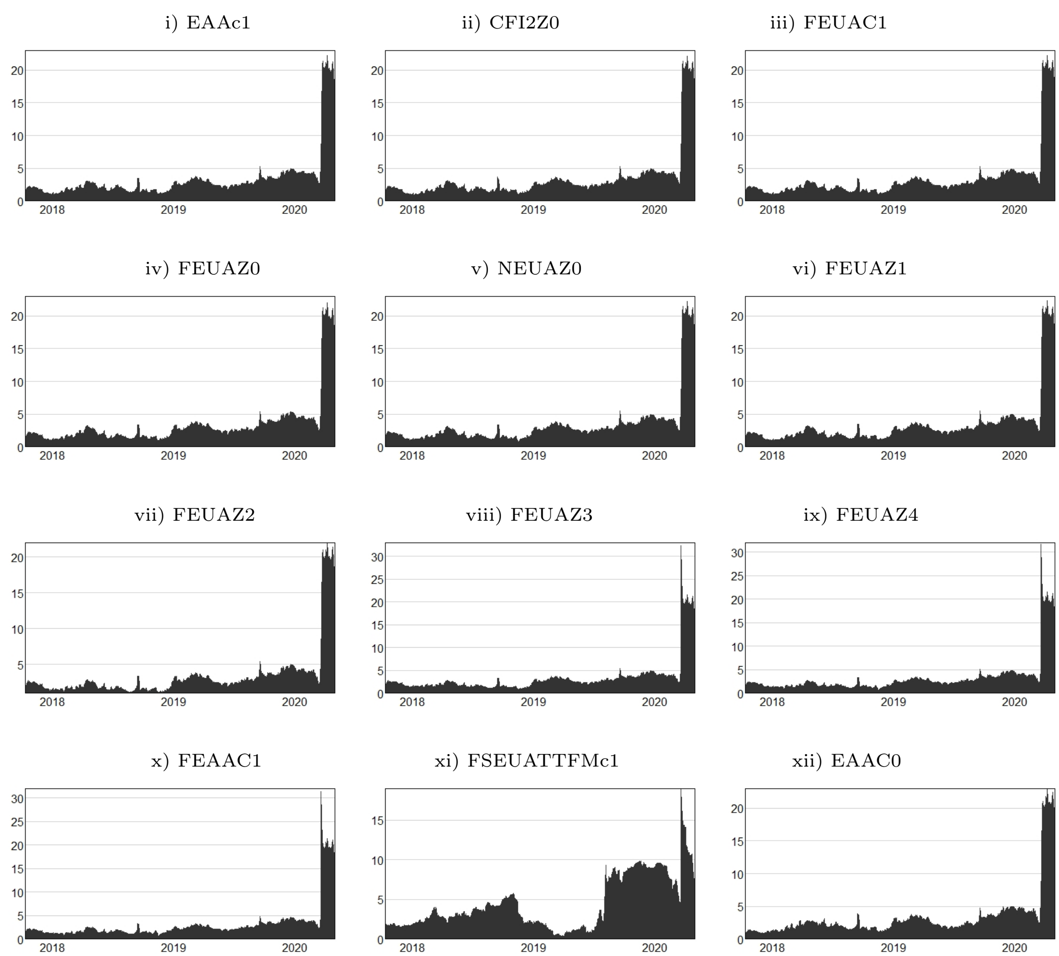
Zhu, B., L. Huang, L. Yuan, S. Ye, and P. Wang (2020). Exploring the risk spillover effects between carbon market and electricity market: A bidimensional empirical mode decomposition based conditional value at risk approach. *International Review of Economics and Finance 67*, 163–175.

Figure 1: Carbon market price volatility



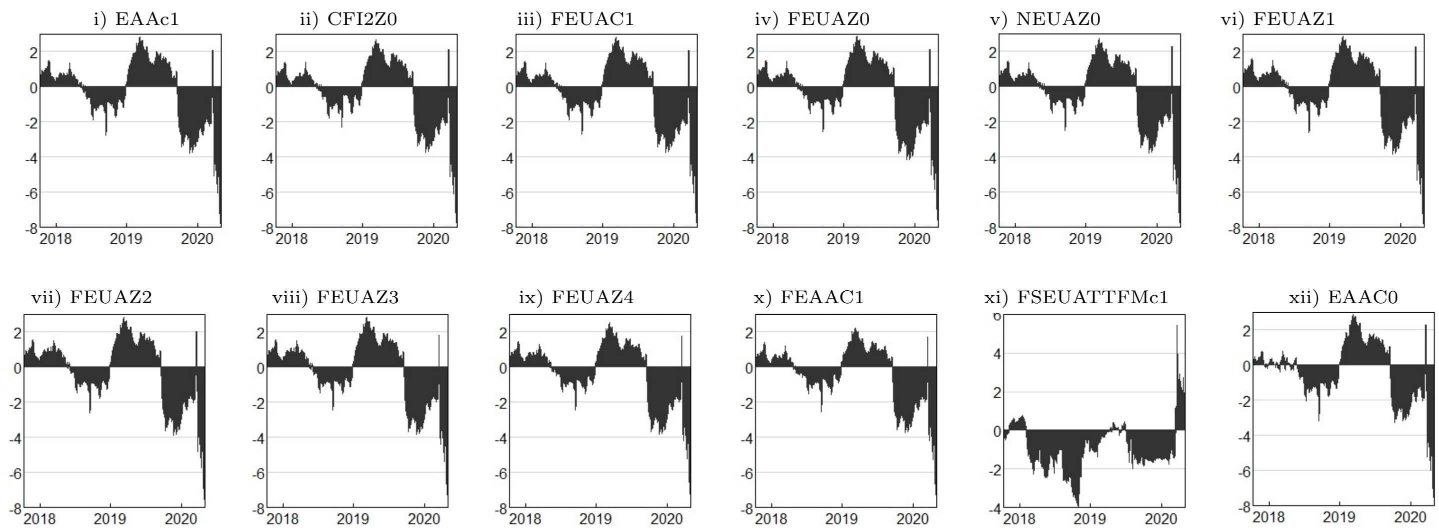
Note: The data sample used for the estimation covers the period from March 2019 through May 2020 and it includes both daily and hourly observations.

Figure 2: Total Directional Volatility Spillovers from WTI onto each Analysed Sector



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].

Figure 3: Net pairwise directional volatility spillovers



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

	CLC1	CFI2Z0	FEUAC1	FEUAZ0	NEUAZ0	FEUAZ1	FEUAZ2	FEUAZ3	FEUAZ4	FEAAC1	EAAZ0	EAAC1	FSEUATT
Mean	0.0175	0.0212	0.0214	0.0211	0.0211	0.0206	0.0201	0.0197	0.0194	0.0215	0.0214	0.0216	0.1292
Median	0.0104	0.0166	0.0169	0.0162	0.0164	0.0159	0.0157	0.0154	0.0151	0.0170	0.0167	0.0169	0.0604
Maximum	0.3196	0.1888	0.1949	0.1888	0.1900	0.1813	0.1747	0.1698	0.1647	0.1960	0.1894	0.1950	4.7944
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Std. Dev.	0.0291	0.0203	0.0207	0.0203	0.0207	0.0198	0.0193	0.0189	0.0185	0.0207	0.0205	0.0210	0.2901
Skewness	5.9850	2.5482	2.5430	2.5460	2.4734	2.5087	2.4795	2.4507	2.4174	2.5017	2.5315	2.5275	8.8336
Kurtosis	49.1277	14.9905	15.1336	14.9712	14.4557	14.5314	14.1754	13.9687	13.6897	14.8085	14.7711	14.6234	111.1740
Jarque-Bera	82,136.5	6,139.1	6,260.2	6,120.8	5,631.3	5,719.7	5,406.3	5,220.1	4,978.2	5,948.5	5,938.3	5,810.5	434,497.1
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	15.15	18.46	18.62	18.32	18.38	17.91	17.52	17.18	16.84	18.72	18.57	18.80	112.12
Sum Sq. Dev.	0.7352	0.3607	0.3720	0.3600	0.3733	0.3430	0.3248	0.3096	0.2978	0.3750	0.3668	0.3846	73.0149
Observations	868	868	868	868	868	868	868	868	868	868	868	868	868

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

Type	CLc1	CFI2Z0	FEUAc1	FEUAZ0	NEUAZ0	FEUAZ1	FEUAZ2	FEUAZ3	FEUAZ4	FEAAc1	EAAZ0	EAAc1	FSEUATT
Higuchi	0.89	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.88
	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02
Peng	0.52	0.68	0.67	0.67	0.67	0.67	0.66	0.66	0.65	0.67	0.68	0.67	0.76
	0.04	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03
R/S	0.56	0.83	0.82	0.84	0.82	0.84	0.84	0.84	0.84	0.83	0.83	0.83	0.76
	0.02	0.03	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.03
Boxed Per.	0.77	0.63	0.61	0.62	0.61	0.61	0.61	0.61	0.61	0.62	0.63	0.61	0.67
	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04

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

	WTI	**Carbon**	**WTI**	**Carbon**	**WTI**	**Carbon**
	CLc1	CFI2Z0	CLc1	EAAc1	CLc1	EAAZ0
WTI	94.30	5.70	94.36	5.64	94.17	5.83
Carbon Product	1.80	98.2	1.95	98.05	2.06	97.94
Directional TO Others	1.80	5.70	1.95	5.64	2.06	5.83
Directional Including Own	96.10	103.90	96.31	103.69	96.23	103.77
NET Directional Connectedness	-3.9	3.90	-3.69	3.69	-3.77	3.77
	CLc1	FEAAc1	CLc1	FEUAc1	CLc1	FEUAc0
WTI	94.57	5.43	94.35	5.65	94.18	5.82
Carbon Product	1.64	98.36	1.72	98.28	1.73	98.27
Directional TO Others	1.64	5.43	1.72	5.65	1.73	5.82
Directional Including Own	96.21	103.79	96.06	103.94	95.91	104.09
NET Directional Connectedness	-3.79	3.79	-3.94	3.94	-4.09	4.09
	CLc1	FEUAZ1	CLc1	FEUAZ2	CLc1	FEUAZ3
WTI	94.23	5.77	94.23	5.77	94.18	5.82
Carbon Product	1.79	98.21	1.88	98.12	1.94	98.06
Directional TO Others	1.79	5.77	1.88	5.77	1.94	5.82
Directional Including Own	96.02	103.98	96.11	103.89	96.12	103.88
NET Directional Connectedness	-3.98	3.98	-3.89	3.89	-3.88	3.88
	CLc1	FEUAZ4	CLc1	FSEUATT	CLc1	NEUAZ0
WTI	94.14	5.86	94.26	5.74	93.64	6.36
Carbon Product	1.91	98.09	8.20	91.80	2.06	97.94
Directional TO Others	1.91	5.86	8.20	5.74	2.06	6.36
Directional Including Own	96.06	103.94	102.46	97.54	95.70	104.30
NET Directional Connectedness	-3.94	3.94	2.46	-2.46	-4.30	4.30

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

	Directional Spillover			Pairwise Spillover			Net Directional Connectedness		
	2019	Q1 2020	Neg. WTI	2019	Q1 2020	Neg. WTI	2019	Q1 2020	Neg. WTI
CFI2Z0	2.152	3.915	21.733	0.254	-1.732	-5.191	91.780	95.502	97.484
EEAc1	2.101	4.026	21.496	0.198	-1.770	-4.749	91.600	96.054	97.868
EEAc0	2.102	4.017	21.508	0.201	-1.819	-4.895	91.840	95.513	97.741
FEAAc1	2.188	3.855	21.860	0.289	-1.848	-4.911	91.786	95.317	97.727
FEUAc1	2.173	3.885	21.800	0.273	-1.831	-4.867	91.737	95.496	97.766
FEUAc0	2.136	3.909	21.693	0.251	-1.851	-5.610	91.683	94.006	97.119
FEUAZ1	2.160	3.855	21.821	0.277	-2.145	-5.791	91.835	93.712	96.962
FEUAZ2	2.164	3.848	21.834	0.281	-2.178	-5.738	91.856	93.608	97.008
FEUAZ3	2.174	3.837	21.845	0.289	-2.239	-5.528	91.899	93.675	97.191
FEUAZ4	2.174	3.815	21.899	0.297	-2.250	-5.888	91.927	92.795	96.877
FSEUATT	1.391	8.499	11.425	-0.480	0.905	2.671	91.017	94.370	95.324
NEUAZ0	1.993	4.181	19.692	0.113	-2.298	-4.831	91.358	92.899	97.797

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.