



HAL
open science

How to 'Trump' the energy market: evidence from the WTI-Brent spread

Catalin Dragomirescu-Gaina, Dionisis Philippos, Stéphane Goutte

► **To cite this version:**

Catalin Dragomirescu-Gaina, Dionisis Philippos, Stéphane Goutte. How to 'Trump' the energy market: evidence from the WTI-Brent spread. 2022. halshs-03843257

HAL Id: halshs-03843257

<https://shs.hal.science/halshs-03843257>

Preprint submitted on 8 Nov 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

How to ‘Trump’ the energy market: evidence from the WTI-Brent spread

Catalin Dragomirescu-Gaina ^a, Dionisis Philippas ^b, Stéphane Goutte ^{c,d}

^a Università Cattolica Del Sacro Cuore, Largo A. Gemelli 1, 20123, Milan, Italy. Email: catalin.dragomirescugaina@unicatt.it.

^b ESSCA School of Management, 55 Quai Alphonse Le Gallo, 92513, Boulogne, Paris, France, Email: dionisis.philippas@essca.fr. Corresponding author: +33 1 41 86 2003. ORCID: 0000-0001-9604-7425

^c Paris School of Business, 59 Rue Nationale, 75013 Paris, France.

^d Université Paris-Saclay, UVSQ, UMI SOURCE, 47 bld. Vauban 78280 Guyancourt, France. Email: stephane.goutte@uvsq.fr.

Abstract

Donald Trump’s use of Twitter was unprecedented. Despite his erratic communication style, some of Trump’s strong statements were made in reference to the U.S. oil & gas industry, in line with his domestic policy agenda aimed at supporting re-industrialization and local investment. Did his Twitter messages actually reach domestic oil producers, refiners and transport operators or rather speculators willing to financially gamble on new information sources? To address this question, we model the WTI-Brent spread, which commonly reflects supply bottlenecks in the U.S. crude oil sector, using a nonlinear approach that reveals the perverse influence of some of Trump’s tweets particularly on market speculative dynamics. Finally, we outline policy recommendations to counteract the market consequences of speculative behaviour driven by political noise.

JEL codes: D80; G14; Q48.

Keywords: WTI-Brent spread; Twitter; speculation.

1. Introduction

Crude oil prices are the most important reference for global energy prices, which are a key factor guiding many of our decisions as a society, from resisting Russian aggression in Ukraine today to embarking on (green) energy transition. The global oil market should be the place where producers, regulators and users of all types interact on a continuous basis, although its global nature and integration can be challenged at times. It is also a contested place for big and small financial investors, traders and speculators as well (Buyuksahin and Harris, 2011). This is because there has always been a substantial geopolitical component to oil prices (Acemoglu et al., 2012). A war waged in the Middle East has different market consequences than an oil supply bottleneck in an industrial hub like Texas, U.S., although global oil prices might increase the same in the short-run. Random events and statements by casual political actors (either individuals or sovereigns) are the usual catalysts for large oil price changes, but they can also raise speculation leading to market disruption. In times of crisis, different regional crude markets might drift apart, with price benchmarks losing their relevance, thus fuelling more uncertainty for market participants. In this paper, we seek to understand the specific role of political factors and their impact on the fragmentation of global oil market. While our analysis here applies to a particular time frame and to a specific political personality, the implications of our results are much broader such as to warrant a detailed discussion that is relevant for a larger readership, ranging from political economists to energy policy specialists and regulators.

The rise of social media and its use for political purposes has undeniably increased (see Gunitsky, 2015; Zhurasvskaya et al., 2020). To navigate across this large online space overflowing with information, we restrict our attention to Donald J. Trump, the 45th U.S.

president, in office from 2017 to 2021. He was regarded as an outspoken politician, who constantly contradicted climate change predictions and placed U.S. economic interests at the centre of his policy agenda. Trump announced his intention to run for presidency in June 2015, which is when our sample begins, becoming the Republican front-runner in March 2016. He received unprecedented media coverage from independent outlets (due to his style, and preference for political confrontations), although he favoured Twitter as his primary means of communication (see Ott, 2017; Lewandowsky et al., 2020; Afanasyev et al., 2021). Before his account was suspended (in January 2021), thousands of foreign media analysts and investors were regularly following his Twitter account for news, hints or indications on future policy moves.¹

“Our great Oil & Gas industry is under siege after having one of the best years in recorded history. It will get better than ever as soon as our Country starts up again. Vital that it does for our National Security!”, tweet by @realdonaldtrump; Mar 26th, 2020 - 7:06:28 PM EST.

Trump’s tweets are an incredibly rich source of information, essentially revealing his policy agenda, which was intended to support re-industrialization and reshoring, including for the oil and gas industry. However, given Trump’s erratic style and the increasing influence of social media (see Kalampokis et al., 2013; Bukovina, 2016), some questions are worth asking. Did the crude oil market become more fundamental-driven or speculative after his tweets? How did Trump really affect WTI prices in Cushing, Oklahoma – the place where oil contracts are traditionally settled for the U.S. market? Were his tweets more about playing political

¹ While his Twitter account was still active in early Jan. 2021, Trump had some 88 million followers [Source: <https://www.dw.com/en/donald-trump-loses-social-media-megaphone/a-56158414>; Retrieved on August 10, 2022]. Several recent empirical studies employ data about Trump’s tweets to gauge their impact on various outcomes (see Lewandowsky et al., 2020; Klaus and Koser, 2021; Machus et al., 2022; among many others).

games rather than enabling economic policy objectives? And finally, who was Trump's main audience? We approach all these interesting questions from an empirical perspective, by exploiting some specific datasets and applying rigorous modelling approaches and testing.

To better understand Trump's influence, we look specifically at the WTI-Brent *spread* which is a proxy for logistical and supply constraints deriving from the different nature and characteristics of the contracts being traded in the two major crude oil markets. WTI is the reference price for pipeline U.S. oil while Brent is the reference price for seaborne oil from the North Sea. Trump's denial about global warming and its consequences is well known; United States withdrew from the 2015 Paris climate accord during Trump's presidency. Accordingly, his economic agenda targeting re-industrialization should have determined an increase in U.S. domestic investment in the oil & gas industry, including in storage and export capacities. The importance of inventories for WTI pricing affects its ability to serve as a global benchmark for oil, and hence can severely affect investors' hedging and risk strategies in commodity markets (Kilian and Lee, 2014).

A large empirical literature investigates the drivers of the WTI-Brent spread (see Buyuksahin et al., 2013; Liu et al., 2015; Ruble and Powell, 2021; among many others), but so far has remained silent about how sensitive this spread is to mere words and tweets by politicians.² Our main contribution is to fill this literature gap and expose the policy implications of these results. We believe our findings are important not only for political

² Financial investors regularly follow market signals to inform their trading decisions, although they interpret those with varying degrees of confidence (Philippas et al., 2021); to this extent, news about oil inventory build-up/drawdowns are a major market mover in U.S. markets. However, political news can also have major impacts on financial markets, although the existing empirical evidence exposes their rather short-term effect (Machus et al., 2022).

economists, but also for policymakers in the broader energy sector, which is becoming increasingly sensitive to policy uncertainty (see Kaminker and Stewart, 2012; Dragomirescu-Gaina et al., 2021).

We show here that tweets made by Donald Trump on subject matters that pertain to “oil” were likely to push the WTI-Brent spread towards wider levels, which are associated with U.S. crude storage bottlenecks. With crude inventories being an integral element that explains U.S. crude market efficiency, Trump’s communication style might have created (perhaps reflexively) enough nuisance at times to push the crude market into a speculative overdrive, at least over the short-run. We believe our results are important, first, from a market efficiency perspective, because commodity (and in particular oil) prices are often subject to large exogenous shocks (e.g., of a geopolitical, regulatory nature, etc.) that can be amplified by speculation (Kilian and Lee, 2014). Second, they are important for energy regulators because supply disruptions caused by oil market volatility have real and immediate economic effects. Third, they are important for financial markets’ supervisory and regulatory authorities, who need to be mindful of the consequences of political influences.

The paper is structured as follows. Section 2 describes the empirical methodology and the data used to obtain the main results, which are then presented and discussed in Section 3. A detailed policy discussion on the possible implications of our results is included in Section 4. Finally, section 5 concludes. An online Supplement provides additional results.

2. Methodology and data

2.1. Main model specification

The WTI-Brent spread came to the fore of many policy discussions after it reached some unprecedented negative levels in 2011; it narrowed down in 2014, only to widen again in 2017. In theory, due to its lower sulfur content, WTI crude should trade at a premium to Brent crude, although this is not what was observed. The main reason for this spread rests on the difference in storage technology between WTI and Brent. In particular, WTI transportation and storage are severely limited due to infrastructure constraints in Cushing, Oklahoma, where the physical settlement of WTI contracts traditionally takes place. The policy relevance of the WTI-Brent spread is due to the importance of WTI inventories, which severely impairs on the ability of WTI price to serve as a global benchmark for oil. Hence, the transmission channel through which political discourse and messages can affect the WTI-Brent spread in our case is investment in storage capacity, which in general is a sensitive endeavour with respect to policy uncertainty (Mazzucato and Semieniuk, 2017).

We build a Markov Switching (MS) model³ to explain these wide fluctuations in the WTI-Brent spread during our sample that starts with the first week of June 2015 (with Trump announcing his candidature) and ends with the final week of 2020 (just days before his Twitter account was suspended). We follow Diebold et al. (1995) and use time-varying probabilities, which allow us to model the influence of policy factors in an easy way. These probabilities are modelled based on the logistic function, with the independent variable being the number of

³ Markov Switching models are very popular in the empirical literature as an efficient tool to capture the inherent non-linearities present in the dynamics of many commodity prices (Choi and Hammoudeh, 2010; Zhang and Zhang, 2015).

Trump's tweets on a specific topic (details in the data section).⁴ Our parsimonious specification for the WTI-Brent *spread* can be summarised as follows:

$$Spread_t(S_t) = \gamma(S_t) + \theta(S_t)X_t + \sigma(S_t)\epsilon_t \quad (1)$$

where t is a time subscript, S_t indexes the current regime and so $\gamma(S_t)$ denotes the regime-specific intercept. Our interest will be the regime-specific vector of parameters $\theta(S_t)$, with X_t being a vector of exogenous variables including: (i) the *futures spread* or price differential of two consecutive WTI futures contracts (calculated as WTI futures price for the 2nd maturity date contract - WTI futures price for the 1st maturity date or the nearest contract); (ii) the *basis* or the spread between the WTI spot price and the price of the nearest WTI futures contract; and (iii) lagged WTI excess reserves. We allow the volatility to be regime specific, hence we will be also estimating $\sigma(S_t)$ with $\epsilon_t \sim N(0,1)$ a normally distributed sequence of innovations.

The inclusion of futures spreads (i.e. the first two elements of X_t) can be justified by market arbitraging arguments. Any substantial and/or persistent difference (i.e. spread) between WTI and Brent prices would open an arbitrage possibility (e.g. for crude oil refiners, transport operators etc.). This arbitrage is more likely in futures markets, where liquidity is greater, but in the end it affects spot prices all the same because WTI futures contracts are settled in physical terms. The relevance of futures prices and differentials for crude spot prices is highlighted in Fattouh (2010), Ruble and Powell (2021) among many others.

The inclusion of WTI excess reserves instead (i.e. third element of X_t) is supported by some convincing empirical evidence. Our WTI *excess crude reserves* are defined as a difference

⁴ Bekaert and Harvey (1995), Dragomirescu-Gaina and Philippas (2013), among many others, use time-varying probabilities in Markov Switching model specifications where policy factors are modelled in a similar way.

between crude reserves reported in Cushing, Oklahoma and its 2-month moving average (both expressed in log terms). Buyuksahin et al. (2013) show that infrastructure bottlenecks in Oklahoma can drive WTI below Brent prices. In a similar vein, Liu et al. (2015) shows that oil supply constraints in Cushing Oklahoma affect the cointegration between WTI and Brent prices. For Kilian and Murphy (2014), crude inventories matter for pricing, helping to identify a speculative component in oil trading. More complex model specifications for the WTI-Brent spread can be found in Mann and Sephton (2016), Kuck and Schweikert (2017), and Ruble and Powell (2021) among many others.

However, due to our relatively short sample (including 290 weekly observations), we prefer to retain only the main ingredients (as discussed in Eq. (1) above) and focus instead on the nonlinear influences of non-market factors stemming from the policy/political realm. In our case, their influence goes through the (logistic formulation of the) transition probabilities before affecting spread levels and volatility in each of the two estimated regimes. Accordingly, the probability of remaining in regime i over the next period is given by:

$$P_{ii,t} = \text{prob}[S_t = i | S_{t-1} = i] = \frac{\exp(\beta(S_t)Z_{t-1})}{1 + \exp(\beta(S_t)Z_{t-1})} \text{ with } i = 1,2 \quad (2)$$

where Z_{t-1} is a two-dimensional vector of 1's (encompassing the constant term) and lagged Trump's tweets on a given topic, while β is a vector of regime-specific parameters that will be estimated through maximum likelihood. Our main insights are derived based on the estimates of β , which we report and discuss in detail in Section 3.

2.2. Data

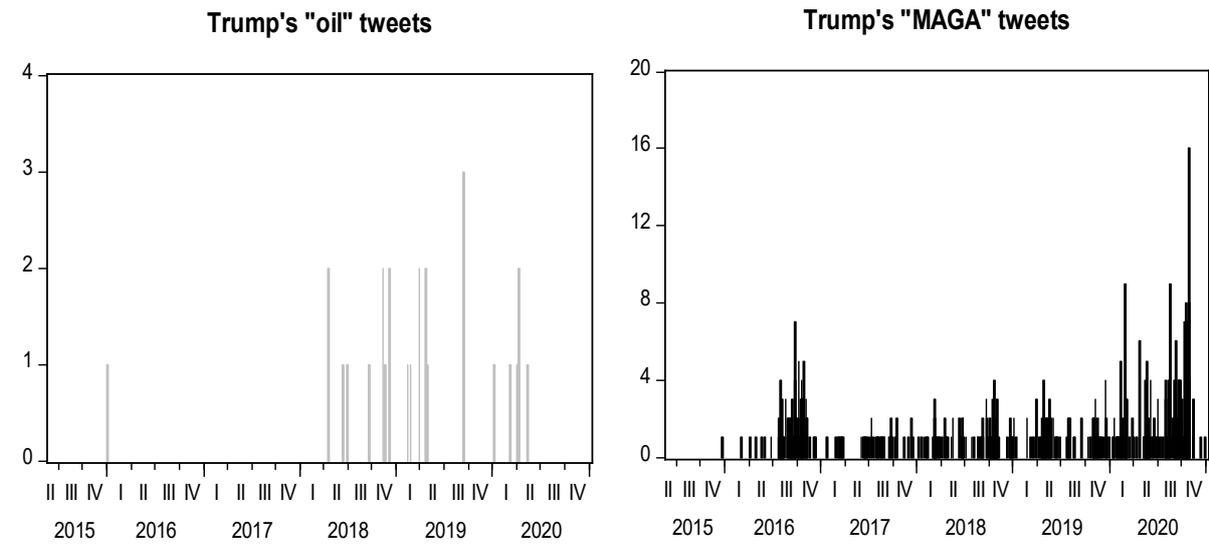
Our dataset is constructed from two main sources, which we complement with data extracted from Bloomberg. First, we draw on the U.S. Energy Information Administration (EIA) for data on Brent and WTI spot and futures prices (all expressed in USD). Weekly crude oil inventories for the U.S. market also come from the same source. Hence, our empirical analysis employs weekly time-series, mainly due to data availability constraints.

Second, we collect the frequency of tweets on specific keywords, drawing on the complete archive of Trump's tweets available on the Internet.⁵ The keywords that we used are the followings: "oil", "crude", "gas", "OPEC", "Saudi Arabia", and "MAGA" (the policy campaign hashtag for "Make America Great Again"). Due to the small number of some of these tweets (e.g. "crude" and "gas"), we only use the first principal component of "oil", "crude", "gas", and "OPEC" taken together. However, we use the last two keywords separately, i.e. "Saudi Arabia" and "Make America Great Again" or MAGA hashtag, in order to separate Trump's messages on his economic agenda from other objectives more closely related to his international geopolitical agenda, e.g. in the Middle East.⁶ Our proxies are then constructed simply by counting the number of relevant Trump's tweets that appear during a given week (Monday to Sunday). For illustrative purposes, we plot Trump's main tweets regarding "oil" and "MAGA" in Figure 1.

⁵ Data is available at <https://www.thetrumparchive.com/>

⁶ Some of Trump's tweets on "Saudi Arabia" are unrelated to oil/gas as they refer to the death of the political dissident Jamal Khashoggi in Oct. 2018. Trump also signed significant contracts for military equipment with Middle East countries.

Figure 1: Trump's tweets, by main keywords



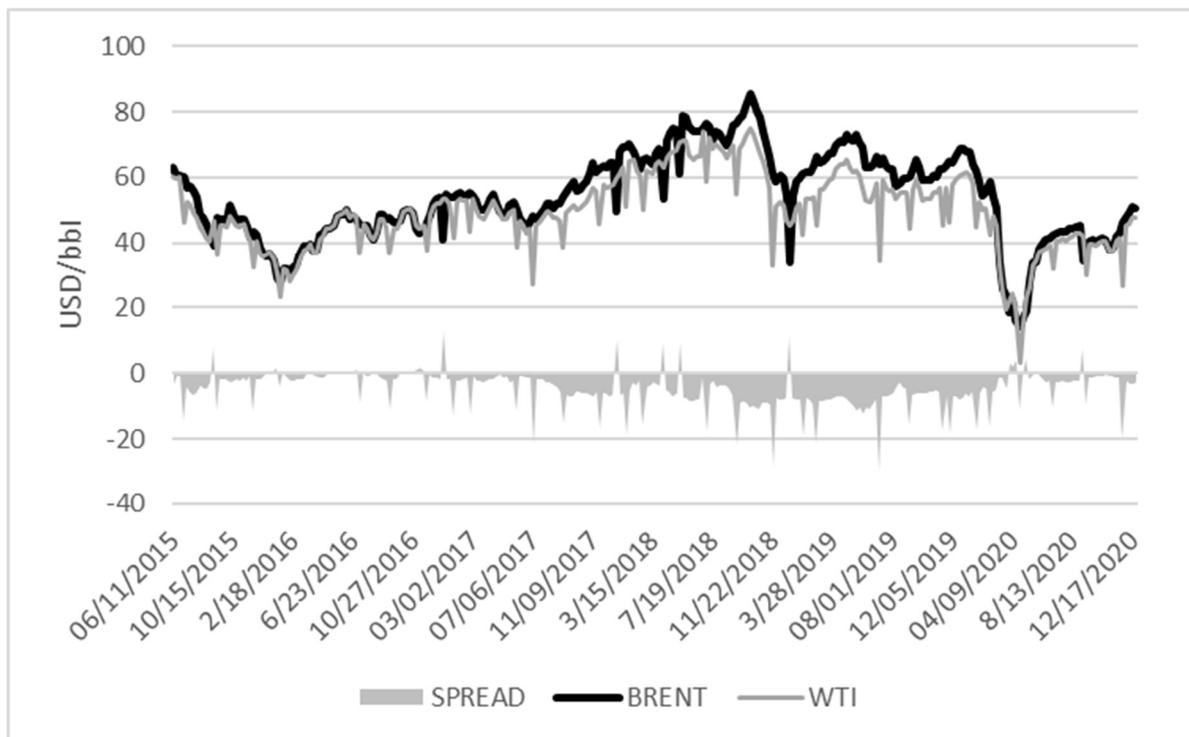
Note: Data frequency is daily for illustrative purposes. All data comes from www.thetrumparchive.com.

From Bloomberg, we download the volume and open interest of WTI futures contracts in order to build a proxy for the speculative behaviour following Chan et al., (2015). This proxy is called the speculative ratio and is defined as the ratio between traded volume and open interest for the same contract. We roll over into the next WTI futures contract 5 trading days before the expiry date of the nearest WTI futures contract.

3. Results and discussion

To begin our analysis, we offer a visual inspection of the weekly time-series of WTI and Brent spot prices, along the WTI-Brent spread in Figure 2. The sample extends over the time since Trump announced his candidacy, in June 2015, and ends in December 2020, with his last days in office (his Twitter account was suspended in early January 2021).

Figure 2: Weekly averages of spot prices for crude and the WTI-Brent spread



Note: Data are from U.S. EIA. All prices are in USD/bbl.

In all this period, there are about 20 weeks during which Trump made at least one tweet using “oil”, “OPEC”, “gas”, or “crude”, including combinations thereof; the most frequent one however is “oil” by far. The use of “Saudi Arabia” is slightly more frequent, but it is inflated due to Trump making repeated references to the death of the political dissident Khashoggi. Trump also used the “MAGA” hashtag more frequently than he used “oil”, obviously because this provided a more accurate reflection of the policy agenda he wanted to promote at home.

Estimates of the model depicted in Eq. (1)-(2) are displayed in Table 1 for the “oil” keyword, which is the most relevant one for our research question. The accompanying Supplement presents estimates for some specification robustness checks, which we only briefly summarize in the next paragraph.

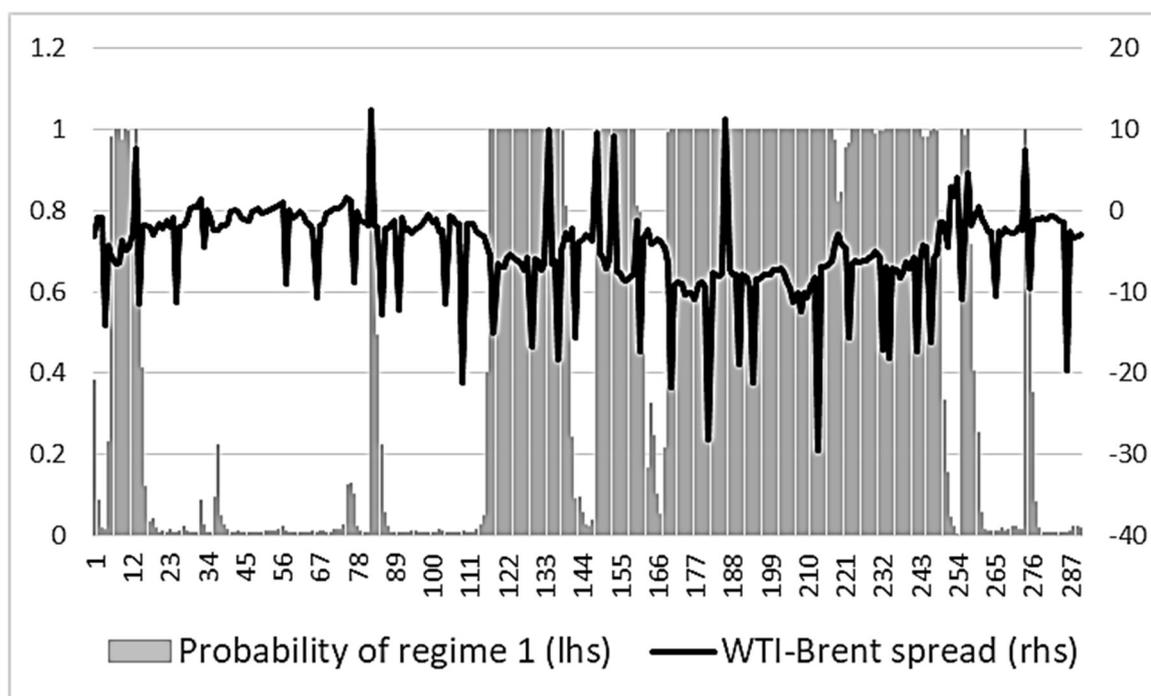
Table 1: Markov Switching specification for the WTI-Brent spread: Trump tweets “oil”

Estimates	Regime 1 ($S_t = 1$)	Regime 2 ($S_t = 2$)
Time-varying transition probabilities		
β : constant	2.804 ^{***}	3.305 ^{***}
β : Trump	11.369	-12.99 ^{**}
Model coefficients		
γ	-5.741 ^{***}	-1.865 ^{***}
σ	4.162 ^{***}	1.155 ^{**}
θ : Futures spread	0.016	1.093 ^{***}
θ : basis	1.043 ^{***}	1.014 ^{***}
θ : lagged excess reserves	-20.358 [*]	-20.358 [*]
Log-likelihood		-669.753
AIC		4.708

Note: A two-regime Markov Switching model with time-varying transition probabilities is estimated. The number of observations is 290, drawn from a weekly sample running from Jun. 2015 to Dec. 2020. The coefficients’ labels are just as in model specifications (1)-(2). Information criteria suggest estimating a single θ coefficient for both regimes in the case of lagged excess reserves. Estimation is performed through Maximum Likelihood using the BFGS method with a Marquardt step method. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

According to Table 1, Trump’s “oil” tweets reduce the persistence of the calm regime 2, thereby increasing the likelihood of transitioning from 2 to regime 1, which is characterised instead by wider spreads, since $abs(\gamma(S = 1)) > abs(\gamma(S = 2))$, and higher volatility. Trump’s tweets push the market to become less efficient and more volatile, which, by itself, is a drawback for the WTI global benchmark status. For a visual inspection of the results, Figure 3 displays the time-series of the filtered probability of being in regime 1, overlapping with the size of the WTI-Brent spread.

Figure 3: Probability of regime 1 and the WTI-Brent spread



Note: The filtered probability of being in regime 1 is on the left-hand-axis, while the spread is on the right-hand-axis. As per estimates reported in Table 1, regime 1 reflects wider and more volatile WTI-Brent spreads.

Turning to Table 1 again, note the negative coefficient associated with lagged excess reserves, an element intimately linked with market speculative behaviour, which we will carefully investigate later. We get similar results when using “Saudi Arabia” as a keyword for Trump’s tweets⁷ (see Table S1 of the accompanying Supplement). This similarity in results seems to suggest that Trump’s “oil”-tweets are more in line with his external policy agenda.

As a first robustness check to our findings in Table 1, we use the first principal component of all Trump’s tweets on “oil”, “crude”, “gas”, and “OPEC” because they encompass similar messages, and redo the estimation. We find similar statistical relevance and implications as we find in Table 1 for “oil” tweets (see Table S2 in the accompanying Supplement). Secondly,

⁷ The correlation with “oil”-related tweets is rather low, at 0.41, but statistically significant. Note also that Trump tweeted about “Saudi Arabia” also when addressing the death of the political dissident Khashoggi.

our results are also robust to a change in the estimation sample. Using a shorter one, running from November 2016 (when Trump was elected as the U.S. president) until December 2020 would deliver similar results and implications (see Table S3 in the accompanying Supplement).⁸

Putting all these findings together, we see that Trump's "oil" tweets went largely against domestic crude producers, refiners, and transport operators whose interest is to have stable pricing, low spreads and volatility for WTI – a pretender to the status of being a global benchmark for crude oil. Therefore, it should be mainly speculators, particularly those interested in Trump's external policy agenda, who profit from his "oil" tweets; in fact, they are those willing to financially gamble on any new information source (including Trump's Twitter account). We confirm this novel but interesting hypothesis by estimating two additional model specifications.

First, we check whether Trump's other (related) tweets have similar influences on the WTI-Brent spread. As already mentioned in the Data subsection 2.2, Trump tweeted more frequently about industry, re-industrialisation, investment etc. – topics that ranked high on his "Make America Great Again" policy agenda. Hence, we want to see whether there are any substantial differences between his tweets in these two policy domains ("oil" vs. "MAGA"). If the market perceived that the two objectives are given similar priority, then there should be no difference at all. In Table 2, we use the "MAGA" hashtag to count the frequency of Trump's tweets and let this proxy instead influence the transition probabilities given by specification

⁸ Trump's tweets would similarly affect transition probabilities in the second regime (just as in Table 1), which is still characterised by narrower spreads, but volatility is higher this time. Hence, it is spread levels (rather than volatility levels) that characterise the same regime where Trump's influence is estimated.

(2).⁹ The results show that these tweets instead reduce the persistence of remaining in regime 1 and thus increase the probability of transitioning to regime 2, where volatility is lower, and spreads are narrower. Hence, there is a clear difference between the market effects of “oil” tweets and “MAGA” tweets, with the latter being more favourable for market efficiency.

Table 2: Markov Switching specification for the WTI-Brent spread: Trump tweets “MAGA”

Estimates	Regime 1 ($S_t = 1$)	Regime 2 ($S_t = 2$)
Time-varying transition probabilities		
β : constant	3.474***	2.89***
β : Trump	-1.788*	0.989
Model coefficients		
γ	-5.734***	-1.866***
σ	4.172***	1.156**
θ : Futures spread	0.039	1.087***
θ : basis	1.046***	1.001***
θ : lagged excess reserves	-20.095*	-20.095*
Log-likelihood	-670.151	
AIC	4.711	

Note: A two-regime Markov Switching model with time-varying transition probabilities is estimated. The number of observations is 290, drawn from a weekly sample running from Jun. 2015 to Dec. 2020. The coefficients’ labels are just as in model specifications (1)-(2). Information criteria suggest estimating a single θ coefficient for both regimes in the case of lagged excess reserves. Estimation is performed through Maximum Likelihood using the BFGS method with a Marquardt step method. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

Second, we follow Chan et al. (2015) and construct a proxy of speculative activity in the WTI market as a ratio between the traded volume and the open interest in the same contract.

⁹ There are 161 weeks in our estimation sample with at least one tweet using “MAGA” as a keyword. Their frequency is higher around election dates (Nov. 2016 and Nov. 2020).

We use the nearest futures contract but roll over into the next contract five trading days before the expiration date, as only a very small number of contracts are settled with physical delivery in Cushing, Oklahoma. The intuition of this proxy is rather simple: when market trading is dominated by speculators, volume is high but open interest remains low; in contrast, when hedgers dominate, then reported open interest is much higher since trades are used to open and maintain positions. To better capture Trump's tweets impact, we work with daily data instead, since using a weekly frequency would reduce the effect we are looking to expose here. Tweets during non-trading days (e.g. weekends or national holidays) are cumulated with tweets from the previous trading day.¹⁰ We estimate two specifications for the daily speculative ratio: (i) a simple first-order autoregressive AR(1) model estimated via OLS and (ii) a simple GARCH (1,1) model specification.¹¹ As an explanatory variable we include Trump's "oil" tweets, always using the *lagged* values in order to deal with possible endogeneity issues. If our hypothesis above is true, more tweeting by Trump about "oil" should have a positive (rather than negative or neutral) impact on the speculative ratio. The positive and statistically significant coefficients associated with the lagged Trump's "oil" tweets in Table 3 clearly confirm our hypothesis above. This result is further reinforced by the fact that similar specifications using lagged Trump's "MAGA" tweets do not yield the same statistical significance. In a separate robustness check (see Table S4 in the online Supplement), we re-estimate the two specifications from Table 3 over a shorter sample that

¹⁰ Omitting Trump's tweets during non-trading days would slightly weaken the statistical significance of the estimates in Table 3, without changing the implications.

¹¹ The Breusch-Pagan-Godfrey heteroskedasticity test rejects at 1% the null of homoskedasticity for the OLS residuals. However, the presence of ARCH errors does not invalidate the OLS estimates, for which reason we present them both here in Table 3. Chan et al., (2015) also estimate GARCH specifications for the daily speculative ratio they propose.

begins when Trump was elected as the U.S. president; results are similar. In a nutshell, lagged “oil” tweets by Trump, but not his “MAGA” tweets, are significant predictors for the current speculative ratio in the WTI futures market.

Table 3: Estimates for the dynamics of the speculative ratio in WTI futures market

Coefficient estimates	AR(1)	GARCH (1,1)
lagged speculative ratio	0.636 ^{***} (0.020)	0.575 ^{***} (0.018)
lagged Trump “oil” tweets	0.178 ^{**} (0.079)	0.282 ^{***} (0.048)
GARCH equation:		
lagged squared error		0.666 ^{***} (0.058)
lagged variance term		0.215 ^{***} (0.029)
Adjusted R ²	0.408	0.392
DW stat	1.94	1.78
AIC	1.562	1.296

Note: The estimation sample includes daily data from Jun. 16th, 2015 until Dec. 31st, 2020. The standard errors are in parentheses below the coefficients’ estimates. Constant terms are not reported to save space. ** and *** denote statistical significance at 5% and 1% respectively.

4. Policy implications and recommendations

Overall, our empirical results suggest that Trump’s tweets about the oil industry did have a statistically significant influence on the dynamics of the WTI-Brent spread, mainly by increasing market speculative activity and making wider spreads more likely. Trump’s erratic communication style (particularly on Twitter) did not help at reducing information nuisance, especially for those market participants willing to financially gamble on any new information

source.¹² Our results here align with a wealth of recent empirical studies on similar topics. Machus et al. (2022) find that Trump's tweets led to increased trading volume but had no lasting consequences on stock prices – both effects being consistent with more speculative behaviour in our view. In a similar vein, Afanasyev et al. (2021) find that market reactions after Trump tweets about Russia are mainly driven by emotions and have a short-term nature.

However, we also saw how Trump's tweets including the "MAGA" hashtag had rather favourable effects on the WTI-Brent spreads, in contrast to his tweets about "oil" or "Saudi Arabia", which largely reflects his external policy agenda. The difference is not surprising. Trump had supposedly more influence on domestic rather than international policy matters, where he chose to adopt a confrontational stance (e.g. versus China). Moreover, global commodity (and especially oil) markets are well-known for amplifying exogenous information shocks and events to the extent of incentivising market speculative behaviour; Trump's tweets unfortunately belong to this category. In Kilian and Lee (2014) for example, several recent geopolitical events (e.g. Libyan Revolution in the early 2011) are found to be responsible for substantial increases in speculative oil demand. Speculative expectations drive large swings in oil and commodity prices, which then affect economic and sometimes geopolitical outcomes (as with the Russian-Ukraine conflict of 2022).

Therefore, the policy discussion should focus primarily on the need to prevent not political statements, messages or tweets (since that would be impossible), but the subsequent investors' reactions that push the market into a speculative overdrive. This discussion is important for energy policymakers because excess price volatility driven by speculative

¹² Beyond Trump's tweets, there is increasing evidence that social media has predictive power over a large set of market outcomes; for an early review (Kalampokis et al., 2013).

behaviour can lead to real supply disruptions, especially since WTI contracts are settled with physical delivery.¹³ We believe financial markets' regulatory and supervisory authorities must be mindful of the market consequences of political noise, even over a short-term horizon, especially when amplified by social media (Bukovina, 2016).

Supervisors together with exchanges should carefully monitor market dynamics, analyse the sensibility of open interest and traded volume to political noise, and react accordingly, for example, by triggering circuit breakers and tightening margin requirements in a more automatic way.¹⁴ Margins calculation at The Chicago Mercantile Exchange (CME) for example is already a complex process, including volatility-based adjustments and taking a portfolio perspective on traders' positions.¹⁵ However, it is still based on a Value-at-Risk framework that feeds mostly on historical market data, except for known upcoming events (e.g. elections) that are taken into account in a pro-active manner; unfortunately, new valid information sources such as social media are not considered. Obviously, adjusting margin requirements with a high frequency such as to match social media viral posts and memes is not feasible, but big data and/or sentiment analysis might help exchanges in monitoring these online platforms in order to detect risk factors before they affect behaviours and market outcomes (Kalampokis et al., 2013).

¹³ A negative WTI price was registered on April 20, 2020 for the nearest WTI futures contract (May delivery). Negative or very small positive oil prices have a huge impact on heavily indebted producers for example.

¹⁴ See the recent proposals put forward by the European Securities and Markets Authority (ESMA) for energy derivatives markets in response to geopolitical tensions. Available at https://www.esma.europa.eu/sites/default/files/library/esma24-436-1414_-_response_to_ec_commodity_markets.pdf.

¹⁵ More details on margin requirements at CME can be found at <https://www.cmegroup.com/clearing/risk-management/futures-and-options-margin-model.html>.

For an early identification of risks, regulators might also consider enforcing self-reporting/disclosures of political interests, including party and campaign donations.¹⁶ For traders with large open positions, confidentiality arguments will prevail in this case, but exchanges and clearing houses have access to such data, which should help their analyses as mentioned above. Striking the right balance between confidentiality and transparency is always hard, but not impossible.

5. Conclusions

Donald Trump offers an interesting case study about how casual political actors and their messages can affect markets and prices, especially in the case of commodities which are more sensitive to policy uncertainty in general. Trump's policy agenda focused on the idea of supporting re-industrialization, reshoring, and local investment, including in the oil & gas industry. Was it anything more than just a *political* agenda? To what extent did Trump influence the local oil producers, or the size of their investments in storage and transportation? We look at two crude oil benchmarks, i.e. WTI and Brent, because differences in their pricing patterns would traditionally reflect supply and storage constraints in the U.S. market. We then estimate a simple non-linear specification to explain the WTI-Brent spread, allowing us to expose the perverse effects of some of Trump's tweets. In particular, we find that his "oil" tweets are associated with higher speculative activity in the energy derivatives market. In contrast, for Trump's MAGA-related tweets we do not find similar influences,

¹⁶ As discussed in Sovacool (2021), useful remedies against corruption in the energy sector imply higher transparency and more disclosure. For long-term investments in emerging markets, his recommendations should work, by helping to minimize conflicts of interests. In fast-moving markets, like those where futures contracts are traded, mandatory disclosures are not feasible due to confidentiality arguments.

suggesting that Trump himself was likely considered a market influencer only by those participants willing to financially gamble on new information sources.

Our policy recommendations for regulators, supervisors and for exchanges draw on these empirical results, aiming at preventing investors' reactions to political noise that might push the market into a speculative overdrive. The implications of feeding speculative behaviour are critical, particularly for commodities markets (see Kaufmann 2011). Volatile energy markets can influence decisions on our collective long-term objectives as a society (e.g. green energy transition). These implications are even more important today when declarations, narratives or simply political noise are amplified by (social) media with an exponential pace, but in a deteriorating geopolitical context for which multiple political equilibria are still possible.

Declaration of competing interest: None.

References

Acemoglu, D., Golosov, M., Tsyvinski, A., Wacziarg, R., 2012. A dynamic theory of resource wars. *The Quarterly Journal of Economics* 127, 283–331. <https://doi.org/10.1093/qje/qjr048>.

Afanasyev, D.O., Fedorova, E., Ledyeva, S., 2021. Strength of words: Donald Trump's tweets, sanctions and Russia's ruble. *Journal of Economic Behavior & Organization* 184, 253–277. <https://doi.org/10.1016/j.jebo.2021.02.002>.

Bekaert, G., Harvey, C.R., 1995. Time-varying world market integration. *Journal of Finance* 50, 403–444. <https://doi.org/10.2307/2329414>.

- Bukovina, J., 2016. Social media big data and capital markets—An overview. *Journal of Behavioral and Experimental Finance* 11, 18–26. <https://doi.org/10.1016/j.jbef.2016.06.002>.
- Buyuksahin, B., Harris, J.H., 2011. Do speculators drive crude oil futures prices?. *The Energy Journal* 32, 167–202. <https://www.jstor.org/stable/41323326>.
- Buyuksahin, B., Lee, T.K., Moser, J.T., Robe, M.A., 2013. Physical markets, paper markets and the WTI-Brent spread. *The Energy Journal* 34, 129–151. <http://www.jstor.org/stable/41970500>.
- Chan, L.H., Nguyen, C.M., Chan, K.C., 2015. A new approach to measure speculation in the oil futures market and some policy implications. *Energy Policy* 86, 133–141. <https://doi.org/10.1016/j.enpol.2015.06.034>.
- Choi, K., Hammoudeh, S., 2010. Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment. *Energy Policy* 38, 4388–4399. <https://doi.org/10.1016/j.enpol.2010.03.067>.
- Dragomirescu-Gaina, C., Galariotis, E., Philippas, D., 2021. Chasing the ‘green bandwagon’ in times of uncertainty. *Energy Policy* 151, 112190. <https://doi.org/10.1016/j.enpol.2021.112190>.
- Dragomirescu-Gaina, C., Philippas, D., 2013. Is the EMU government bond market a playground for asymmetries?. *The Journal of Economic Asymmetries* 10, 21–31. <https://doi.org/10.1016/j.jeca.2013.09.001>.
- Diebold, F.X., Lee, J.H., Weinbach, G.C., 1995. Regime switching with time-varying transition probabilities, in C. Hargreaves, Ed.: *Nonstationary Time Series Analysis and Cointegration*. Oxford University Press, London. <https://doi.org/10.1515/9780691219585-009>.

Fattouh, B., 2010. The dynamics of crude oil price differentials. *Energy Economics* 32, 334–342. <https://doi.org/10.1016/j.eneco.2009.06.007>.

Gunitsky, S., 2015. Corrupting the cyber-commons: social media as a tool of autocratic stability. *Perspectives on Politics* 13, 42–54. <https://doi.org/10.1017/S1537592714003120>.

Kalampokis, E., Tambouris, E., Tarabanis, K., 2013. Understanding the predictive power of social media. *Internet Research* 23, 544–559. <https://doi.org/10.1108/IntR-06-2012-0114>.

Kaminker, C., Stewart, F., 2012. The role of institutional investors in financing clean energy. *OECD Working Papers on Finance, Insurance and Private Pensions*, No.23, OECD Publishing.

Kaufmann, R.K., 2011. The role of market fundamentals and speculation in recent price changes for crude oil. *Energy Policy* 39, 105–115. <https://doi.org/10.1016/j.enpol.2010.09.018>.

Kilian, L., Lee, T.K., 2014. Quantifying the speculative component in the real price of oil: The role of global oil inventories. *Journal of International Money and Finance* 42, 71–87. <https://doi.org/10.1016/j.jimonfin.2013.08.005>.

Kilian, L., Murphy, D.P., 2014. The role of inventories and speculative trading in the global market for crude oil. *Journal of Applied Econometrics* 29, 454–478. <https://doi.org/10.1002/jae.2322>.

Klaus, J., Koser, C., 2021. Measuring Trump: The Volfefe index and its impact on European financial markets. *Finance Research Letters* 38, 101447. <https://doi.org/10.1016/j.frl.2020.101447>.

- Kuck, K., Schweikert, K., 2017. A Markov regime-switching model of crude oil market integration. *Journal of Commodity Markets* 6, 16–31. <https://doi.org/10.1016/j.jcomm.2017.03.001>.
- Lewandowsky, S., Jetter, M., Ecker, U.K., 2020. Using the president’s tweets to understand political diversion in the age of social media. *Nature Communications* 11, 1–12. <https://doi.org/10.1038/s41467-020-19644-6>.
- Liu, W.M., Schultz, E., Swieringa, J., 2015. Price dynamics in global crude oil markets. *Journal of Futures Markets* 35, 148–162. <https://doi.org/10.1002/fut.21658>.
- Machus, T., Mestel, R., Theissen, E., 2022. Heroes, just for one day: the impact of Donald Trump’s tweets on stock prices. *Journal of Behavioral and Experimental Finance* 33, 100594. <https://doi.org/10.1016/j.jbef.2021.100594>.
- Mann, J., Sephton, P., 2016. Global relationships across crude oil benchmarks. *Journal of Commodity Markets* 2, 1–5. <https://doi.org/10.1016/j.jcomm.2016.04.002>.
- Mazzucato, M., Semieniuk, G., 2017. Public financing of innovation: new questions. *Oxford Review of Economic Policy* 33, 24–48. <https://doi.org/10.1093/oxrep/grw036>.
- Ott, B.L., 2017. The age of Twitter: Donald J. Trump and the politics of debasement. *Critical Studies in Media Communication* 34, 59–68. <https://doi.org/10.1080/15295036.2016.1266686>.
- Philippas, D., Dragomirescu-Gaina, C, Goutte, S., Nguyen, D., 2021. Investors’ attention and information losses under market stress. *Journal of Economic Behavior and Organization* 191, 1112–1127. <https://doi.org/10.1016/j.jebo.2021.09.040>.

Ruble, I., Powell, J., 2021. The Brent-WTI spread revisited: A novel approach. *The Journal of Economic Asymmetries* 23, e00196. <https://doi.org/10.1016/j.jeca.2021.e00196>.

Sovacool, B.K., 2021. Clean, low-carbon but corrupt? Examining corruption risks and solutions for the renewable energy sector in Mexico, Malaysia, Kenya and South Africa. *Energy Strategy Reviews* 38, 100723. <https://doi.org/10.1016/j.esr.2021.100723>.

Zhang, Y.J., Zhang, L., 2015. Interpreting the crude oil price movements: Evidence from the Markov regime switching model. *Applied Energy* 143, 96–109. <https://doi.org/10.1016/j.apenergy.2015.01.005>.

Zhuravskaya, E., Petrova, M., Enikolopov, R., 2020. Political effects of the internet and social media. *Annual Review of Economics* 12, 415–438. <https://doi.org/10.1146/annurev-economics-081919-050239>.