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Abstract

This paper analyses the informational efficiency of the WTI crude oil markets using a recently proposed quantitative measure for market inefficiency. The procedure measures the extent to which observed oil price behaviour deviates from the Random Walk benchmark which represents an efficient market. The key findings are, first, that crude oil market inefficiency varies over time. Second, abrupt increases in inefficiency occur during extreme episodes such as the price downturns witnessed in 2008, 2014, and early 2020, as well as the begin of the Ukraine war in 2022. Third, the paper puts forward the interpretation of oil market inefficiency as oil market turbulence. This occurs when the quantity of information the market has to process is exceptionally high. Fourth, the paper demonstrates that oil market turbulence (or the drivers behind it) have negative macroeconomic consequences.

JEL-Codes: C220, E300, G140, Q020, Q310.

Keywords: crude oil markets, efficient market hypothesis, quantity of information, fractional integration.

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1 Introduction

Fama (1970) famously stated "a market in which prices always 'fully reflect' all available information is called 'efficient'." Empirically testing this so-called Efficient Market Hypothesis (EMH) is subject of a vast literature. Tests of the so-called weak-form of the EMH are based on the evaluation of the random walk hypothesis. Prices in an efficient market are said to follow a random walk; past returns do not have any predictive power. There is no serial dependence in the returns that can be exploited for forecasting purposes. This paper uses a recently proposed quantitative measure for market inefficiency, based on a new interpretation of the fractional integration parameter d. This approach allows one not only to analyse whether or not a particular market is efficient but also how efficient - or inefficient - a market is. It is, furthermore, possible to analyse how the degree of inefficiency of a market changes over time and to compare that degree across markets.

For a number of reasons, the crude oil market is the ideal study object for the application of this method. Ever since the oil crises witnessed in the 1970s, it has been subject of heavy scrutinising. Among the first papers which are worth highlighting is Hamilton's (1983) analysis of oil and the macro economy. While that paper deals with the macroeconomics of oil price shocks, papers such as Hamilton (2003) deal with the question "What is an Oil Shock?" Recent examples for fundamental research on this market include Baumeister, Korobilis, and Lee (2022) and Bornstein, Krusell, and Rebelo (2023). Much of this research deals with the US economy and/or the US crude oil market; for this reason, this paper analyses prices for the crude type West Texas Intermediate (WTI, Cushing). The crude oil market, finally, is of high geopolitical relevance, has been dominated by OPEC, a cartel with remarkable instinct for self-preservation; crude oil is a fossil resource which links it to climate change;and there is an oil extraction and processing industry which is of vast dimension.[1]

What this paper finds can be summarised as follows: First, the degree of inefficiency of the WTI crude oil market varies over time, but there is no sys-

[1] Smith (2009) poignantly asks: World Oil: Market or Mayhem?

tematic decline in the level of inefficiency due to e.g. markets which mature. The degree of inefficiency of the WTI market, for example, is higher prior to 2006, but varies over time to a much lesser degree. Post 2006, there is a considerable degree of variation. Second, abrupt increases in the degree of inefficiency post 2006 occur during extreme oil price episodes: the oil price downturns witnessed in 2008, 2014, and 2020, respectively. Third, this paper proposes to interpret the degree of inefficiency of the crude oil market as degree of oil market turbulence. This occurs when the quantity of information which has to be processed by a market is exceptionally large and, thus, it is more likely that investors do not agree on how to interpret the new information and what the updated valuation of the commodity should be (Banerjee & Kremer, 2010; Bollerslev, Li, & Xue, 2018). Sustained oil price declines are rare events and the circumstances of the above-mentioned declines have been unprecedented. Thus, oil market turbulence is closely related to, but nevertheless conceptually different from what has been discussed under the labels of Lo's (2004) Adaptive Market Hypothesis (AMH) as well as measures for uncertainty (Jurado, Ludvigson, & Ng, 2015). Fourth, the paper demonstrates that oil market turbulence (or the drivers behind it) have negative macroeconomic consequences.

This analysis contributes to three important streams of literature. There is, first, the literature on empirically testing the EMH. Within this literature, the application of quantitative rather than qualitative procedures to empirically test the EMH became standard. The main reason for this development is that market efficiency is not an absolute concept but a market characteristics that evolves dynamically over time and varies across markets (Rösch, Subrahmanyam, & Van Dijk, 2017). The idea to measure the degree of market efficiency also features prominently in Lo's (2004) AMH. The method used in this paper has been proposed by Duan, Li, Urquhart, and Ye (2021). Second, the so-called "difference-in-opinion" literature predicts that disagreement among investors about how to interpret new information leads to increases in market activity and market volatility. In specific, Banerjee, Kaniel, and Kremer (2009) show that disagreement about higher-order beliefs can lead to asset price predictability. This papers empirical findings empirically support this notion. The crude oil market is, third, subject of rather fundamental research efforts. Bornstein et al. (2023), for example, develop a structural model of the oil industry which they embed in a general equilibrium model of the world economy. The key question they address is how the emergence of fracking affects the global macro-economy. To put this differently: for one of many exhaustible resources, a new extraction technology emerges. This new technology affects supply of this resource in such way that this has global macroeconomic consequences. This paper finds that oil markets are more inefficient during periods of drastic oil price declines: 2008, 2014, and 2020. Periods with sustained oil price declines, however, are rare; in addition, there are good fundamental reasons for the observed declines: the Great Financial Crisis, the oversupply of the global oil market (Baumeister & Kilian, 2016), and the outbreak of the COVID pandemic. The paper proposes to not interpret oil market inefficiency in a literal manner, but as oil market turbulence; and, thus, in a way that suggests that the state of the crude oil market provides information about the state of the global economy. In this sense, it is of similar quality as Bornstein et al. (2023). Worth noting is also Baumeister et al. (2022), who, however, look the opposite direction: these authors construct a new index of global economic conditions by combining measures from a large number of sources and show that the newly proposed measure is superior to existing measures of global economic activity such as world industrial production. The purpose of their exercise is to forecast real oil prices as well as global petroleum consumption.

The empirical approach used in this paper is the quantitative measure for market inefficiency recently proposed by Duan et al. (2021). The key idea of this approach is to measure market inefficiency through the extent to which the observed price behaviour deviates from the Random Walk benchmark. Duan et al.'s (2021) approach is similar in essence to Kristoufek and Vosvrda (2013, 2014) and Sattarhoff and Gronwald (2022). While the former base their measure on Hurst exponents, Sattarhoff and Gronwald (2022) use a multifractal approach. Duan et al.'s (2021) measure for market efficiency is based on the novel interpretation of fractional integration. In that approach, the order of integration d of a time series can be a fractional number between 0 and 1. This paper employs the so-called Feasible Exact Local Whittle estimator to estimate d. Duan et al. (2021) gauge the degree of inefficiency of a market using the absolute difference between the estimate of d and 1: $D = |1 - d|$. To measure dynamic efficiency, i.e. how efficiency is varying over time, this paper uses a 2-year-rolling window approach.[2]

The remainder of the paper is organised as follows: Sections 2 discusses data and methods used in this paper. Section 3 presents the results obtained from the application of the inefficiency measure. Section 4 carefully interprets this results from the perspective of oil market fundamentals; Section 5 explains why oil market turbulence is an appropriate interpretation of the observed oil market inefficiency and discusses the relationship between oil market turbulence and economic uncertainty. Section 6 analyses the macroeconomics of oil market turbulence. Section 7 offers concluding remarks.

2 Data and Method

The daily data for West Texas Intermediate Cushing, Oklahoma crude oil spot prices in US$/bbl, which include Free on Board (FOB) cost, is considered to reflect the global crude oil market.[3] The data is obtained from Bloomberg using the ticker symbol 'USCRWTIC [index]' for the period of 02 January 1997 to 02 September 2022.[4]

Processes characterised by fractional integration $I(d)$ have garnered increasing interest among empirical researchers in the fields of economics and finance. This is because $I(d)$ processes can effectively capture specific long-

[2] As robustness check, this paper also uses a 4-year as well as a 10-year window; see the Appendix.

[3] FOB implies that the seller is responsible for transportation and loading expenses to the shipping port. The gravity of WTI, as measured by the American Petroleum Institute (API), is 39, and its sulfur content is 0.34. API is a standard indicator of the density of petroleum liquids compared to water, aiding in comparing the densities of different petroleum liquids.

[4] The USCRWTIC Index typically aligns with the front-month NYMEX (New York Mercantile Exchange) crude oil contract, except during its three-day delivery scheduling period following the expiration of the front-month contract.

term features within economic and financial data (for details, see Zaffaroni and Henry (2003)). This paper employs the methodology introduced by Duan et al. (2021), which utilises a framework based on fractional integration, particularly using Shimotsu's (2010) semiparametric Feasible Exact Local Whittle (FELW) estimator. Shimotsu (2010) introduce a modified (two-step) ELW estimator, tailored for economic data analysis, to account for an unspecified mean (which needs to be estimated) and a polynomial time trend. This estimation approach complements the fully extended local Whittle estimator introduced by Abadir, Distaso, and Giraitis (2007), which uses a fully extended discrete Fourier transform. A fully extended local Whittle is based on the Type I process, whereas FELW is founded on the Type II process.[5] This framework is employed to investigate the efficiency of the WTI crude oil market.

Table 1: Memory properties of a given price series (y_t) with different d values.

d **Value**	**Persistence of shocks**	**Market efficiency**	**Information transmission**	**The close degree to an efficient market**
$d > 1$	Expansionary memory, explosive over time	Inefficiency	Excessive transmission	-
$d = 1$	Permanent memory	Efficiency	Complete transmission	Efficient Market
$0.5 \leq d < 1$	Long memory	Inefficiency	Partial transmission	High degree
$0 < d < 0.5$	Long memory	Inefficiency	Partial transmission	Lower degree
$d = 0$	Short memory	Inefficiency	None	Zero degree
$d < 0$	Long memory	Inefficiency	Reverse transmission	-

Note: This table provides information on the memory properties of a given price series (y_t) across different integration orders (d) and outlines their corresponding effects on market efficiency. Adapted from "Dynamic efficiency and arbitrage potential in Bitcoin: A long-memory approach," by K. Duan, Z. Li, A. Urquhart, and J. Ye, 2021, *International Review of Financial Analysis*, 75, p. 4, (https://doi.org/10.1016/j.irfa.2021.101725). Copyright 2021 by Elsevier Inc.

[5] See Shimotsu and Phillips (2006) for further details on the Type I and Type II process.

Duan et al. (2021) follows Hamilton (1994) to explain different forms of "memory" within a given time series to identify potentially existing fractional integration order that is a crucial metric for quantifying the level of market informational efficiency.[6] Moreover, this accommodates the fractional integration order by incorporating the concept of "long-memory" within the model system.

The empirical analysis is initiated by estimating d-value i.e. fractional integration order of crude oil price series (y_t) by using the Feasible Exact Local Whittle estimator (FELW) introduced by Shimotsu (2010). Considering that overly high or low bandwidths can result in a reduced or increased number of valid observations utilised in the estimation of d using the FELW methods (Shimotsu, 2010), causing unstable outcomes, a moderate bandwidth of 0.6 is chosen to generate the time series for d. Later, the d-value is used to gauge the degree of market efficiency. Table 1 (Duan et al., 2021) show the statistical (memory) properties of y_t at varying values of d, along with the corresponding indications of market efficiency.

To examine how the informational efficiency of the WTI crude oil market evolves over time, market efficiency is assessed by using a self-derived index D in this study. This D index is created by computing the absolute difference between 1 and the fractional integration order that provides insights into the oil market's evolving nature of efficiency.

$$D_t = |1 - d_t|$$

where d_t is the estimated fractional integration order at time t. In particular, a 2-year rolling window is used to estimate the d-value. The index D, determined by the disparity between d values and 1, inversely signifies the level of market efficiency. In other words, a higher D indicates a larger absolute gap, reflecting a more inefficient market and a lower degree of mar-

[6] Later, they adopt the Fractionally Cointegrated Vector Autoregressive (FCVAR) model introduced by Johansen (2008) and Johansen and Nielsen (2012) that accounts for both short-run error corrections and long-term links among the target variables. For the details of the model see Section 3.1 of Duan et al. (2021)

ket efficiency. Hence, D can also be seen as a representation of the degree of market inefficiency.

This approach is directly comparable to the analysis of market efficiency using Hurst exponents, proposed by Hurst (1951). The Hurst exponent, (H), quantifies whether a time series is uncorrelated (H = 0.5), persistent (H > 0.5), or anti-persistent (H < 0.5). Loosely speaking, Hurst exponents measure the long-run memory of time series. Although the seminal work of Hurst (1951) first appeared in hydrology study, there has since been numerous applications into the financial markets specifically in the area of EMH of indices including commodities (Kristoufek, 2019; Tiwari, Umar, & Alqahtani, 2021); cryptocurrencies (Dimitrova, Fernández-Martínez, Sánchez-Granero, & Trinidad Segovia, 2019; Kristoufek & Vosvrda, 2019); stocks (Di Matteo, Aste, & Dacorogna, 2005; Matos, Gama, Ruskin, Al Sharkasi, & Crane, 2008). The connection between EMH and Hurst exponent is deduced when the exponent of a series, H=0.5, which implies a random walk without long memory. This is consistent with the EMH which asserts that markets are unpredictable due to the random walk behaviour of prices. Thus, series with H higher than 0.5 indicates long-run memory with a higher predictability level (see Horta, Lagoa, & Martins, 2014). Duan et al. (2021) point out that the Feasible Exact Local Whittle estimator (Shimotsu, 2010) mitigates the weaknesses of this traditional method.

3 Oil Market Inefficiency

This section presents the empirical results. Figure 1 shows the WTI price data along with the rolling window estimates for both the fractional integration parameter d and the inefficiency measure D.[7] It is evident that the estimate for d fluctuates around 1; this represents the Random Walk and corresponds to the value for an efficient market. Taking a closer look yields the insight that, prior to the oil price hike in 2008, d is found to fluctuate mostly between 0.8 and 1. Between 2006 and 2008, d is found to increase

[7] Please note that each of the rolling window estimates marks the end of one 2-year-rolling window.

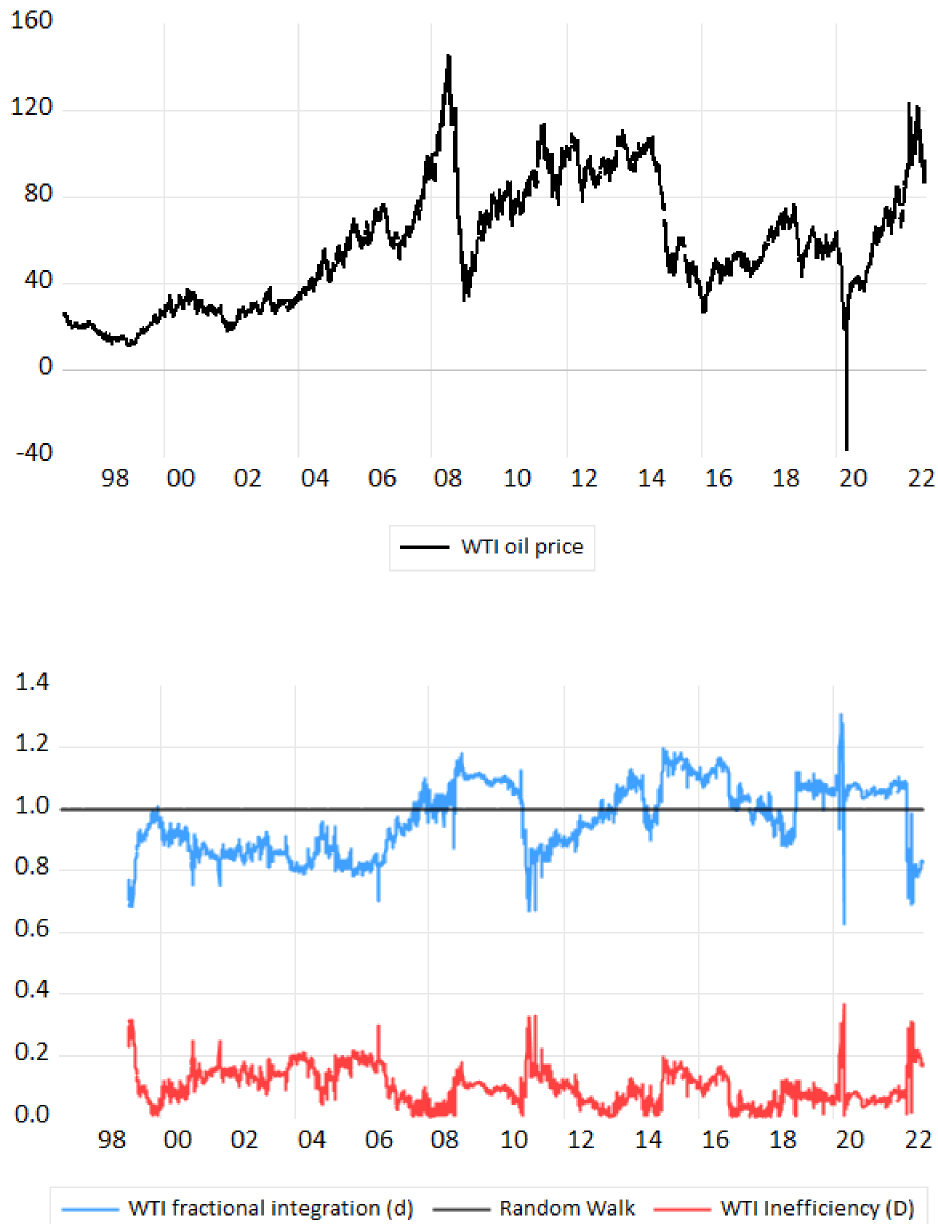


Figure 1: Inefficiency of WTI Oil Prices.

slightly to values around 1. Overall, the d estimates vary, but in an unsystematic manner. With the begin of the steepest part of the 2007/2008 oil price hike, d increases to values above 1. This means that the prices are explosive.[8] Post 2008, the estimates of d fluctuate stronger than prior to 2006; mostly between 0.8 and 1.2, but on a few occasions outside this range. There are sharp increases and decreases of d, mostly driven by idiosyncratic oil price episodes. Individual observations seem to have a certain influence on the estimates. Worth highlighting is that the estimates of d increase to values well above 1 whenever WTI price strongly declines: 2008, 2014, and 2020.

As explained above, Duan et al. (2021) propose to interpret the absolute distance between d and 1 as a measure of the degree of inefficiency of a market: $D = |1 - d|$. The resulting inefficiency measure D for the WTI market is found to fluctuate generally between 0 and 0.4. There is no obvious long-run trend in this measure; e.g., the inefficiency is not systematically decreasing over time as a result of a maturing market. This is the first main finding of the analysis of oil market inefficiency. D, just as d, is found to be larger prior to 2006 than in the rest of the sample, just below 0.2; but the value is largely stable. Post 2006, in contrast, D is found to fluctuate to a larger extent; the main determinant is oil price behaviour during specific oil market episodes. Noteworthy are the abrupt increases in D during the oil price declines mentioned above. During the steepest part of the oil price increase prior to the 2008, inefficiency is found to be close to 0. In other words, the WTI market is highly efficient. Subsequently, the inefficiency measure sharply increases to 0.1 This is lower than pre-2006, but nevertheless considerably higher than during the steepest part of the oil price increase. From the 2010 until mid 2014, the inefficiency measure is found to fluctuate at low levels between 0 and 0.1; safe for the short price hike in 2010. The degree of inefficiency is found to be the lowest in 2012. This period overall is characterised by largely stable oil prices; they fluctuate around 100 USD per barrel. The sudden oil price decline in the second half of 2014 yet again leads to an abrupt increase in the inefficiency measure from

[8] This finding is consistent with Gronwald (2016).

around 0.1 to 0.2 Once this oil price decline is no longer included in the two-year rolling window, the inefficiency measure decreases again to around 0.1. It fluctuates around that value throughout 2016-2022; except for yet more extreme episodes: the negative WTI prices witnessed at the beginning of the COVID pandemic and the price hikes associated with the Russian invasion of the Ukraine in 2022.

To summarise, the inefficiency measure D is found to increase abruptly whenever there is an oil price downturn. There are also periods in which the degree of inefficiency is found to be low: 2006-2008, 2013, and 2016-2018. During these periods, however, the oil price exhibits different kinds of behaviour: a sharp increase, relative stability, and a gradual increase, respectively. In other words, there does not seem to be a strong association between oil price episodes and periods with low degrees of inefficiency. As this observation leads to the second main finding of this analysis, the oil price downturns of 2008, 2014, and 2020 are now analysed in more detail.

Figure 2 shows the WTI price data as well as the inefficiency measure D for two oil price downturn episodes: 2008/2009 and 2014/2015. The former contains the steeper part of the price increase before the peak in July 2008 as well as the sharp decline associated with the begin of the Global Financial Crisis. It is noticeable that the inefficiency measure begins to increase only in the fourth quarter of 2008, from its lowest value in the entire sample to about 0.1. This delay is attributable to the estimation of the parameter d: the share of observations from this decline period has to be sufficiently large before these can drive the estimated d. In 2014/2015, a similar picture emerges: D increases with a certain delay. An important difference, however, is that oil prices have been comparatively stable prior to the 2014 decline. In addition, the increase in D is even sharper than in 2008. In short, the WTI market is found to be less informationally efficient during extreme oil price episodes. The label "extreme" is certainly also appropriate to describe the price developments of 2020: The upper panel of Figure 3 illustrates that oil prices began to decline in early 2020 already, before COVID has been declared a pandemic by the WHO. The decrease becomes steeper in March of that year; the sharpest decline, however, has been witnessed in April.

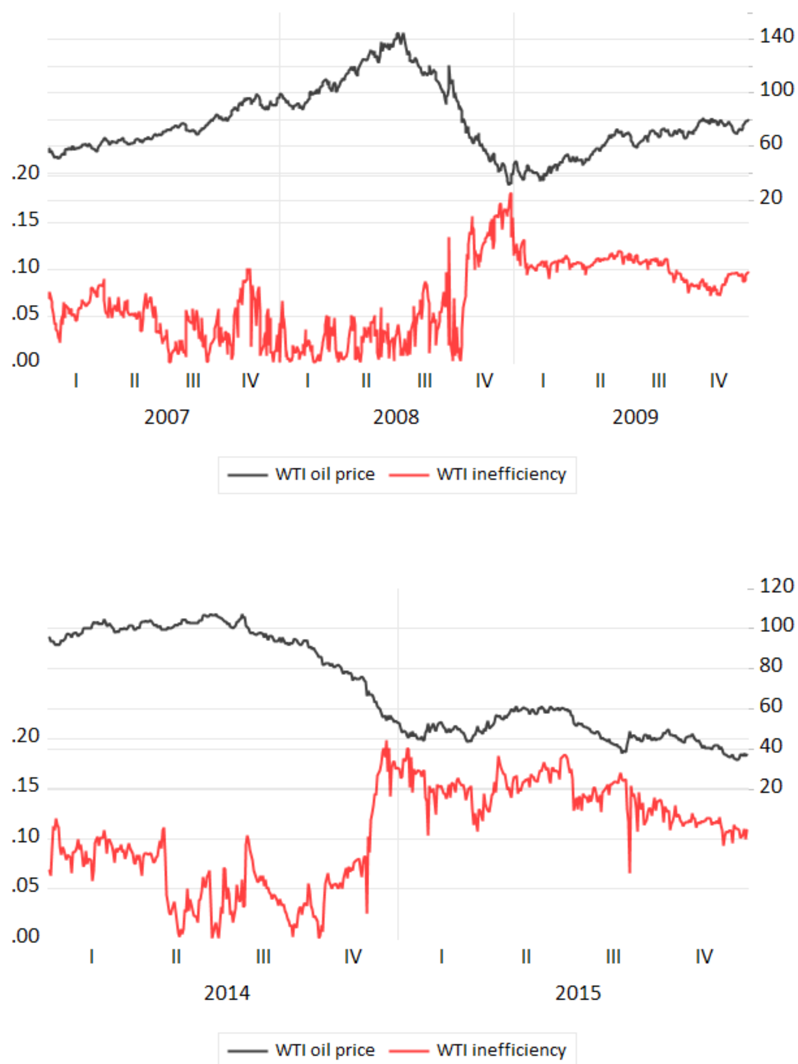


Figure 2: Inefficiency of WTI markets 2007-2009 and 2014-2015.

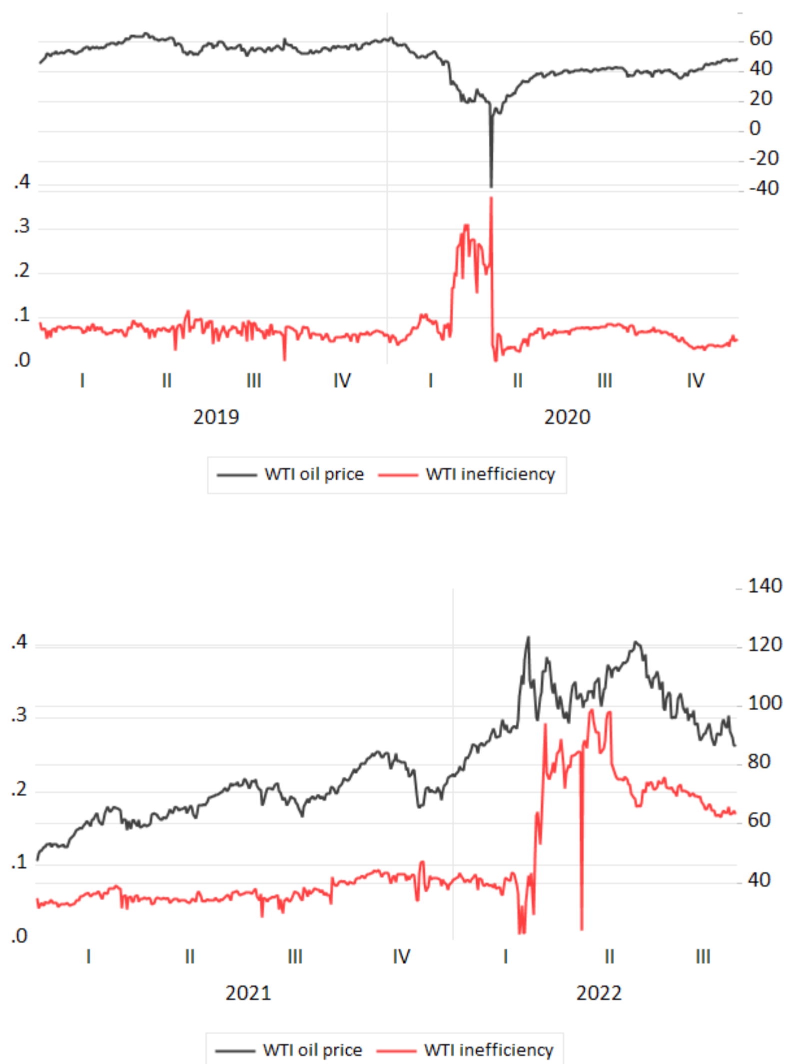


Figure 3: Inefficiency of WTI markets 2019-2020 and 2021-2022.

Consistent with findings discussed above, the inefficiency measure begins to increase with the begin of the steeper decrease in March 2020.

The next extreme oil price episode follows suit immediately: the oil price sharply increased in response to the Russian invasion of the Ukraine in early 2022, which is followed by rather volatile price movements during the remainder of 2022. Also in this case, the inefficiency measure sharply increases; yet again after the steep decline that follows the initial price increase. Subsequently, the inefficiency measure remains high throughout 2022.

4 Market Inefficiency and Oil Market Fundamentals

Having presented the empirical results in detail, this section now proceeds with a careful interpretation and discussion of those. As highlighted above, there are sharp increases in market inefficiency during periods in which the oil price declines: 2008, at the beginning of the Global Financial Crisis, in 2014, and in 2020. According to Baumeister and Kilian (2016), sustained oil price declines are rare events. In addition to the ones included in the sample period of this paper, only the decline in 1986, after Saudi Arabia's decision to no longer stabilise oil prices, is comparable.

In other words, when oil market participants are confronted with declining oil prices, these episodes are not only challenging as such; this is likely to be a situation many market participants will not have experienced at all before. It is, furthermore, worth noting that the vast majority of academic research on the macroeconomics of oil price shocks is concerned with the analysis of oil price increases (Gronwald, 2008; Kilian, 2008). Finally, 2008 marks not only the begin of the Global Financial Crisis, which is an extreme event as such; it also marks the end of the Great Moderation, a period of decreased macroeconomic volatility in the US that began in the mid 1980s. It would be an understatement to refer to this simply as an oil price decline. More appropriate would be to refer to this as an unprecedented situation; the market environment is extremely challenging. The objective of Baumeister and Kilian's (2016) paper is to discuss extensively the underlying economics of major oil price declines. As they mainly focus on the oil price decline in 2014, they only briefly discuss the events in 2008. The paper does not contain any explicit judgement of whether or not that decline is justified from an economic perspective; they only state that this decline has been caused by the Great Financial Crisis 2008 and they are discussing why Saudi Arabia did not manage to stabilise the oil price in its role as swing producer. As also Smith (2009) highlights, the oil price is known for responding strongly to small fluctuations in economic fundamentals.

Oil market inefficiency also drastically increases during the 2014/15 oil price decline. One important difference is that this decline does not come after a steep increase as in 2008, but, to borrow an expression from Baumeister and Kilian (2016), after "a period of comparative stability". These authors also highlight that the severity of this decline even surprised industry experts. As for the underlying reasons of this decline, Arezki and Blanchard (2019) find it is attributable to demand and supply shocks that occurred in the second half of 2014; in particular surprise increases in global production. The arguments used by Arezki and Blanchard (2019) can be seen as standing in the tradition of Hamilton (2003) according to whom unexpected changes in production are among the main drivers of oil price fluctuations. In addition, they represent the notion that oil prices are inherently unpredictable. Baumeister and Kilian (2016), whose VAR-based analysis allows them to decompose the observed oil price decline into a predictable and an unpredictable part, fundamentally deviate from this notion. They begin their detailed discussion by emphasising that oil prices during this period have been considerably more variable than any of the economic fundamentals they include in their analysis, e.g. global oil production, global real economic activity, crude oil inventories. Subsequently, they show that "more than half of the observed decline in the price of oil of USD 49 was predictable in real time as of June 2014 and hence must have reflected the cumulative effects of earlier oil demand and supply shocks." When using the term predictable in real time, Baumeister and Kilian (2016) mean predictable using only information publicly available as of June 2014. The authors are even able to quantify the following: 11 USD of the predictable decline are attributed to adverse demand shocks prior to July 2014; further 16 USD of this predicable decline to effects of positive demand shocks. This implies that less than half of the decline has been unpredictable at that point and the authors attribute this to a shock to oil price expectations in July 2014 as well as a negative demand shock that occurred only in December 2014.

To discuss this from a statistical perspective, recall that weak-form tests of the EMH are based on simple Random Walk tests. This implies that the price returns are white noise; the returns are not related to each other, there is no pattern in the data that can be exploited for forecasting purposes. The finding of higher inefficiency during decline period simply means that the trading activity in complex environments produces a pattern in the data that deviates from the Random Walk benchmark. During unprecedented situations like the oil price decline periods 2008, 2014, and 2020, it has been impossible to predict how much lower the oil price would get; until at some point the market participants seem to have found consensus in this regard. As a result, oil prices stabilised again. However, also the period prior to the oil price peak in 2008 can be described as unprecedented. Crude oil prices have never been higher and also have never increased at this rate. During thus steepest part of oil price increase in the first half of 2008, however, the oil market is found to be highly efficient. The following Section 5 discusses in more detail how the arrival of information affects market activity.

The idea of efficient markets and the notion that prices in efficient markets follow random walks do not seem to be able to capture, however, the developments during the 2014 oil price episode. Recall that up until the middle of that year, this paper's empirical results show that oil prices behave closely to a Random Walk; the inefficiency measure is as low as 0.05. According to this measure, the crude oil market is highly efficient in this period. Recall, however, that Baumeister and Kilian (2016) find that there is publicly available information which is not reflected in the prices yet. From Fama's (1970) perspective, according to which "a market in which prices always 'fully reflect' all available information is called 'efficient'", this market is clearly inefficient as there is information which is not reflected in the price despite being publicly available. Starting from June 2014, market participants gradually include this information in the price; the result is the witnessed oil price decline. This price adjustment, which is justified from fundamental perspective, leads to a deviation from Random Walk behaviour of the price. The inefficiency measure used in this paper increases to above 0.15; thus the market is considered less efficient that prior to the begin of the price adjustment. To summarise, the crude oil market and the way prices are determined in this market seems to defy being correctly classified as either efficient or inefficient market. For these reasons, this paper proposes to interpret crude oil market inefficiency as oil market turbulence. The following section discusses this in more detail.

5 Turbulence, Uncertainty, and the Quantity of Information

As discussed above, the empirical analysis in this paper finds the oil markets to be more inefficient during oil price downturn periods witnessed in 2008, 2014, and 2020. The discussion that follows focusses on the following two aspects: first, Fama's (1970) definition of an efficient market: "a market in which prices always 'fully reflect' all available information is called 'efficient'." Second, the fact that the classification into efficient or inefficient is based deviations of observed price behaviour from the random walk assumption - in other words, on properties of the oil price time series.

One way to label the oil price downturn periods mentioned above would be to say that these are periods in which uncertainty is high. How to measure (economic) uncertainty, in turn, has for a long time been a very active research area. Prominent recent contributions include papers by Jurado et al. (2015) as well as Baker, Bloom, and Davis (2016). The former base their measure on a large set of economic and financial variables while the latter is based on newspaper articles. Highly relevant is also the measure for oil earnings uncertainty proposed by Ma and Samaniego (2020). This measure is based on forecasts and forecast errors from a large survey of analysts regarding financial performance of firms in the US oil and gas industry. In addition, Castelnuovo and Tran (2017) propose to interpret Google Search Volumes (GSV) as measure for uncertainty. The key assumption of that paper is that economic agents use google to search for information when they are uncertain. The higher the search frequency of uncertainty-related keywords, the more uncertainty/ambiguity the users perceived. Thus, search terms which are associated with (future) uncertainty will be used more frequently in times of high levels of uncertainty. Google Search Volumes, in addition, have also been used in the economic literature to measure investor attention (Da, Engelberg, & Gao, 2011) as well as demand for information (Vlastakis & Markellos, 2012).[9] The message that emerges from the latter is that demand for information is changing over time.Vlastakis and Markellos (2012) argue there is this change when market conditions change and that demand for information increases during periods of higher returns. They also noted that demand for information has an increasing function with the level of risk aversion in the market. What is more, (Vlastakis & Markellos, 2012) also discuss changes in supply of information. In their paper, they use news headline data from the Thomson Reuters NewsScope Archive Database. How, in turn, prices (and trading volumes) in financial markets respond to new information has been analysed in a vast literature, too. There is a seminal paper by Mitchell and Mulherin (1994) who measure information flow by using the number of news announcements. They find that the number of Dow Jones announcements and market activity are directly related. Equally influential is the paper by French and Roll (1986) which finds that increases in stock return volatility are caused by the arrival of information and the reaction of traders. Engle, Hansen, Karagozoglu, and Lunde (2021) document that the arrival of public information is related to changes in return volatility of US stock prices; Bollerslev et al. (2018) further analyse the relationship between trading intensity and spot volatility around public news announcements and find that the volume-volatility elasticity around important news announce-

[9] Da et al. (2011) state that changes in the level of attention by investors can be captured by search frequency in Google (Search Volume Index-SVI) and the sophistication level of investors. In particular, the authors document that SVI directly captures the attention of retail investors and is capable of predicting higher stock prices as well as predicting price reversal within the year. In addition, changes in attention (measured by SVI), the paper noted are due to the changes in trading activities (captured by number of orders and share volumes) of individual retail investors.

ments to be below unity. This finding is consistent with predictions from a theoretical model in which investors "agree to disagree". In that type of "difference-of-opinion" class model see Kandel and Person (1995) as well as Banerjee and Kremer (2010), investors' interpretation of news and updated valuations of assets do not coincide. This creates additional trading motives. Bertelsen, Borup, and Jakobsen (2021) find that the relationship between the level of stock market volatility and public information flow is non-linear.

To summarise: first, the quantity of information which has to be processed in financial markets is changing over time. The literature on empirically testing the weak-form EMH is silent in this regard. Second, it has been well documented that the arrival of new information affects return volatility. Return volatility, however, is just another property of time series data. Thus, this paper argues that in periods of high uncertainty or when large volumes of information has to be processed, the price behaviour can deviate from the random walk assumption, and, thus, it would not be useful to simply use the label inefficient. It should be noted that in oil markets, there is no such thing as regular news announcements. Oil prices respond to various forms of information that comes from various types of sources; economic and political, announcements from various sources such as OPEC, official government sources and statistical agencies, but also consultancies and other market observers. The task to process all this information is particularly challenging during extreme oil market episodes such as the ones in 2008, 2014, 2020. The underlying economic events are unfolding slowly; over time, more and more information becomes available; new interpretations of information become available, analysts and consultants give their view, etc. In any case, it is plausible to assume that there is a quantity of information is larger during extreme oil price episodes than in more tranquil economic periods.

The relationship between quantitative measures of market efficiency and crisis periods has been discussed already in the literature. The popular method is the calculation of Hurst exponents. Kumar and Deo (2013) conducted a pre- and during-GFC study on 20 global financial indices documenting a larger Hurst exponent (presence of long-run memory) during the 2008 financial crisis than pre-crisis period. This conclusion is however contrary to Kristoufek (2019) who argued that lower Hurst exponents are expected during crisis period with the reasoning that during crisis, the activities of short-term investors are anticipated to exceed those of long-term investors, thus causes the H to decrease.[10] In a more comprehensive study, Horta et al. (2014) explore the dynamic behavior of the Hurst exponent over time and its usefulness to detect the effects of financial crises in terms of efficiency and financial contagion across markets. They find that Hurst exponents are larger (evidence of long-run memory) during the GFC period for all market but smaller for the tranquil period. The authors noted reduction in investor base and liquidity as a potential reasoning behind the higher Hurst exponents (absence of random walk behaviour) during the GFC period. Lastly, Horta et al. (2014) observed that the development levels of markets relate to the evolution of Hurst exponents from tranquil to the GFC and the Euro debt crisis periods. In specifics, they found that estimates of Hurst exponents for most developed markets were insignificantly affected during the crisis whereas exponents of lower-level markets were significantly impacted. This is also consistent with Di Matteo et al. (2005).

Lo (2004) proposed the Adaptive Market Hypothesis (AMH) based on evolutionary approaches to address the dichotomy between the EMH (the conjecture that all information is rationally incorporated into prices) and behavioural economics critiques of market irrationality where prices are driven by greed and fear instead. The argument for Lo's AMH framework rests on the fact that evolutionary principles and behavioural biases such as competition, adaptation, natural selection, overconfidence, loss aversion, overreaction among others are merely indicative of the adaptive nature of individuals to a changing environment through heuristics. For example, experimental economists and psychologists have long document behavioural

[10]It is crucial to note that the connection between Hurst exponents and EMH is also subject to the development level of markets. As noted by Di Matteo et al. (2005), more developed markets often exhibit smaller Hurst exponents (indicating market efficiency-EMH) than less developed markets. Similar conclusion was also drawn by Kristoufek and Vosvrda (2014) who document Hurst exponents to be well below 0.5 for most developed markets.

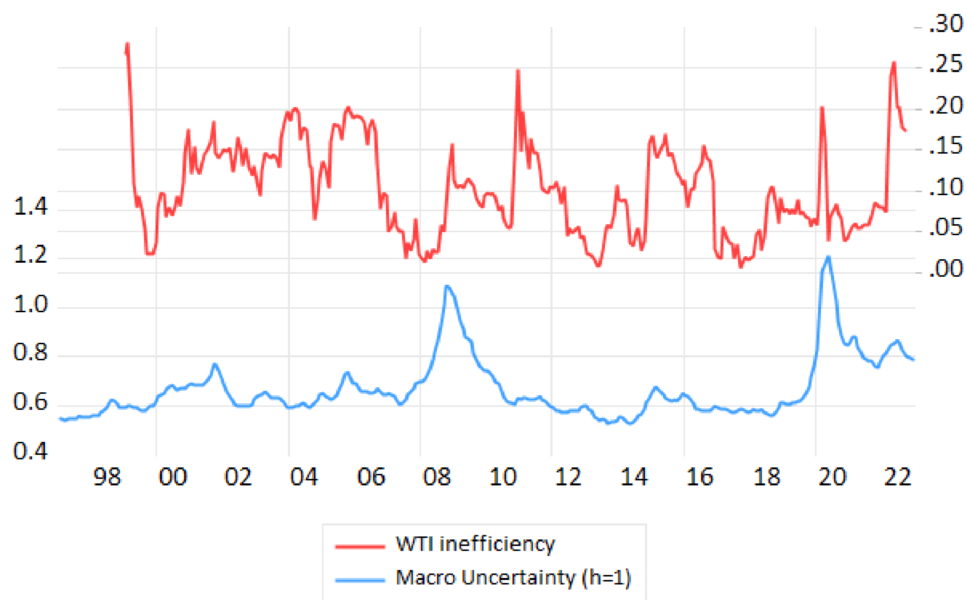
predispositions that are common to human decision-making during times of uncertainty (Tversky & Kahneman, 1978) such as overreaction (De Bondt & Thaler, 1985), loss aversion (Kahneman & Tversky, 2013), and overconfidence (Barber & Odean, 2001; Fischhoff & Slovic, 2014). Thus, the EMH detractors contend that investors frequently exhibit predictable and financially disastrous behaviour, which is often irrational.

The higher degree of inefficiency found during the oil price downturns seems generally to be in line with predictions of the AMH. However, it nevertheless seems to be unsatisfactory to attribute the empirical findings of this paper only to behavioural issues. The pattern in the results is very strong. While the 2008 GFC certainly can be considered a new environment market participant have to adopt to, this is not the case for the 2014 oil price episode. There is a complex mix of oil supply and demand information which is publicly available and is gradually incorporated into the oil price. In a nutshell, it seems unsatisfactory to simply use the label inefficient to describe a market such as the crude oil market in extreme episodes such as the ones discussed in this paper.

The relationship between the empirical results of this paper on the one hand and the two established measures for uncertainty proposed by Jurado et al. (2015) as well as Baker et al. (2016) is now going to be discussed in more detail. In addition to these, this paper also uses a measure for quantity of information based on google search volumes as well as the Crude Oil ETF Volatility Index (OVX) published by the Chicago Board Options Exchange. To capture quantity for oil market information, this paper uses Google search volumes for the simple term "oil price". Finally, considered is also a measure called oil earnings uncertainty which has been proposed by Ma and Samaniego (2020).

Figures 4 to 6 show time series plots of these measures, each of which are plotted together with the WTI inefficiency measure obtained in this paper.[11]

[11] As the uncertainty measures are calculated at monthly frequency, the frequency of the inefficiency measure has been converted from daily to monthly. The exception is the OVX which is calculated at daily frequency.



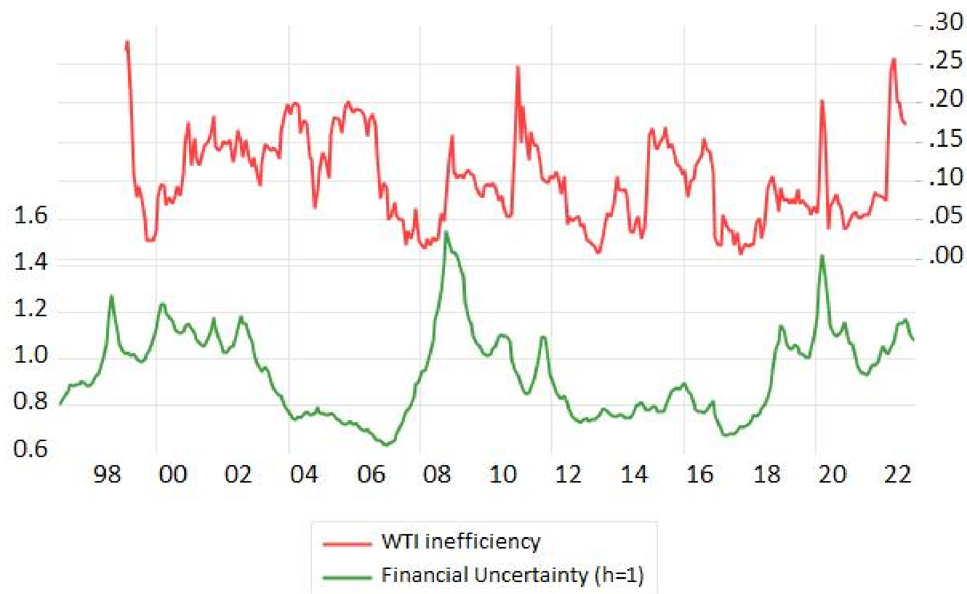


Figure 4: WTI inefficiency and Jurado et al.'s (2015) measures of financial as well as macroeconomic uncertainty

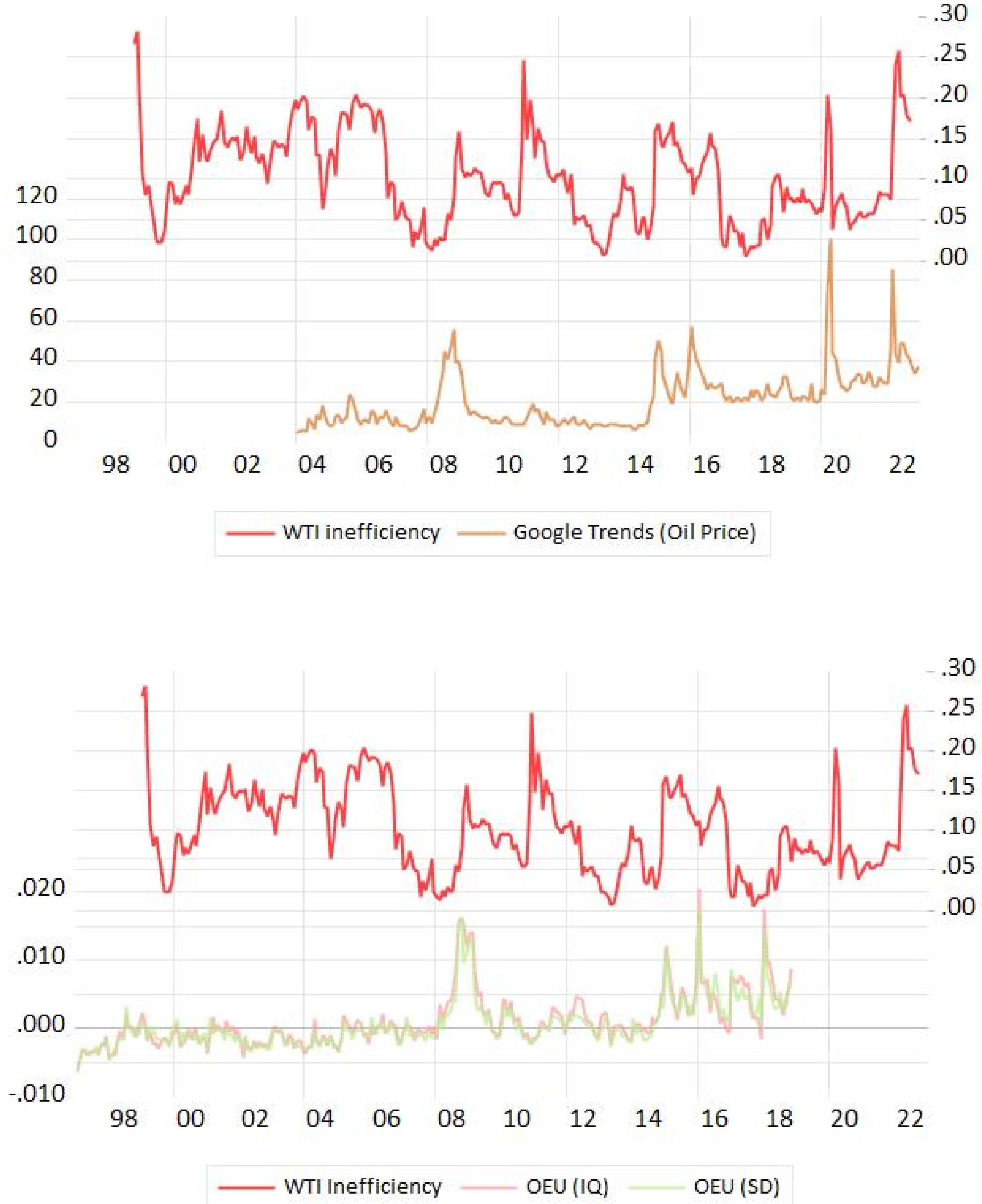
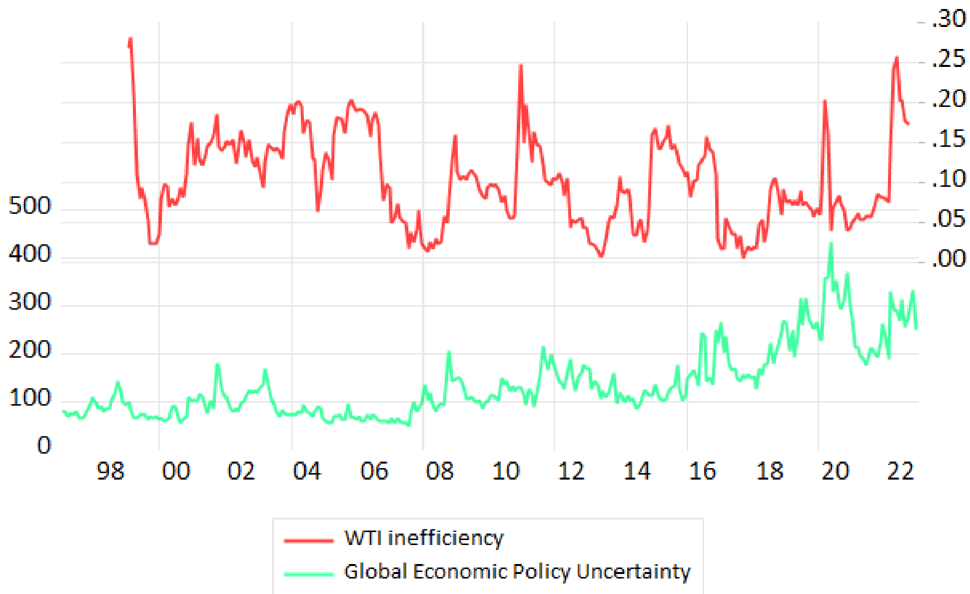


Figure 5: WTI inefficiency and Oil Earnings Uncertainty as well as Google search volumes for "oil price".



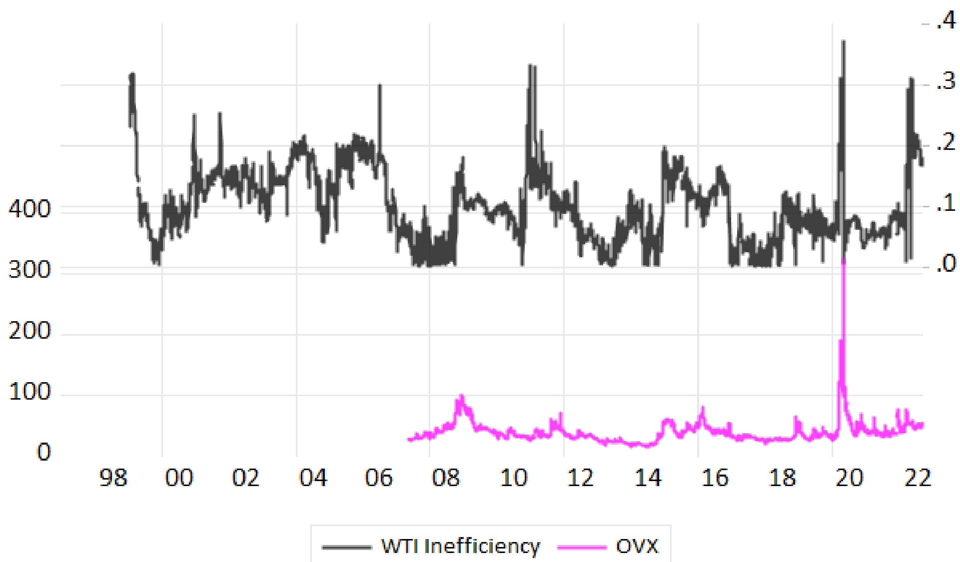


Figure 6: WTI inefficiency and CBOE's Crude Oil ETF Volatility Index as well as Baker et al.'s (2016) global economic policy uncertainty.

Visually inspecting Figure 4 shows that both uncertainty measures proposed by Jurado et al. (2015), first, fluctuate to a smaller extent than the WTI inefficiency measure, and, second, increase strongly in 2008 and 2020.[12] These peaks occur at the same time also the inefficiency measure peaks, but overall the correlation of these measures is small; see Table 2.

Table 2: Correlations of measures

	WTI Ineff.	Macro U.	Fin. U.	Google	GEPU
WTI Ineff.	1.000	0.121	0.016	0.129	-0.125
Macro U.	0.120	1.000	0.776	0.576	0.433
Fin. U.	0.016	0.776	1.000	0.481	0.503
Google	0.129	0.576	0.481	1.000	0.602
GEPU	-0.125	0.433	0.503	0.602	1.000

The upper panel of Figure 5 reveals that the Google-based quantity for information measure also exhibits an upward shift; this, however, occurs in 2014. In addition, there are sharp increases in the quantity of information whenever the oil prices decline - just those declines discussed earlier in this paper. These increases in search volumes yet again coincide with increases in the WTI inefficiency measure obtained in this paper. The lower panel shows the oil earnings uncertainty measure by Ma and Samaniego (2020)[13] Note that these authors propose four different uncertainty measures. The ones shown here are based on dispersion of the forecasts; thus, they measure in particular the extent of disagreement between forecasters.[14] Evident is that this measure drastically increases in 2008/09 as well as in 2014. In addition, there is also an upward shift in the level of oil earnings uncertainty in 2014. Thus, disagreement among forecasters of financial performance of the oil and gas sector in the US is particularly large when the periods are turbulent. Noteworthy is also how similar the oil earnings uncertainty measure and the

[12] Jurado et al.'s (2015) uncertainty measures can be found here: https://www.sydneyludvigson.com/data-and-appendixes.

[13] This data is currently only available until 2019. It has been taken from the data appendix of the published paper.

[14] Shown are the interquartile-based as well as the median-standard-deviation-based versions of the oil earnings uncertainty index. For details, see Ma and Samaniego (2020).

Google-based quantity of information measure are.

The upper panel of Figure 6 shows that Baker et al.'s (2016) uncertainty measure behaves very differently compared to the ones proposed by Jurado et al. (2015): there is an upward shift in 2007/2008 in the level of global economic policy uncertainty which is followed by a persistent increase of this measure.[15] In addition, the increases associated with events such as the Global Financial Crisis and the begin of the COVID pandemic do not stand out as much. However, many of the increases in this measure occur at the same time as the WTI inefficiency measure also increases. Finally, it becomes apparent that increases in crude oil market inefficiency coincide with increases in the OVX (lower panel of Figure 6). OVX also exhibits a small upward shift in 2014. This implies that volatility is higher in the aftermath of the 2014 downturn. One difference is that OVX increases in the first half of 2008 already and that the peak in volatility in 2020 dwarfs the remaining changes in volatility. The following summary is appropriate: whenever the OVX increases, crude oil market conditions have been challenging. This is consistent with predictions of the difference-in-opinion literature. It is implausible to assume that simply behavioural factors such as those discussed under the label AMH can explain this behaviour. It seems to be the case that there is a larger quantity of information that has to be processed. For all the reasons discussed above, oil market turbulence seems to be an appropriate label for periods with sharply decreasing oil prices and sharp increases in the measure for market inefficiency.

6 Macroeconomics of Oil Market Turbulence

Having visually compared the different measures, the focus is now turned to the analysis of the macroeconomic effects of oil market turbulence. It is a common approach in the macroeconomic uncertainty literature to analyse the macroeconomic effects of uncertainty. Typically, a standard VAR model is used; the variables in the VAR are supposed to represent the macro econ-

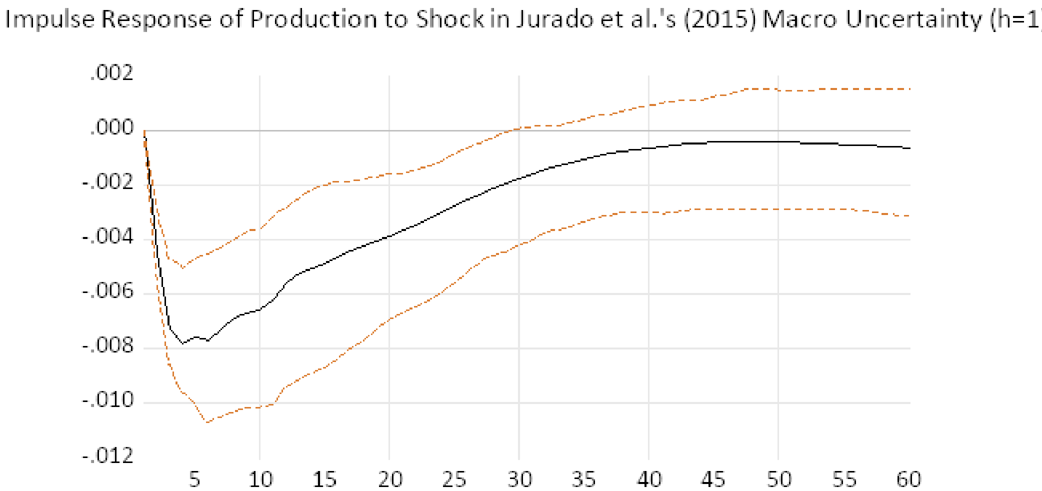
[15] Baker et al.'s (2016) uncertainty is from here: http://www.policyuncertainty.com/global_monthly.html.

omy just as in Sims's (1980) seminal paper. Jurado et al. (2015) borrow the VAR they apply from papers such as Christiano, Eichenbaum, and Evans (2005) and Bloom (2009). They simply add one of the uncertainty measures they propose at a time to these macro VAR models.

The VAR used in this paper is a smaller version of the one proposed by Christiano et al. (2005). The following variables have been included: log(real IP), federal funds rate, log(S&P index), growth rate of M2, as well as one of the following measures: Jurado et al.'s (2015) macro uncertainty (h=1), Baker et al.'s (2016) global policy uncertainty, the oil market turbulence measure proposed in this paper, and, finally, the quantity of information measure.[16] The data is at monthly frequency; 6 lags of the endogenous variables have been included. The reason for using this smaller-scale VAR is that the period of observation in this paper, 1999-2022, is considerably shorter than that in the reference papers; in consequence, the number of observations available for the estimation of the VAR is considerably smaller. Otherwise the procedure is identical to Jurado et al. (2015); an impulse response analysis is performed. A Cholesky decomposition has been applied to identify the shocks. The ordering of the variables is as shown above.

Figure 7 displays the impulse response of production to a shock in the established uncertainty measures. It is evident that production sharply declines after a shock in Jurado et al.'s (2015) macro uncertainty measure occurs. The response is highly significant and persistent. In contrast, there is no significant reduction of production to a shock in Baker et al.'s (2016) global policy uncertainty measure. This finding can be attributed to the data properties described above: Jurado et al.'s (2015) measure is dominated by two major economic events while Baker et al.'s (2016) measure exhibits a very different pattern. Figure 8 displays the impulse response of production to a shock in the newly created measures, quantity for information measured through Google search volumes for "oil prices" as well as the oil market turbulence measure. There is a reduction in production after a shock in these measure occurs. This reduction is significant; however weaker

[16] OVX is only available from 2007. Thus, a macroeconomic analysis of this measure is not meaningful because of the shortness of this time series.



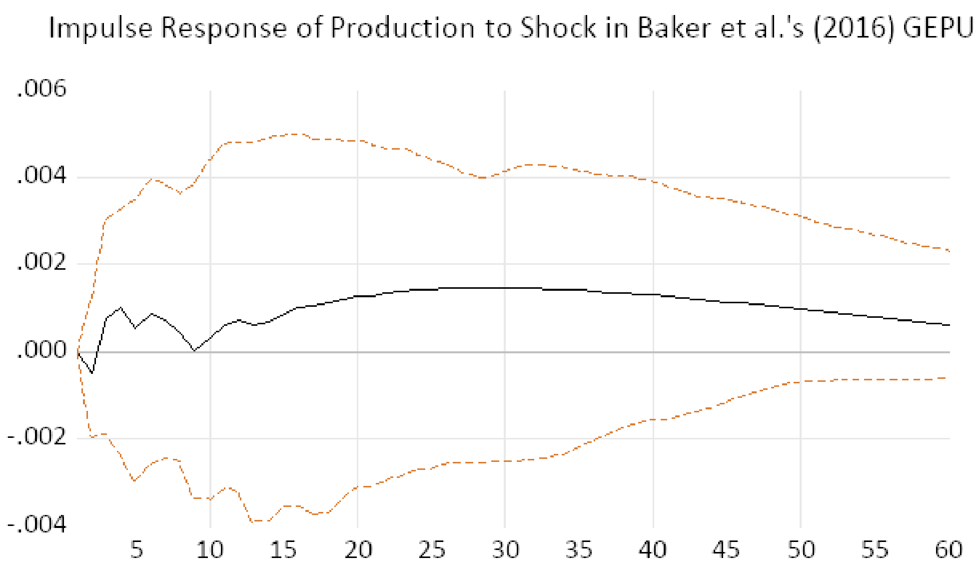
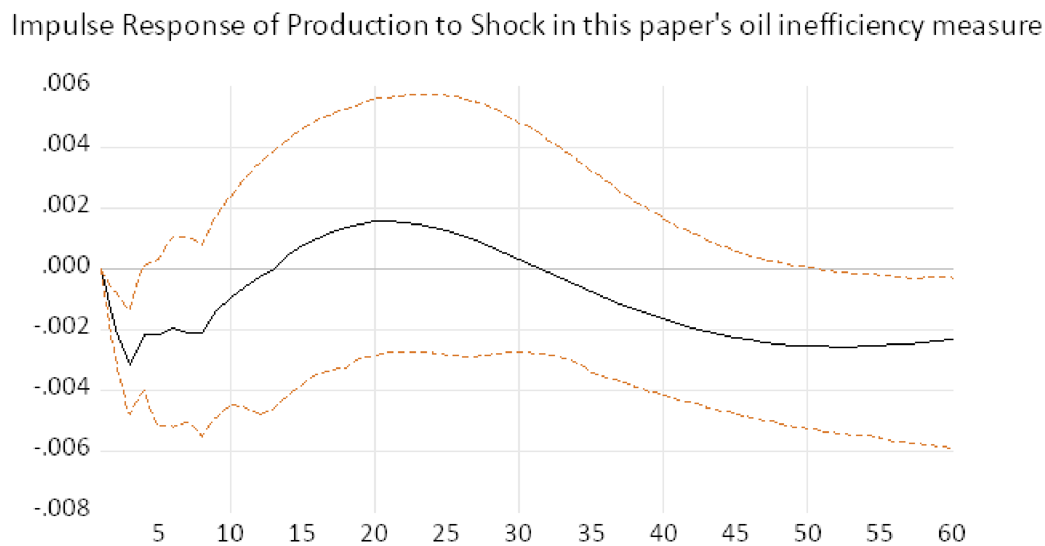


Figure 7: Impulse Response Analysis. Shocks are One S.D. (d.f. adjusted) Innovation. 95% CI using Kilian's unbiased bootstrap with 200 bootstrap repetitions and 499 double bootstrap reps.



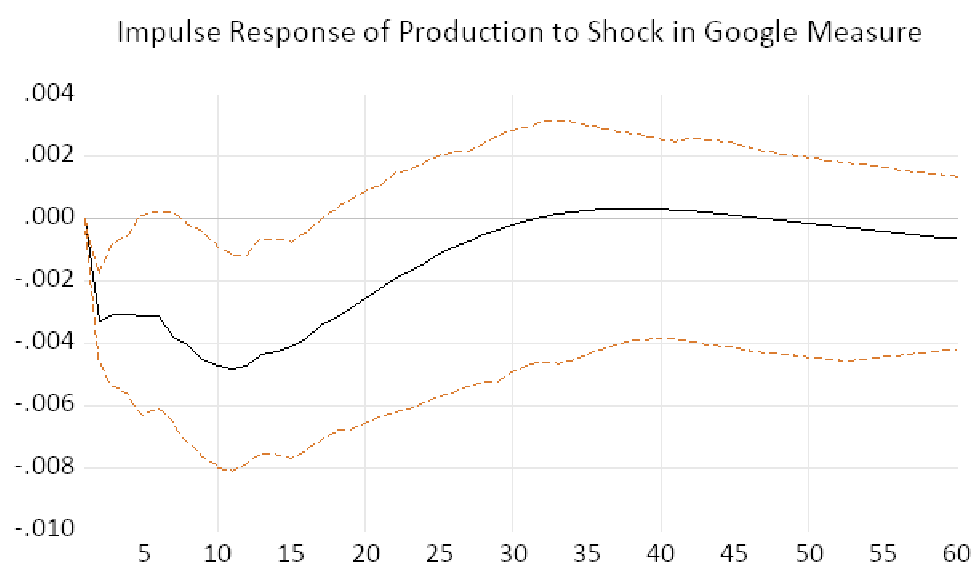


Figure 8: Impulse Response Analysis. Shocks are One S.D. (d.f. adjusted) Innovation. 95% CI using Kilian's unbiased bootstrap with 200 bootstrap repetitions and 499 double bootstrap reps.

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and not as persistent as the reduction in response to a shock in Jurado et al.'s (2015) macro uncertainty measure. This is also attributable to the data properties: that measure is characterised by two very pronounced peaks, one in 2008 and one in 2020.[17] The remaining time that measure does not fluctuate considerably. This explains why the response of production to a shock in this measure is this sharp. The oil market turbulence measure generally fluctuates to a larger extent, and the finding of a negative response of production seems to be attributable to the increases in this measure in 2008 and in 2020. In addition, it also contains oil market specific episodes such as the dramatic decline in 2014. The shape of the demand for information measure is more similar to Baker et al.'s (2016) global policy uncertainty, but the peaks are more pronounced. Those peaks, in turn, occur just when the inefficiency measure peak. This explains the reduction in production.

7 Conclusions

This paper uses a recently proposed measure for financial market inefficiency to analyse the informational inefficiency of the WTI crude oil market. The key findings are, first, that crude oil market inefficiency varies over time. Second, abrupt increases in inefficiency occur during extreme episodes such as the price downturns witnessed in 2008, 2014, and early 2020. Third, the paper proposes to interpret the measure for inefficiency as oil market turbulence. Fourth, the paper demonstrates that oil market turbulence (or the drivers behind it) have negative macroeconomic consequences.

The finding of a larger degree of inefficiency during extreme oil price episodes such as oil price downturns and the interpretation as oil market turbulence warrants a more detailed discussion. It is worth noting that the observed price movements can largely be explained by fundamental economic factors; see Baumeister and Kilian (2016) as well as Arezki and Blanchard (2019). In general, oil price declines are rare events; historically, both the general public and academia have been concerned to a much larger extent

[17] Gronwald (2008) also shows that the shape of impulse responses can be driven by a very small number of observations.

about price increases (Gronwald, 2008; Kilian, 2008). Oil price declines such as those witnessed in 2008, 2014, and 2020 occur in periods for which the term uncertain seems to have been created for. The outbreak of the global financial crisis in combination with an unprecedented record level of oil prices just earlier that year is certainly a very complex environment. The extent of the downturn 2014 surprised, according to Baumeister and Kilian (2016), even industry experts. In addition, this decline occurred after oil prices have been remarkably stable for extended periods. Finally, it was also highly uncertain how the outbreak of the COVID pandemic would affect the global economy in general and the crude oil market in specific.

Labelling a market as more inefficient in such extraordinary periods seems unsatisfactory. Substantial oil price declines are rare events and often have good fundamental reasons. For this reason, this paper proposes to interpret this inefficiency measure as measure for oil market turbulence. There is a close relationship between this and attempts to measure economic as well as policy uncertainty. One key message that emerges from this paper is the following: the overall economic and political environment in which markets such as the crude oil market are embedded in, can change. Sometimes, these changes are abrupt and drastic. During these periods, the quantity of information the market has to process is exceptionally large. Following the so-called "difference-in-opinion" literature, investors do not necessarily agree on how to interpret this information; thus, market activity and volatility increases. Recall that empirical tests of the weak-form of the Efficient Market Hypothesis merely detect deviations from Random Walk behaviour. This paper argues that the increases price volatility leads to a stronger deviation of observed prices from the Random Walk and provides empirical support for Banerjee et al.'s (2009) finding of price predictability as an outcome of differences in beliefs. Thus, whenever the oil market cannot process information because of disagreement among investors on how to interpret this information, these periods must be turbulent. This is the reason why this paper proposes to interpret the measure for market inefficiency as measure for oil market turbulence.

There is, however, another more fundamental concern. Prior to the 2014 oil price decline, the behaviour of crude oil prices has been close to that of a Random Walk. Baumeister and Kilian (2016) demonstrated, however, that more than half of this decline was predictable using publicly available information. In a nutshell: the crude oil market seems to defy a characterisation using EMH.

Appendix A

For the results presented in this paper, a 2-year-rolling window has been used to estimate the informational inefficiency of the WTI market in a dynamic manner. This Appendix shows the results for a 4-year as well as a 10-year-rolling window; see Figure 9. It is evident that all key results, in particular the strong fluctuation pre 2006 and the sharp increases in inefficiency during the oil price downturns 2008, 2014, and 2020 features. Note that this is not necessarilry the case as the sample periods now have different lengths and are, in this sense, not directly comparable.

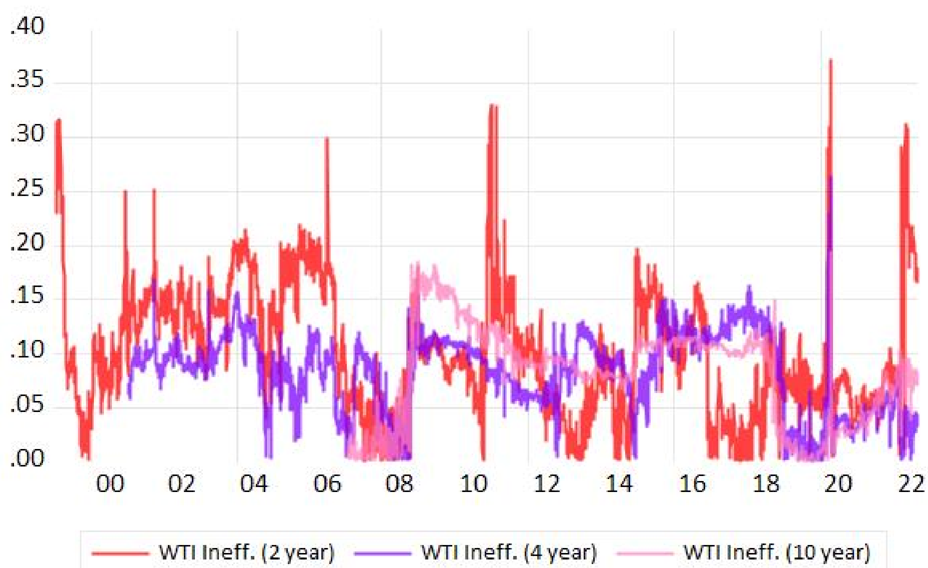

Figure 9: Robustness analysis.

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