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Revisiting WTI–Brent spread and its drivers

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ABSTRACT

We made two key contributions to energy economics and finance by revealing new insights on the WTI–Brent spread (WBS). Our first exercise engages with the stylized facts of the WBS and its role as an indicator, identifying the time around the shale oil revolution as a turning point in the mean- and persistence-based shifts in the spread's time-series properties. The second exercise delves into the fundamental connection between the WBS and key US-based and international market factors. We utilized three sets of explanatory factors, representing demand, supply, and uncertainties. The data for this study were sourced primarily from Refinitiv Eikon and EIA, spanning from 1988 to 2020. The results affirmed demand-side variables to have predictive power for widening spreads, whereas supply-side factors, such as oil rig counts, *trans*-US pipeline flow, and import from Canada, contributed to spread shrinkage. This finding specifically held in robustness check using quantile-based regression. Supplementary causality tests revealed that economic conditions contain greater causal influence than market-based indicators, suggesting that the spread traders respond more to fundamental drivers than financial sentiments.

1. Introduction

Watershed events, such as the shale oil revolution and the exogenous health crisis of the COVID-19 pandemic, have triggered large-scale shifts in the global energy landscape. This has impacted the dynamics of crude oil markets, making more important than ever the proper understanding of the implications of these events and the resultant price drivers. This study strives to answer two research questions about the WBS. The first question deals with the timing of changes in (mean and persistence of) the time-series properties of this spread. The second question deals with the fundamental connection between the WBS and various US-based and international market factors, including demand, supply, and uncertainties. By examining these factors, we were able to shed light on the drivers behind spread widening or shrinkage, generating valuable insights into the intricate relationship between the WBS and market dynamics.

Globalization and the breakneck pace of Chinese economic growth over the last two decades have seated global oil prices as an indicator for businesses with ties to energy and governments. Many studies show the importance of oil prices in setting energy policies for economies and businesses. Brigida [1] displays that the WBS is influential for oil-exporting countries. On the industry side, a Royal Bank of Canada economics report illustrates that exposure to volatile spreads can translate to macroeconomic hardship for businesses, investment levels, and governments' fiscal budgets for oil-producing countries. The most vulnerable are economies with export exposure to the US. This importance has recently risen due to system-wide economic shocks resulting from the COVID-19 pandemic. The state of the art on research surrounding WBS is as follows. The earliest works have mostly focused on technical factors, such as market integration. The focus then shifted to macro fundamentals, such as supply and demand sources. With the availability of new data sets, studies started to emerge on the nexus between WBS and economic and policy uncertainties. Interestingly, we do not observe an integrated approach encompassing statistical, fundamental, and behavioral perspectives to gain a multi-dimensional view of this complex relationship. Moreover, a lack of research attention to this domain has been observed recently—especially since the onset of the COVID-19 pandemic. This event acted as an exogenous shock, and literature is scarce on how the dynamics of the spread changed in response to it. Thus, we utilized a multitude of univariate and multivariate techniques to reveal new insights surrounding the stylized facts on the WBS by date-stamping shifts in their time-series properties

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and directionality. Our second and more material contribution flows from the application of a technique called the *recentered* influence function (RIF) method, which facilitated gleaning new insights on the antecedents of the WBS predicated on realized and anticipatory market forces. Our findings contribute to energy research literature straddling multiple domains: on the methodological front, we demonstrate the utility of innovative techniques, such as the RIF; in economics, we underscore the market efficiency and macro-fundamental dimensions of the WBS.

Our investigation is timeous given the lack of recent academic attention to the dynamics of WBS [1,2]. Many papers indeed study the dynamics on an individual basis. The spread, however, attracts undeservedly lower attention—especially since the onset of the COVID-19 pandemic, which has impacted energy markets substantially [3]. This study's overarching objectives are to clarify the structural relationships between the WBS and macro- and market-fundamentals utilizing innovative and appropriate econometric methods and use the generated insights to highlight the spread's policy and risk management implications. In this regard, we have contributed to the findings of Reboredo et al. [4] and Ji et al. [2]. We date-stamped structural breaks in the time-series properties of the spread, marking a novel attempt at understanding the evolving market efficiency in this spread, which implicates the futures contracts traded based on it [5,6].

One of the innovations of this research is the application of improved econometric techniques to tease out the relevant factors driving the spread. To this end, we noticed that the influence function (IF) technique has gained traction in the robust estimation of forecasting models. The IF is broadly instrumental in understanding a model's behavior and debugging and detecting data set errors. More specifically, our estimation approach within the IF framework traced the baseline model's prediction patterns through the learning algorithms and back to its training data—as common in machine learning investigations. Correspondingly, in the spirit of Firpo et al. [7]; we relied on a subset of such algorithms—the RIF—to investigate the impact of a range of selected demand- and supply-type explanatory factors as well as the global perception of financial markets and geopolitical uncertainties on the marginal (unconditional) distributions of the WBS. The RIF has received considerable scholarly attention in recent years, specifically concerning the estimation of a large set of distributional statistics [8–10]. Moreover, following the intuition from Rios-Avila [11]; we extended this analysis to an examination of seemingly unrelated RIF (SURIF), which accounts for (i) an estimation of the impact of explanatory variables across different quantiles of the WBS and (ii) analyzing multiple distributional statistics simultaneously. These innovations, on the whole, coordinated to an overarching estimation result suggesting the potency of statistics to potential outliers in data while obtaining asymptotic standard errors of otherwise complex distributional statistics. In short, the RIF approach facilitated granular quantification of the marginal effects of demand, supply, uncertainty, and miscellaneous relevant factors determining the conditional distributions of the spread. The findings derived from it are unique, so our effort contributes to the literature, showing that the method is versatile and can be applied or extended to other markets and asset classes at the intersection of market dynamics and economic determinants. Moreover, we advance the current understanding of the spread beyond the foundational work of Kaufmann [12] through the usage of more advanced quantile-specific tools to capture nonlinearity effects on a broader set of explanatory variables across multiple market regimes. This has led to new strategic insights, e.g., how speculative trading drives spreads at the lower quantiles of the spread.

We organize our paper as follows: (1) building a narrative from existing literature, (2) the development of our hypotheses, (3) discussing our estimation techniques and explaining our results, and (4) concluding with a brief summary of the implications of our findings and suggesting possible future avenues for exploration.

2. Literature review

2.1. Introductory overview of WBS

Before surveying the academic literature leading to the development of our hypotheses, the reader should be familiarized with an overview of the chemical properties, logistics, economic forces, and production factors of the West Texas Intermediate (WTI) and Brent benchmarks. Chemically, both WTI and Brent qualify as light and sweet crude oil. The term *light* refers to the American Petroleum Institute's classification of gravity levels, which determines if the oil will float or sink in water. Meanwhile, the sweet-to-sour spectrum indicates the extent of sulfur content. WTI and Brent are among the sweetest products available and thus attract the producers, as fewer resources are necessary for refinement. This sharply contrasts the heavy and sour crude oil sourced from Mexico (Maya), Saudi Arabia, Venezuela (Merey), etc. Production-wise, WTI is produced exclusively in the US—near Texas—and is thus the choice benchmark for US-based businesses. In contrast, Brent is extracted in the North Sea and is popular as a benchmark in the European and Middle Eastern markets. In fact, favorable geographical location has resulted in Brent accounting for over 60% of global oil trades. Even the OPEC members rely on Brent as the benchmark.

Although both are chemically similar, WTI has commanded a mild premium over the years thanks to being slightly sweeter in nature. In other words, historically, the WBS has been positive for a good number of years. This changed in the 2010s, as the shale oil boom in the American Permian basin led to a supply glut in the continent. As per EIA reports circa 2020, WTI production accounts for slightly over a third of overall American crude oil production. This downward pressure on WTI's price pushed WBS into negative territory. There are good reasons to believe the negative spread will persist into the foreseeable future. This is partly due to Brent's innate geographical advantage of being based at Sea, hence its relative proximity to export destinations. In contrast, WTI is produced in landlocked regions in the US, requiring expensive pipelines for transportation and massive storage facilities. To overcome these barriers, the US is presently expanding its pipeline infrastructure to facilitate faster consumer reach through enhanced connectivity to prominent US harbors. Depending on the speed and efficiency of these extended networks, the WBS may well shrink and even revert to positive levels.

In recognition of these differences, financial markets have priced the two benchmarks differently, causing one of the markets to move more aggressively in relation to the other. In this respect, market traders generally rely on a number of key factors, including the geopolitical tensions within the oil-exporting economies, natural disasters inducing demand–supply disruptions, content and composition of crude oils, and the time zones and locations of different trading platforms, to determine the price of the benchmarks. Specifically, while the Brent oil traders are generally on the watch for the likely geopolitical tensions rising in the Middle East, their WTI counterparts monitor possible demand–supply disruptions in the US in response to severe climate conditions. Meanwhile, traders often keep an eye on the demand–supply status of the crude oils, given their sulfur contents and gravities. Likewise, the different trading time zones and the locations of various platforms where the benchmark crude oils are traded are the key determinants of the prices and, therefore, the WBS. The New York Mercantile Exchange is the hub for trading the WTI future contracts, while the Brent futures are traded in the Intercontinental Exchange in London. Such contrasting features not only have predominantly explained the historical price discrepancies between the two benchmarks but also helped in understanding the distinctive behavior of the WBS and the ensuing market volatility, especially at the onset of the COVID-19 pandemic.

2.2. Benchmark leadership

The importance of WTI and Brent contracts in setting global oil prices is extensively documented. Studies show that these contracts are instrumental in determining interest rates [13–15], investors' portfolio positions, producers' inventory decisions [16], and working capital management [17]. Notably, Koldziej and Kaufmann [18] highlight the role of speculative activities in these contracts and their cumulative spillover into global energy prices. The heavy interest of speculators in these benchmark futures is, in fact, commonly recognized as a driver of their price differentials [19]. Moreover, given the diverse roles of these competing benchmarks in local and global economic dynamics, research attention on the spread between them has become plenteous. The following paragraphs thematically summarize these studies.

Research attention surrounding the WBS is attributable to its contract's introduction and subsequent liquidity under the CME. Present literature considers its key drivers to be the depletion of North Sea crude oil, the transformation of the US shale oil, and the rescission of the ban on exporting crude oil. Among different costs associated with the WBS, transportation is regularly thought to be the most prominent [20]. For instance, Kleit [21] used an arbitrage cost approach to estimate the transaction costs between oil regions, concluding that transaction costs between oil markets are drivers of different cost figures. In a more recent study, Reboredo [22] investigated the dependence structures of WTI and Brent by developing an assumption of a giant pool and found affirmative results. Lately, however, a debate has arisen, stating that geographically proximal markets tend to be more integrated than farther markets [23, 24]. Moreover, organizational barriers, such as exchange rates, create speculation opportunities. These debates build upon earlier postulations in the literature that changes in supply and demand, seasonal changes, transportation costs, convenience yield, and exchange rate volatility influence the benchmark differentials.

The role of financial markets in pricing oil benchmarks cannot be understated. Given the synergetic role of financial markets in price discovery and facilitating the transfer of risks through futures, empirical works inspecting this nexus have skyrocketed lately. Many studies report that the pricing mechanism is heavily regime-dependent [25–27]. Others highlight the role of behavioral biases and psychological aspects as influential parameters worthy of incorporating for modeling purposes [28,29]. These results align with the popular narrative of hyper-financialized commodity market facts in general.

The potential for WTI and Brent prices to interfere with the supply and demand side forces of global economies has also garnered research attention. Interestingly, few studies actually found a significant link between the spread and supply–demand balances. Key in this regard is the work of Fattouh [30]; who concludes that the spread is a proper technical benchmark because it does not reflect the world's supply–demand balances. Some causal ambiguity in this issue remains, however. For instance, [31] underline the influence of supply and demand factors on price changes of WTI and Brent futures. More recently, using the supply and demand approach with respect to the geographical location of oil markets, alongside considering the productivity of the oil markets, Buyuksahin and Robe [32] conclude that the supply of oil in North America, the imports from Canada, and the changes in prices of crude oil futures are significant for imbalances in the supply and demand in crude oil markets in the short run. Overall, there seems to be some evidence indicating that WBS reflects not only industry-related issues but also country- and region-wide concerns.

The significance of the WBS extends to the risk management profession as well. In fact, ever since the two futures contracts debuted, researchers have advanced a conjecture that the global oil markets behave as a giant singular pool. Adelman [33]; in particular, popularized a globalization-oriented view of the effect of the spread. This led to many studies on market price discovery [34], lead-lag relationship [35], and arbitrage opportunities. A view contrary to the above is Weiner's [36] regionalization hypothesis: oil market prices depend on local factors, local government policy, and local market shocks. Ad rem to this hypothesis is an important recent work by Palao et al. [37]; who consider whether the fresh crude oil futures market based in China has a realistic chance of dethroning the WTI–Brent legacy.

At any rate, studies dealing with the risk management aspect began to proliferate after 2011, coinciding with the early stages of price deviation between the two benchmarks [38]. This could be motivated by the increase in the absolute value of the spread for the period of 2011–2013. Among recent important findings on this issue is the report of Kuck and Scweikert [39]; who investigated the long-run relationship between five different oil markets (WTI, Brent, Bonny Light, Dubai, and Tapis) for the period of 1987–2015. The authors report strong evidence of coupling between the international benchmarks. This finding can be slightly problematic for the latter hypothesis because it predicts the WBS to remain close to unity, which clearly did not transpire. Nevertheless, the classic finance school of thought believes that the price of the futures commodity is influenced by monetary policy, economic cycles, and speculative factors. However, whether variations in the said antecedents drive the WTI–Brent differentials has remained comparably under-explored.

Allied with unraveling the risk factors of the WBS is portfolio insurance. Noticeable research interest exists on the temporal characteristics of commodity prices and the reasons for the separation of WTI and Brent futures markets [40]. These matters implicate portfolio diversification, risk sharing, and better allocation of assets. Integral to this theme is the integration of oil markets. Ghoshray and Trifonova [41] show that the international crude oil markets are integrated. Ji and Fan [38] arrive at the same conclusion using a graph theoretic approach. The authors also account for localization effects and conclude that the South and North America and Africa oil markets are stable. Using a co-integration technique of high-frequency data, Liu et al. [42] show that shocks from Cushing and variables related to the delivery of WTI and Brent are significant drivers of the cointegrating relationship. Some have also connected investor sentiments to this sort of risk [43].

Various factors that underpin the WBS dynamics are time-varying in nature. Early evidence of this came in the form of structural change tests on univariate WBS series. Historically, prices of crude oils moved very close to each other with a difference of $ $\pm$ 3. WTI has typically been dearer. A reversal of this stylized fact has inspired many modern studies. Structural breaks in levels are also one of the most common econometric investigations in this domain. For instance, Narayan et al. [44] investigated the structural changes in oil spot prices by distinguishing between the slope and the intercept of the predictive regressions on futures prices and discovered two structural changes in the oil market: 1988 and 2007. Narayan et al.'s methodology appears more sophisticated and improves upon earlier work, some of which detected unusual structural breaks; e.g., Du et al. [45] found a break at the end of 1999. Meanwhile, Kim et al. [46] confirmed the existence of a long-run relationship between WTI/Brent and Dubai, considering structural breaks for the period of 1997–2012.

Furthermore, Buyukshahin et al. [19] discovered a structural break between WTI and Brent in the long term within 2008–2012. In addition, Chen et al. [47] used the CUSUM-squared technique and the conventional unit root to measure the break dates between WTI and Brent and analyze the spread stationarity, respectively. The authors found a persistence in the behavior of WBS in the late stage of 2010. They also note that the spread showed nonstationary behavior in December 2010 and recommend that future researchers adopt a current-events-based approach that may narrow the spread and convert the price behavior process from non-stationary to stationary. [48] found a two-way causal relationship between the Brent/WTI and Argus Sour Crude Index and note that this relationship pivoted from early 2011 onward. Similarly, Caporin et al. [49] examined the WTI–Brent relationship and time-stamped two structural breaks between 2000 and 2017. Their findings connect the boom of shale oil products to the change in the spread relationship.

Recent research has shown the existence of a positive relationship with drilling activities. As drilling activities plummeted between 2008 and 2016 due to the low price of crude oil, this connection has changed

Table 1
Literature matrix.

Study	Time	Market	Instrument	Method	Key Findings
Overview of WTI- Brent Spread					
[63]	1993–2016	WTI and Brent	Weekly spot prices	Simulation model of world oil prices.	The is a structural break in the WTI–Brent price spread in January 2011 and a break in the corresponding shapes of the futures curves around the same time.
[64]	2007–2017	WTI and Brent	Daily spot prices	Multivariate BEKK-MGARCH	There is high and volatile correlation between WTI-Brent. Long-term movements of WTI and Brent are driven by the same dynamics, confirming the 'one great pool' hypothesis. Effects of WTI over Brent in short term are in a negative direction.
[48]	2013–2015	WTI, Brent and Argus	Daily spot prices	Nonlinear Granger causality test	Bi-directional causality is captured for Brent and WTI. Unidirectional causality from WTI and Brent to Argus is captured.
[65]	2002–2014	WTI, Brent and Oman	Daily spot prices	Error Correction Models (ECM)	There has not been a reversion to the long run relationship among WTI-Brent since the reversal in spread between the WTI and Brent. WTI, Brent and Oman move to restore the long run relationship in at least one regime.
[66]	2007–2017	WTI-Brent and Dubai	Daily spot prices	VAR-GARCH-BEKK Model	The volatility spillover effect between the crude oil price and airlines' stock price is more significant than the return spillover effect. Compared with Korea's airlines, China's airlines are influenced more by the oil price change, implying that spillover effects owing to oil price are closely related to the different characteristics of the air transport markets of the two countries.
[67]	1980–2009	WTI and Brent	Quarterly spot prices	OLS regression	Index of global real economic activity is the only driver of persistence in real oi prices.
[31]	1991–1995	WTI and Brent	Daily and Monthly oil prices	OLS regression	The daily volatility in the cash spread is about one sixth the price volatility of either oil while the average price spread is only one fourteenth the average oil price. The volatility in the price spread takes its highest value in the months near maturity.
[30]	1997–2008	Sahara, Maya, Bonny, Brent, WTI, Dubai, Lloyd blend	Weekly crude oil prices	Threshold Autoregressive	Strong evidence of threshold effects in the adjustment process to the long run equilibrium.
[68]	1993–2013	WTI and Brent	Daily spot prices	Markov Switching Miltifractal Volatility Model	MSM models fit the oil returns data better.
[69]	1986–2013	WTI and Brent	Monthly spot prices	Mean Predictive Error model	The benchmark of no-change model can be significantly outperformed by a model selection strategy with restricted models for longer horizons.
Importance of WTI- Brent Spread for Risk Management					
[70]	2007–2018	WTI and Brent	Daily spot prices	Mutual information (MI) and Maximum Entropy Method (MEM)	Increase in the information flow between oil volatility index and the spot variance of Brent returns. Decrease in the information flow with WTI. Direction of the information flow is from oil volatility index to both oil spot variances.
[37]	2018–2020	WTI, Brent and SC	Daily Brent, WTI and SC futures contracts	Lead-lag relationship	Brent is the only influential oil futures market and WTI is the most sensitive one. SC is only sensitive to Brent news, even though the WTI market has the highest trading volumes
[71]	2000–2016	WTI and Brent	Monthly spot prices	Forecasting analysis	WTI crude oil price would take a shock upstream tendency in the short term.
[72]	1997–2009	WTI and Brent	Daily spot prices	Multivariate volatility models (CCC, VARMA-GARCH, DCC, BEKK and diagonal BEKK)	Optimal portfolio weights of all multivariate volatility models for Brent suggest holding futures in larger proportions than spot. Optimal hedge ratios from each multivariate conditional volatility model give the time-varying hedge ratios. The hedging effectiveness indicates that diagonal BEKK is the best model for optimal hedge ratio calculation in terms of reducing the variance of the portfolio.
[73]	1986–2006	WTI and Brent	Daily spot prices	Empirical Mode Decomposition (EMD)	EMD-based neural network ensemble learning model is good at forecasting.
[74]	1989–2004	Oil, Coal, Natural Gas	Daily prices	Error Corrrection Models (ECM)	World oil market is a single, highly integrated economic market. Coal prices at five trading locations across the United States are cointegrated. Crude oil, coal, and natural gas markets are only very weakly integrated.
[75]	2000–2014	WTI-Brent, Dubai, Tapis and Nigeria	Daily spot prices	Error Corrrection Models (ECM), VAR Model	Long-term equilibrium relationship between the major crude oil markets from 2000 to 2010.
[76]	2007–2017	WTI, Brent and Dubai	Daily spot prices	Forecasting analysis	Long-term memory properties of the mispricing portfolios stabilize when the time period of the analysis enlarges.
[77]	2001–2013	WTI and China	Daily spot prices	VAR	Return and volatility spillovers between China and world oil markets are bi-directional and asymmetric.

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Table 1 (*continued*)

Study	Time	Market	Instrument	Method	Key Findings
[78]	2003–2018	WTI-Brent- OPEC Market	Daily oil price	Quantile Regression Neural Network	The developed model has ability to capture downside risk estimates with significantly improved precision.
[79]	2007–2017	Non-financial sector of China	Annual data	Generalized Method of Moments (GMM)	There is a negative relationship between enterprise financialization, and technology innovations and this relationship is stronger for firms with low R&D intensity and high financial leverage.
[80]	2004–2017	Energy sector of China	Annual data	Difference- in-differences (DID)	China's Air Pollution Prevention and Control Action Plan has shown a positive impact on energy efficiency in the thermal power sector, and this led to the adaptation of cleaner and more efficient technologies.
[81]	1997–2017	Spillover of financial cycles in China	Quarterly data	Vector Autoregression (VAR)	There is a linear effect of economic policy uncertainty, bilateral trade intensity and capital flow on China's financial cycle spillover.
[82]	1986–2021	Crude Oil	Daily spot prices	Long Short-Term memory (LSTM)	The authors find that the LSTM model outperforms traditional models in terms of forecasting accuracy and suggest that the LSTM model is a promising tool for predicting crude oil prices.
Drivers of WTI-Brent Spread					
[34]	1987–2019	WTI and Brent	Weekly spot prices	Fractionally Cointegrated Vector Auto Regressive (FCVAR)	WTI- Brent are globalized. The Brent–WTI price spread follows a long memory process. The Brent drives the Brent-WTI price structure.
[42]	2008–2011	WTI and Brent	1 s and 1 min prices	Vector Error Correction Model (VECM)	Cointegration between in the financial and physical layers of the WTI is relatively infrequent and ever declining. Brent futures contract is the primary venue for price discovery in the Brent market.
[81]	Its Listing-2018	WTI and Brent and Chinese agriculture futures	Monthly spot prices	Markov-switching GRG copula	There are two structural states of Markov switching between the futures prices of different agricultural commodities and crude oil futures price.
[83]	2013–2014	WTI and Brent	Daily spot prices	GARCH regression	There is no asymmetry of tail dependence and no asymmetric conditional volatility in crude oil returns.
[84]	1999–2016	WTI, Brent and six currencies	Daily prices	Diag-BEKK model	The optimal portfolio weights and optimal hedge ratios estimations demonstrate a time-varying behavior.
[85]	1990–2015	WTI and Brent	Daily prices	OLS regression	Predictability of WTI and Brent is not necessarily improved after adding a fundamental variable to the predictive regression. The combination over forecasts from individual models generates more accurate volatility forecasts than the benchmark of autoregressive model for oil volatility.
[86]	2001–2018	WTI, Brent and BRICS equity index	Daily spot prices	Nonparametric conditional value-at-risk causality (NCoVaR)	There is a significant long-term dependence coherency between the Russian, Brazilian and South African stock markets and oil shifts.
[87]	2005–2016	WTI, Brent, Dubai	Monthly crude oil spot prices	Partial Autocorrelation Function (PACF) and GARCH approach	During the first period of oil price decline, real demand reduction seemed to play a more prominent role compared with the other factors. Some supply factors, measured by U.S. shale oil production, combined with real and speculative demand factors, played an important role during the period of second oil price drop.
[88]	2003–2016	WTI and Brent	Weekly spot prices	Mildly Explosive/Multiple Bubbles Testing Strategy	There is no evidence that the VIX decisively affected oil price levels during the sample period.
[89]	2011–2012	WTI and Brent	Daily spot prices	Clayton Copula Model	The agricultural commodity and energy future prices are highly correlated and exhibit positive and significant relationship.
Structural changes in Crude Oil Literature					
[47]	1988–2014	WTI and Brent	Daily and weekly spot prices	CUSUM of the squares-based test	There is stationarity change in the spread process from level to first difference.
[49]	2000–2017	WTI and Brent	Monthly spot prices	Vector Error Correction Model (VECM)	There are two structural break, in February 2011 and in October 2014. WTI and Brent crude oil prices had a long-run relationship up to 2011. No cointegration existed during the period of widening of the spread. A new long-run relationship arises after the closing of the gap.
[90]	1987–2012	WTI and Brent	Daily spot prices	ARMA–GARCH	OPEC's announcements especially the "cut" and the "maintain" decisions have a significant effect on both returns and volatility of the crude oil markets, particularly that of the WTI. They detect five (six) breakpoints for the WTI (Brent) oil markets for the sample of study. The presence of structural breaks reduces the persistence of volatility.
[91]	1987–2012	WTI and Brent	Daily spot prices	GARCH-TGARCH	Two structural breaks occur in 1990 and 2008 which coincidentally correspond to the Iraqi/Kuwait conflict and the global financial crisis. They found the vidence of persistence in the oil price volatility of WTI and Brent although the latter appears more

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Table 1 (*continued*)

Study	Time	Market	Instrument	Method	Key Findings
					persistent than the former. They also found the evidence of leverage effects in both oil prices and therefore, investors in the oil market react to news.
[92]	1994–2016	WTI and Brent	Monthly spot prices	SVAR	There is a structural break in December 2010. For the period of 1994–2010, the spread is sensitive to production shocks.
[93]	1991–2004	WTI and Brent	Weekly spot prices	Lagrange Multiplier (LM) test	Each of the oil price series can be characterised as a random walk process and that the endogenous structural breaks are significant and meaningful in terms of events that have impacted on world oil markets.
[94]	2011–2016	Nigerian Sovereign Bond, Brent oil and West Texas Intermediate (WTI)	Daily spot prices	VARMA-AGARCH	There is a significant cross-market volatility transmission between oil and sovereign bond market with ample sensitivity to structural breaks.
[95]	1990–2009	WTI and Brent	Weekly spot prices	Bi-variate GARCH	The degree of persistence of volatility can be reduced via the incorporation of these structural changes in the volatility model.
[96]	1991–2009	WTI and Brent	Weekly spot prices	GARCH models	The ability of WTI in reflecting market conditions decreases sharply. In the short run, the WTI distortion is related to its price discount problem. In the long run, WTI's price discount problem coexists with a positive forward curve and both have harmed the price discovery role of WTI.
[97]	2002–2012	WTI, Brent, Dubai and Tapis	Daily spot prices	DCC-MGARCH	Most information spillover among global crude oil markets varies over time. The presence of evolving market linkages among global crude oil markets. The impulse analysis shows that market information has a significant positive impact on timevarying information spillover.

Note: This table overviews the salient literature on WTI-Brent spread. The papers are arranged thematically for the reader's convenience.

so that the significance of rig counts may not be obvious in the crude oil prices because of the presence of lags. Developments in North Dakota are a prime example [50]. This relationship is often non-linear and driven by various parameters, such as oil production, efficiency of rigs, drilling costs, inflation of oil products, oil speculations, and inventory changes [51]. In this regard, Ringlund et al. [52] discovered a positive relationship between crude oil price and rig activity by employing dynamic regressions for non-OPEC countries. However, the strength of this relationship for different locations, depending on the structure and reaction of oil rigs to price fluctuations, was subject to change.

The study of Mohn and Osmundsen [53] draws attention to distinctive categories of the relationship between crude oil prices and rig counts (drilling activities), which are not often observed in the literature. They state the following: as oil prices drop, drilling activities reduce with higher portions, and the level of oil extraction has a negative association with volatility and underground risks.

Petroleum Administration for Defense Districts (PADDs) are another parameter influencing oil prices. Severin Borenstein and Ryan Kellogg [54] point out that PADD flow has a significant effect on oil prices. They investigated the relationship between PADDs and refined products. According to the authors, having increased the oil production of the US and Canada's pipeline capacity, a substantial reduction in prices of crude oil in the US relative to internationally traded oil ensued. However, these relative changes did not pass through gasoline and diesel. They state that crude oil trading between the Gulf Coast and Mid-West is capacity constrained, referred to as PADD flows. Moreover, their study did not reject the findings on the possibility that refined products—-produced from costly products—are near or on the production capacity of PADD2 on the Gulf Coast.

Additionally, the study of Kolodziej and Kaufmann [18] extended the analysis of causal relations between trader positions and oil prices as well as the price discovery process for long- and short-run positions. The paper employed a cointegrating vector autoregression model, which includes trader positions, inventories in PADD2, and the spot price. Their study reported a bi-directional relationship between oil prices and trader positions. In a more recent study, Blair et al. [55] shed light on the short- and long-run existence of regional differences in the price pass-through from crude oil spot prices to retail gasoline pump prices. The authors used PADD-reported gasoline production data. In this regard, by constructing impulse response functions for the price pass-through behavior of each PADD, the authors could examine differences between PADDs.

While considering the macro-fundamental antecedents of the WBS, prior literature has, at times, hinted at the salience of uncertainty sentiment prevalent in financial markets or stemming from regulatory indecision. A copious body of literature has examined the nexus between policy uncertainty and a wide array of financial instruments in the past five years. Given the theoretical merit of macroeconomic uncertainty transmitting (potentially dissimilarly) to WTI and Brent prices, we postulate that accounting for this confounder would lead to a better-rounded view of WBS dynamics. In support of these hypotheses, we drew on the theoretical work of Bernanke [56].

A synthesis of literature from the seminal papers and their derivative studies claims that effects of uncertainty on crude oil prices flow through four different channels: (a) business cycle [57], which indicates the positive effect on crude oil; (b) risk premium [56], with negative effects on not only crude oil but also sometimes consumption and future investment; (c) financialization of commodities [58] due to a surge in demand of asset allocation; and (d) transmission effects [59] from oil prices to various economic activities. In terms of variable choice, modern works have relied on news-based uncertainty proxies developed by Baker et al. [60]; who introduced a measurement for economic policy uncertainty (EPU). Most empirical works indicate that commodity prices co-move with EPU. The recent study by Yang [61] discusses the causal relationship between EPU and crude oil shocks, revealing that crude oil acts as a receiver of information from EPU regardless of time. Additionally, the author critically compared the relationship of WTI and Brent with EPU and found Brent to be more sensitive to global EPU. This finding extends the report by [62], pointing out that news-based uncertainty has a positive influence on crude oil prices across different frequencies.

We inferred three themes from the preceding review: two major and one minor. The former focuses on the statistical properties of the spread, its mean reversion tendencies, trading dynamics, risk profile, etc. Another strand is macro-fundamental in nature. A nascent stream of papers draw a link between various energy instruments and global uncertainties. Not entirely novel, this subgroup's locus of interest is an extension of theoretical concerns discussed in papers within the second major stream. Verifying them empirically, however, has been rarely possible until the recent proliferation of uncertainty data sets. This extrapolated structure of WBS research has guided us in constructing a framework in pursuit of the questions we posed in the Introduction section. This is illustrated in Table 1, which itemizes the existing studies underpinning our framework.

3. Time-series features of the WBS

Data for the current study were sourced from the Refinitiv Eikon database and EIA, and the uncertainty-related indices were from the respective authors' websites. We utilized various data frequencies, ranging from daily to monthly series. Specifically, we investigated the technical antecedents of the WBS time series using all data frequencies, while the macro-fundamental drivers of the spread were examined using monthly data only. This study covered a period of three decades, from June 1988 to November 2020. We specified our test model with the WBS serving as the dependent variable, while the independent variables broadly represented the aggregate US-based demand- and supply-type factors, as well as proxies for global uncertainty. More specifically, the demand-type variables were indices of Aruoba–Diebold–Scotti (ADS), representing the US business condition in terms of factors like growth, industrial production, employment payroll, and purchasing managers' index (PMI), which is used to measure the US economic activity based on a survey of purchasing managers. Correspondingly, the supply-type factors were PADD oil flows from the Cushing oil hub in Oklahoma (PADD2) to the Gulf Coast (PADD3), the number of operational oil rigs in the US (OILRIGS), and the import of Canadian oil (CANIMP). With respect to indicators of global uncertainty, we employed the CBOE volatility index (VIX) as well as the geopolitical risk (GPR) index. The GPR index was developed by Caldara and Iacoviello [98]; reflecting the tensions associated with war events, terrorist attacks, and military threats that affect the normal course of international relations. Finally, we used a country-level production variable for a selected number of representative economies having substantial production of light sweet oil, namely Algeria, Angola, Egypt, Libya, Nigeria, Norway, Russia, and the UK. All variables were transformed into a natural logarithm form.

This segment of our investigation contributes by giving historical context to interpret factors that underly the conditional spread distribution. It also helps advance the understanding of evolving market relationships and price anomalies, which inform firm strategies and decisions of key traders as well as policymakers. With respect to the technical analysis of the data, we aim to conduct a thorough examination of the time-series properties of the WBS, with a view toward detecting signals of structural breaks in the mean and persistence of the series. These approaches are intuitive for several reasons, given the historical context of the two benchmark indicators. For example, we can gain valuable insights into the price volatility of the WBS, which triggers significant shifts in the market dynamics and the relative supply–demand conditions [99,100]. In fact, we built upon specific examples and precedents from past research showing the importance of structural breaks for the WBS. Ji et al. [2] show this for the US shale boom and OPEC's shifts in policy. An earlier work by Gulen [101] shows the importance of structural breaks for arbitrageur interest, while Aruga [102] identified a link between the decoupling dynamics and the global financial crisis. These helped establish the rise and fall of financial motives of market participants tied to different landmark events. Intuitively, more synchronized movements suggest greater market integration [12]. This helps support the unified pool theory. Decoupling, meanwhile, necessitates a differentiated hedging strategy. Regulators also monitor such structural break points, as it may necessitate interventions similar to Commodity Futures Trading Commission's (CFTC's) position limit to reign in speculation. The existing literature likewise underscores the implications of the historical performance of the benchmark oil indicators on portfolio allocation and hedging strategies involving spot and futures contracts. The long-run relationship and persistence of the two benchmarks have been the subject of widespread controversy in several studies [48,102,103]. Notably, these studies suggest that the analysis of structural breaks can provide an understanding of the extent of co-movement or decoupling within the two markets. We believe these investigations can potentially offer significant implications for various stakeholders in the industry, including the business operators in the oil industry, speculators and arbitragers in the energy futures markets, as well as energy regulatory administrations.

4. Methodology

4.1. Structural breaks via mean

Literature on modeling the WBS is already mature. The bulk of the studies account for a structural change in the underlying process through a change in mean. The Chow break-point test has been the most commonly applied test in this regard, with Buyuksahin et al. [19] being its seminal exponent. Yu et al. [104] did the same in a dual "divide and conquer" and "data-characteristic-driven-modeling" forecasting approach. In this study, we applied a battery of tests from the CUSUM family with progressive levels of complexity to arrive at a consistent timestamp of structural changes. We commenced with a standard OLS-CUSUM test [105].

$$wbs_t = \mu + \beta 1\left(t \geq t_0^*\right) + \epsilon_t \tag{1}$$

in Equation (1), $\mu_t = \mu + \beta 1(t \geq t_0^*)$ for all positive values of time (day) t. It is also a deterministic regression mean sequence, and its coefficient signifies a possible mean shift. The mean term μ here is the constant term in the equation, representing the baseline spread. The β term captures the indicator function representing the impact of an event or a threshold. t_0^* is the threshold time after which a requisite condition is met or an event occurs. If t exceeds this value, the indicator function assumes the value of 1; otherwise, it is 0. The last term captures the error at time t, accounting for unobserved factors.

The above test yielded an S_0 value of 31.977, with a p-value of 0.00. This convincingly suggests that the mean is not constant over time. Subsequent literature, however, shows that the classic CUSUM test is unreliable for persistent time series. [106] overcome this by accounting for short memory. Applying their test, we rejected the null hypothesis of a constant mean with a $d \sim 1$. We note, however, that simulation studies have shown that this test can be unreliable, even for mid-range values of d. In fact, Wenger et al. [107] have shown that even for fractionally integrated white noise vectors, this test is biased toward rejection. As a workaround, we first checked via a Whittle estimator to have a clearer picture of the order of fractional integration. We first assumed the following:

$$f_t^*(wbs) = f_t^*(0) + C(wbs)^2 + \epsilon_t \tag{2}$$

in this equation, $f_t^*(wbs)$ represents a function f_t^* evaluated in time t, with respect to the WBS. $f_t^*(0)$ is the value of f_t^* during period t when WTI and Brent carry the same price. $C(wbs)^2$ is a quadratic term where C stands for a coefficient or function applied to the WBS. The last term captures the error at time t, accounting for unobserved factors. The quadratic term suggests that the spread may have a non-linear effect on f_t^*. Under this framework, the true value of the long-memory parameter (d) was invoked in the following equation:

Table 2
Descriptive statistics.

Panel A- Quarterly Data		Demand Variables				Supply Variables			Uncertainty Variables	
	WBS	*ADS*	*PMI*	*BALTIC*	*KILIAN*	*PADD*	*OILRIGS*	*CANIMP*	*VIX*	*GPR*
Mean	−1.3612	−0.3006	52.2900	1945.5615	5.2466	24841.9846	499.2308	2289.8802	19.6104	87.4402
Standard Error	0.4430	0.2231	0.4169	144.7298	5.3044	2499.2933	32.4421	93.0284	0.7143	5.9492
Median	0.9050	−0.1208	52.7000	1442.0000	−2.9010	8583.0000	379.0000	2141.0000	17.5900	64.3250
Standard Deviation	5.0513	2.5433	4.7530	1650.1738	60.0125	28496.3286	369.8971	1056.5993	7.9218	67.8317
Kurtosis	4.0139	91.8038	1.2394	9.6422	0.8883	1.3643	1.4050	−0.6796	3.3235	16.5693
Skewness	−1.9868	−8.5441	−0.8267	2.9339	0.7791	1.5915	1.4712	0.6007	1.6491	3.2752
Minimum	−20.2700	−26.6737	34.5000	429.0000	−137.4359	5373.0000	114.0000	850.2580	9.5100	25.5200
Maximum	4.4300	7.9662	60.6000	9589.0000	184.1759	110278.0000	1592.0000	4784.4840	53.5400	545.2600
Count	130	130	130	130	128	130	130	129	123	130
Panel B- Monthly Data										
Mean	−1.5193	−0.2357	52.1912	1950.2539	3.8009	24378.1347	500.5725	2291.4741	19.2826	86.8416
Standard Error	0.2673	0.0940	0.2448	86.8759	3.0717	1429.6994	18.7967	53.3366	0.4046	3.3849
Median	0.8950	−0.0865	52.6000	1418.5000	−4.9222	8528.5000	371.5000	2131.4190	17.1900	63.7650
Standard Deviation	5.2523	1.8474	4.8088	1706.8401	60.1153	28089.1373	369.2967	1047.8981	7.7510	66.5035
Kurtosis	3.5444	121.9226	0.7927	9.4796	0.9039	1.4594	1.2880	−0.6822	4.5118	12.3112
Skewness	−1.9004	−8.9162	−0.7683	2.8862	0.7957	1.6202	1.4514	0.5917	1.6408	2.8715
Minimum	−24.6500	−26.6737	34.5000	317.0000	−159.6442	4629.0000	108.0000	848.3550	0.0000	23.7400
Maximum	5.4000	7.9662	61.4000	11440.0000	190.7287	110278.0000	1596.0000	4784.4840	59.8900	545.2600
Count	386	386	386	386	383	386	386	386	367	386

Note: This table presents an overview of summary statistics for WTI-Brent spread and its drivers, which are categorized into demand-type, supply-type and uncertainty variables. The sample period spans from June 1988 to November 2020. The precise variable definitions are provided in Section 3.

Table 3
Change-point detection via mean.

		0.9	0.95	0.99	Test Statistic	Test Statistic 95%	Test Statistic 99%
CUSUM Ratio	Against change from I (0) to I (1)	3.51	4.61	7.69	1471.39		
Break: August 07, 2010	Against change from I (1) to I (0)	3.51	4.61	7.69	4.01		
	Against change in unknown direction	4.63	5.88	9.24	1471.39		
CUSUM Ratio [Without Directionality]	Against change from I (0) to I (1)	3.51	4.61	7.69	861.09		
Break: August 07, 2010	Against change from I (1) to I (0)	3.51	4.61	7.69	2.36		
	Against change in unknown direction	4.63	5.88	9.24	768.06		
CUSUM Ratio [With Directionality]	Against change from I (0) to I (1)					762.91	615.20
Break: August 07, 2010	Against change from I (1) to I (0)					2.09	1.67
	Against change in unknown direction					692.81	559.92

Note: This table reports the break-date identification test results for WTI-Brent spread due to a change in mean. The test statistics are compared against the 1% critical values. The terms I(0) and I(1) represent different regimes—i.e. before and after the structural change.

$$f_t(wbs) = \frac{\sigma_Z^2}{2\pi}\left[1 + \frac{2\pi f_Y^*(0)}{\sigma_Z^2} + wbs_0^{-2d_0}\right] + O\left(wbs^{2-2d_0}\right) \tag{3}$$

here, a variance term σ_Z^2 is introduced to account for the dispersion in the process Z. d_0 is a parameter that serves as a scaling factor. The large O notation represents the order of the magnitude of the remainder term in approximation. The main stands for the relationship between $f_t(wbs)$ and the WBS, comprising a constant part and a component that scales with wbs^{-2d_0}. This specifies a power–law relationship. The volatility component captures uncertainty in the system, and it has a scaling relationship with WBS. Meanwhile, the big O notation captures the system's asymptotic behavior as WBS approaches a certain value. The intention here is that it accounts for approximation error or higher order terms that the main expression overlooks. For a stationary series, the latter part of Equation (3) was trivial, allowing us to fit a local form of the model as follows:

$$g_\theta(wbs) = b_0\left(1 + b_1 wbs^{-2d}\right) \tag{4}$$

The spectral density of the WBS process is, therefore, $|a(x)|^2 \sigma_\epsilon^2 / (2\pi)$, and the entire series can be expressed this way:

$$f_t(wbs) = x^{-2d_t} f_t^*(wbs) \tag{5}$$

For the value of bandwidth, statistical literature appears to favor 0.65 for the Whittle test. To be doubly sure, we ran a range of different bandwidths and found $d > 0.50$ in all cases. Wenger and Lechinski [108] proposed two self-normalized CUSUM tests—type-A and type--B—improving further on this test. Their specifications were as follows:

$$Z_\delta^A := \sup_{\tau \in [\tau_1, \tau_2]} \left| \frac{1}{T^{1/2} \widehat{\sigma}_{A,\delta}} \sum_{t=1}^{[\tau T]} \widehat{\epsilon}_t^A \right| \tag{6}$$

$$Z_\delta^B := \sup_{\tau \in [\tau_1, \tau_2]} \left| \frac{1}{T^{1/2} \widehat{\sigma}_{B,\delta}(\tau)} \sum_{t=1}^{[\tau T]} \widehat{\epsilon}_t^A \right| \tag{7}$$

The aforesaid paper's simulations showed that the former test is superior when the break is in the middle of the series and that the latter is more capable of identifying a break near the start or end. With the benefit of hindsight about the WBS dynamics and knowledge of prior literature, it is a fair assumption that our expected break dates were neither near the start nor the end. We thus proceeded to employ the fixed type-A test with a bandwidth of 10.

The descriptive data pertaining to our research are provided in Table 2. Panel A displays the summary statistics using quarterly data, while Panel B uses monthly data. In this regard, quarterly data indicate that the majority of demand variables were negatively skewed to the left. Nonetheless, the supply and uncertainty variables were skewed to the right. Likewise, the same behavior was documented for monthly data. In addition, the standard deviation of WBS based on monthly data was marginally greater than the spread based on quarterly data.

Table 3 presents the results and the detected dates based on the test

Table 4
Change-point detection via change in memory.

	Regular	LKT	GPH	BW = 0.65	BW = 0.75
Breakpoint	November 10, 2010	November 8, 2010	November 10, 2010	November 10, 2010	November 10, 2010
d1	0.6732	0.6726	0.6095	0.6497	0.6080
sd1	0.0285	0.0285	0.0386	0.0232	0.0349
d2	0.9129	0.9132	0.9262	0.9050	0.8745
sd2	0.0264	0.0264	0.0341	0.0214	0.0325

Note: This table reports the identified break-dates via persistence shift. The d1 and d2 indicate distinct bandwidths, including 0.65 and 0.75, respectively. Higher values of d1 and d2, where a value closer to 1 is considered desirable, together with d2 being greater than d1 for the observed breakpoints, suggest the presence of persistent structural breakpoints. For theoretical discussions on this methodology, we refer the reader to research conducted by Ref. [113] (LKT) and [112] (GPH).

Table 5
RIF Regression using Monthly Data.

	SPREAD iqr(90 10)	SPREAD iqratio(90 10)	SPREAD variance
ADS	0.330	0.138	0.188
(Default)	(0.242)	(0.101)	(0.174)
(Robust)	(0.084)***	(0.035)***	(0.098)
(Bootstrap)	(1.295)	(0.322)	(0.605)
PMI	0.951	0.391	0.304
(Default)	(0.503)*	(0.210)*	(0.360)
(Robust)	(0.419)**	(0.175)**	(0.300)
(Bootstrap)	(0.460)**	(0.155)**	(0.296)
PADD	−0.451	−0.186	−0.127
(Default)	(0.120)***	(0.050)***	(0.085)
(Robust)	(0.106)***	(0.044)***	(0.033)***
(Bootstrap)	(0.272)*	(0.085)**	(0.040)***
OILRIGS	0.925	0.390	0.334
(Default)	(0.098)***	(0.041)***	(0.070)***
(Robust)	(0.131)***	(0.055)***	(0.093)***
(Bootstrap)	(0.437)**	(0.148)***	(0.093)***
CANIMP	0.837	0.348	0.225
(Default)	(0.204)***	(0.085)***	(0.146)
(Robust)	(0.153)***	(0.064)***	(0.061)***
(Bootstrap)	(0.434)**	(0.140)**	(0.068)***
VIX	0.380	0.158	0.311
(Default)	(0.144)**	(0.061)***	(0.103)***
(Robust)	(0.137)***	(0.057)**	(0.201)
(Bootstrap)	(0.191)**	(0.073)**	(0.175)*
GPR	−0.168	−0.072	−0.130
(Default)	(0.085)**	(0.035)**	(0.061)**
(Robust)	(0.066)**	(0.028)**	(0.064)**
(Bootstrap)	(0.133)	(0.051)	(0.055)**
CONS	−12.320	−4.170	−4.544
(Default)	(2.364)***	(0.988)***	(1.695)***
(Robust)	(2.286)***	(0.956)***	(2.275)**
(Bootstrap)	(6.585)*	(1.915)**	(2.925)
AVERAGE	0.5066	1.1795	0.12512
N	365	365	365

Note: This table presents RIF regression estimates analyzing how explanatory factors affect key moments of the WTI-Brent spread distribution. Unlike linear models, this model provides granular insights into distributional impacts. For example, arbitrage and supply factors consistently shift dispersion and skewness while financialization impacts variance more. The marginal effects are estimated using default, robust, and bootstrap standard errors.*, **, and *** indicate 10%, 5%, and 1* statistical significance, respectively.

values surpassing the critical values at 1% significance. Although our identified break dates were non-controversial, Narayan and Popp [44] warn that frequency-specific idiosyncrasies can mislead solitary break-point identifications. As such, we re-estimated the above tests for weekly and monthly frequencies to determine whether materially different results would emerge, but the results were identical. We concluded that the break-dates, though not identical, were fairly consistent. These identified dates proved useful later in this study in re-sampling to verify whether the underlying dynamics of the WBS would differ according to unlike regimes. The next subsection covers our attempt to time-stamp shifts in the persistence of the WBS series.

Table 6
SUR RIF Regression using Monthly Data on Quantiles.

	SPREAD 20th Quantile	SPREAD 40th Quantile	SPREAD 60th Quantile	SPREAD 80th Quantile
ADS	0.220	−0.007	−0.018	−0.007
(Default)	(0.115)*	(0.028)	(0.027)	(0.027)
(Bootstrap)	(0.504)	(0.100)	(0.042)	(0.048)
PMI	−0.303	0.197	0.092	0.127
(Default)	(0.238)	(0.060)***	(0.057)	(0.056)**
(Bootstrap)	(0.322)	(0.070)***	(0.072)	(0.065)**
PADD	0.061	−0.046	−0.012	−0.035
(Default)	(0.056)	(0.014)***	(0.013)	(0.013)***
(Bootstrap)	(0.076)	(0.035)	(0.014)	(0.012)***
OILRIGS	−0.501	−0.076	−0.042	−0.027
(Robust)	(0.046)***	(0.011)***	(0.011)***	(0.011)**
(Bootstrap)	(0.124)***	(0.028)***	(0.010)***	(0.008)***
CANIMP	−0.374	−0.210	−0.118	0.003
(Default)	(0.096)***	(0.024)***	(0.023)***	(0.022)
(Bootstrap)	(0.116)***	(0.027)***	(0.038)***	(0.023)
VIX	−0.067	0.026	−0.011	0.017
(Default)	(0.087)	(0.017)	(0.017)	(0.016)*
(Bootstrap)	(0.070)	(0.022)	(0.016)	(0.013)
GPR	−0.012	0.015	0.015	0.025
(Default)	(0.040)	(0.010)*	(0.010)	(0.010)***
(Bootstrap)	(0.043)	(0.010)	(0.011)	(0.011)**
CONS	9.037	4.846	4.235	3.147
(Default)	(1.121)***	(0.278)***	(0.268)***	(0.264)***
(Bootstrap)	(2.562)***	(0.780)***	(0.258)***	(0.254)***

Note: This table presents Seemingly Unrelated Regression estimates of RIF models analyzing how explanatory factors differentially affect quantiles of the WTI-Brent spread distribution. We derive disaggregated and granular marginal effects compared to linear models. For example, inventory shifts lower quantiles more while financialization impacts upper quantiles. The marginal effects are estimated using default, robust, and bootstrap standard errors.*, **, and *** indicate 10%, 5%, and 1* statistical significance, respectively.

4.2. *Structural breaks via persistence shift*

Academic and practitioner research both recognize the fundamentally driven nature of the WBS. Evidence still exists, however, suggesting that the technical features of the spread are exploitable to generate abnormal returns. In fact, the CME group describes on its website that the tradable WBS contract responds well to technical analysis strategies. If still valid, this stylized fact is expected to show up in the long memory properties of the spread's time series. It also implicates both benchmarks' timing, extent, and nature of fundamental information absorption. To illustrate further, let us assume that the WBS is at a stationary level. This would mean that shocks will have a short-lived effect and dissolve fast. In contrast, if it were an $I(1)$ process, shocks would have infinite reverberations. In other words, shocks would be felt far in the future and theoretically never die out. If the order of integration fell between 0 and 1, shocks would neither dissolve quickly nor persist infinitely. Instead, a hyperbolic decay would ensue. Said another way, the present value of the WBS would depend marginally on past values and even less so if the shocks were in the distant past. Given the development of literature on fractional integration and mounting evidence that economic/financial phenomena are $I(d)$ where $1 > d > 0$,

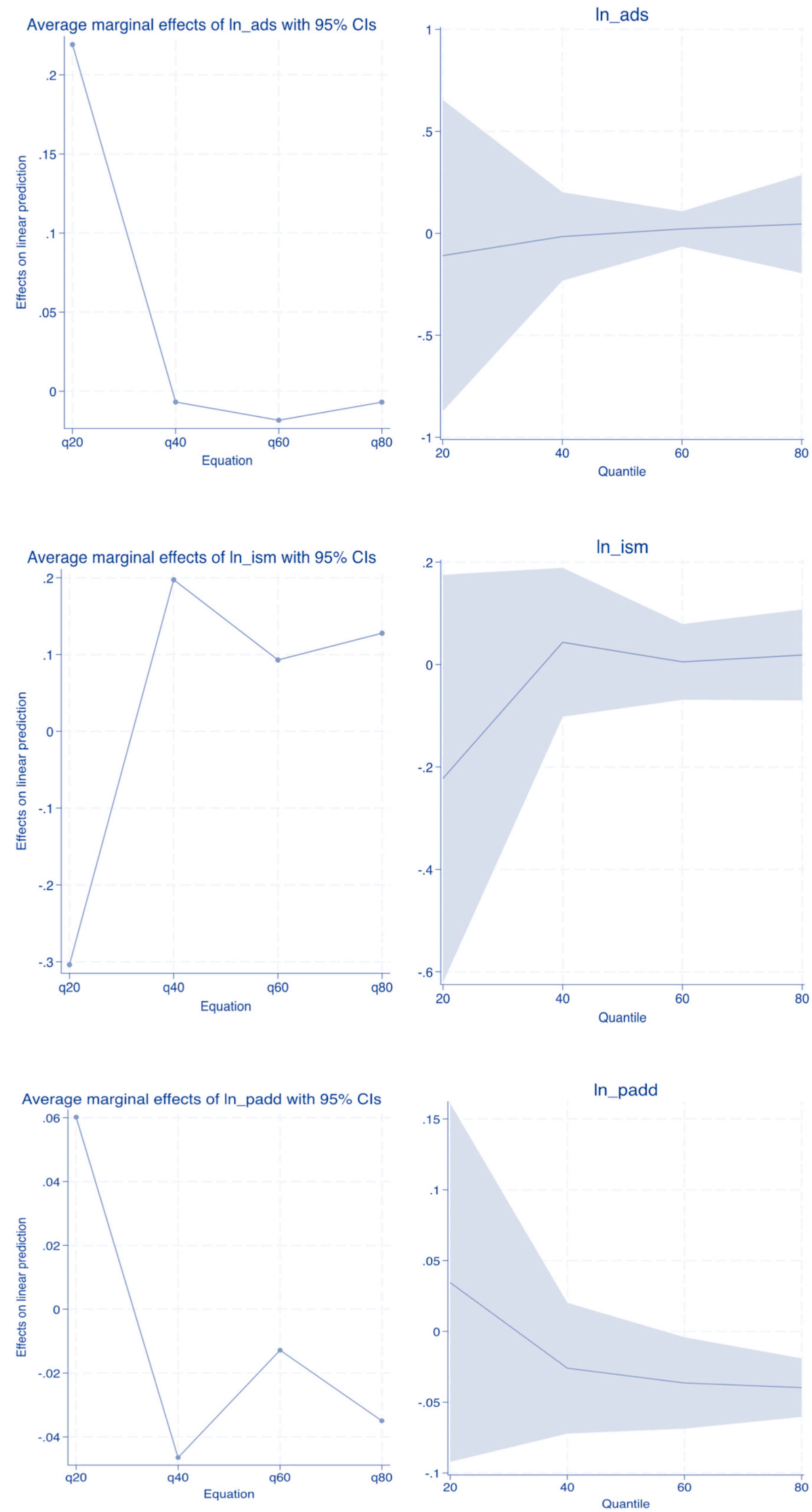

Fig. 1. Unconditional vs Conditional Quantile Regression Estimates.
Note: This figure illustrates a graphical representation of the comparison of the unconditional quantile regression (UQR) estimates against the unconditional quantile regression (CQR) estimates. The lines depict the estimates of WBS across the 20th to 80th quantiles. The plots in the left-hand-side illustrate the estimates of UQR whereas those in the right-hand-side depict the conditional quantile regression (CQR) estimates.

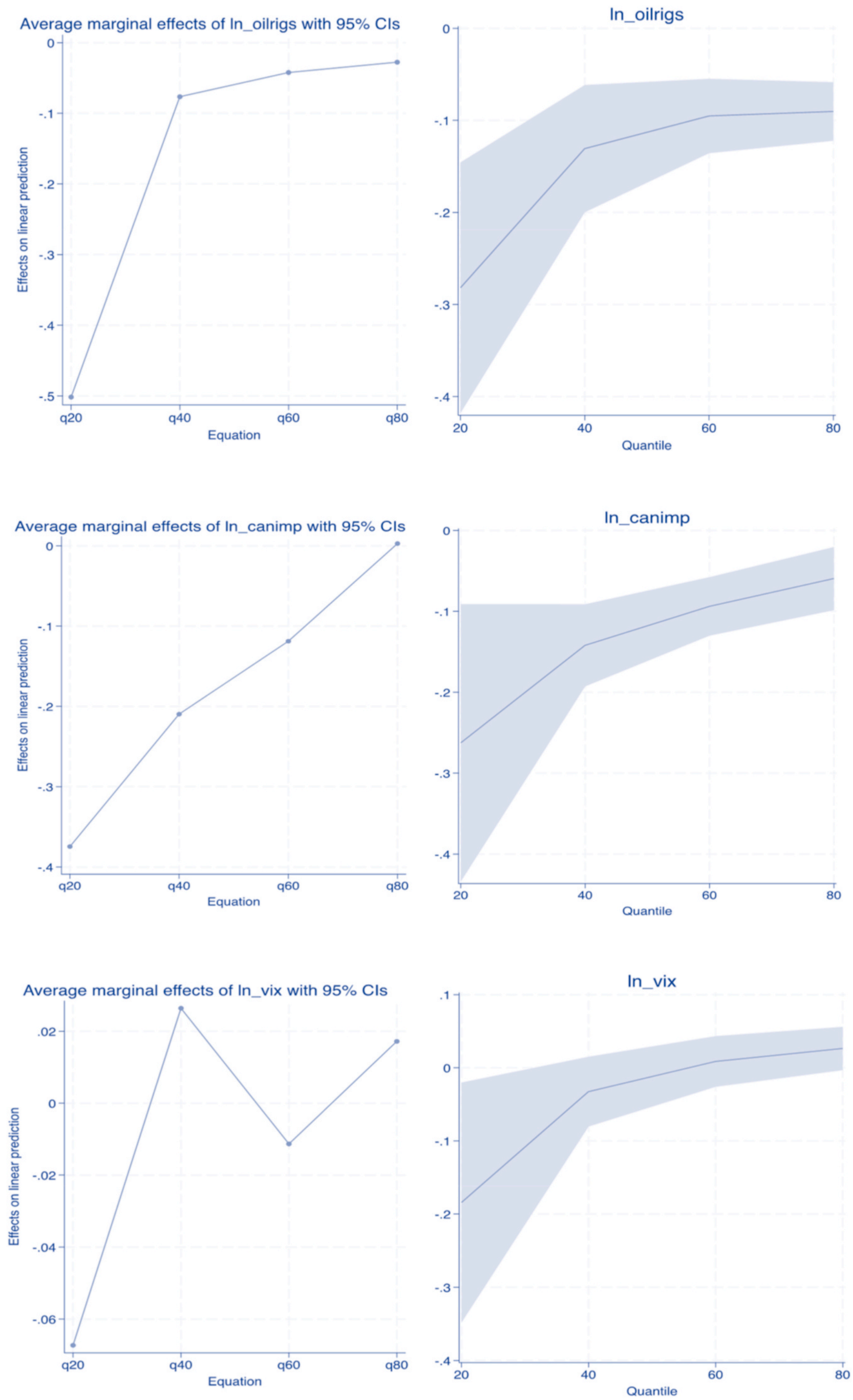

Fig. 1. (*continued*).

it was worthwhile ascertaining if the WBS would exhibit the same. A seminal work in this regard is by Sibbertsen and Kruse [109]; who developed a method to identify the transition of a process from $d \in [0, 0.5]$ to $d \in [0.5, 1]$ and then $d \in [1, 1.5]$, or the other way around. Martins and Rodrigues' [110] approach even allows a transition to and from negative values of d.

Table 4 reports the identified break dates due to a persistence shift for different types of estimators. The first is the regular estimator developed by Busetti and Taylor [111]. The Leybourne, Kim, and Taylor (LKT) (2007) estimator relies on the long-run variance of residuals with a chosen $m = 0$, representing the number of lagged covariances. Correspondingly, the Geweke and Porter-Hudak (GPH) (1983) estimator follows a two-step procedure involving a separate estimation of autoregressive parameters in specific sub-samples before and after the potential break dates and a combination of the estimated parameters using a weighting scheme. The reported statistics in the last two columns are associated with additional adjustments made based on a selection of bandwidth-tuning parameters used to control the degree of smoothing in the WBS time series. In effect, it determines the number of frequencies used for estimation. Our results collectively evidenced detected breakpoints in persistence in November 2010. The obtained $d1$ and $d2$ parameters represented the semiparametric estimates of integration orders

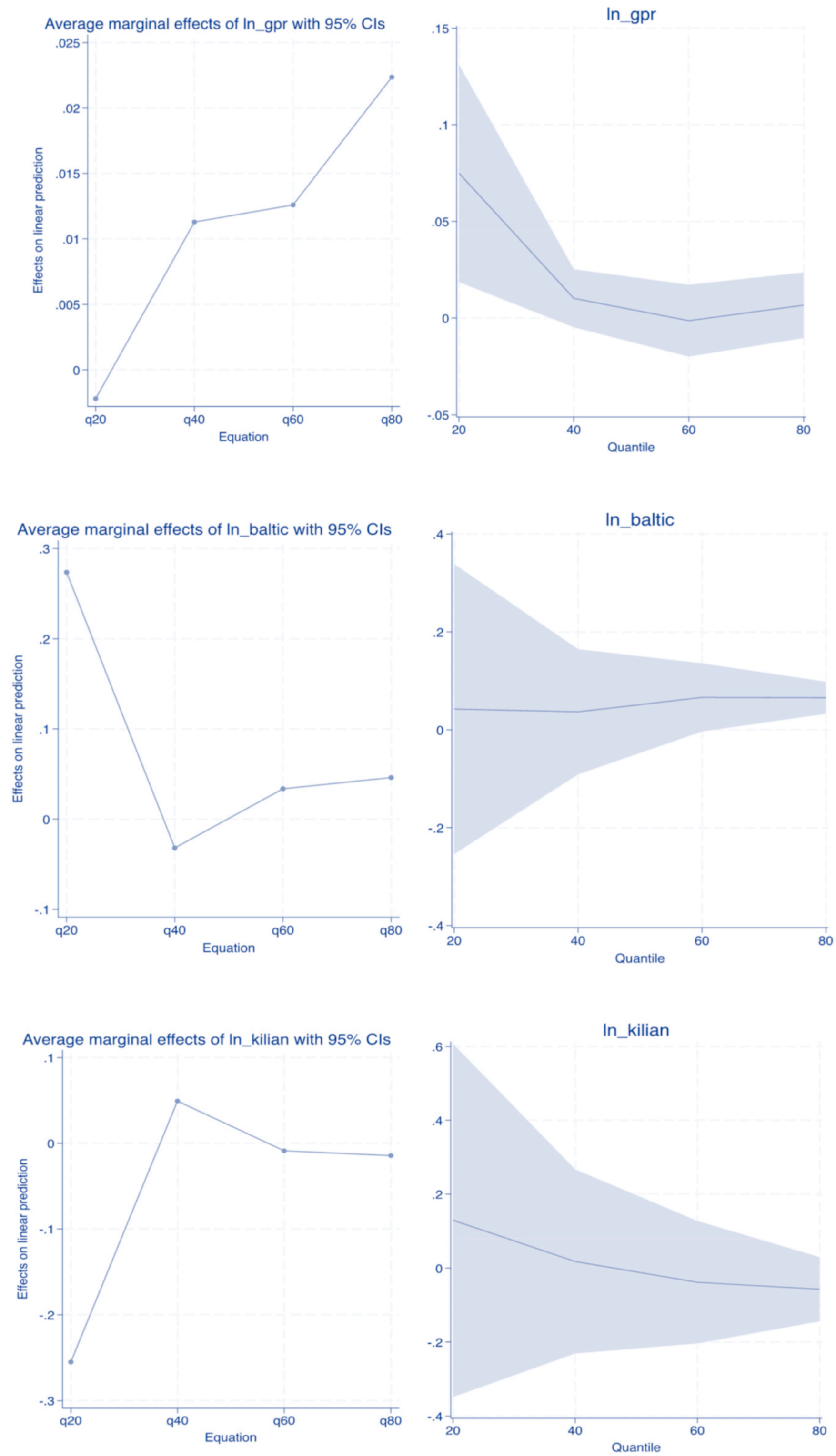

Fig. 1. (*continued*).

in the two regimes, with the *sd*1 and *sd*2 parameters denoting standard deviations of the estimates. We found evidence suggesting relatively consistent coefficient magnitudes on orders of integration across all specifications. Table 4 displays two distinct CUSUM-type tests for a change in persistence that Leybourne, Taylor, and Kim (LKT) (2006) and Geweke, Porter, and Husak [112] (GPH) suggested on two different bandwidths (0.65 and 0.75, respectively). Table 4 exhibits that d_1 and d_2 were positive and that d_2 was greater than d_1 for the identified breakpoints (November 10, 2010 and November 10, 2010), indicating a persistent structural break.

4.3. RIF

Our endeavor to disentangle the fundamental drivers of the WBS relied on a robust testing method, the RIF, in view of the most recent innovations in the estimation of regression models, allowing for

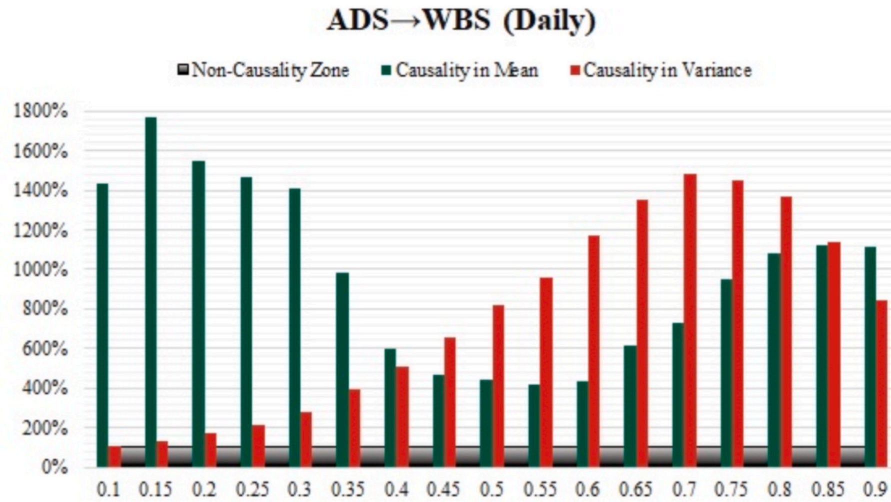

Fig. 2. Causality Analysis for ADS (Daily Frequency)
Note: This table reports the quantile-based causality results for Aruoba-Diebold-Scotti (ADS) Index vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

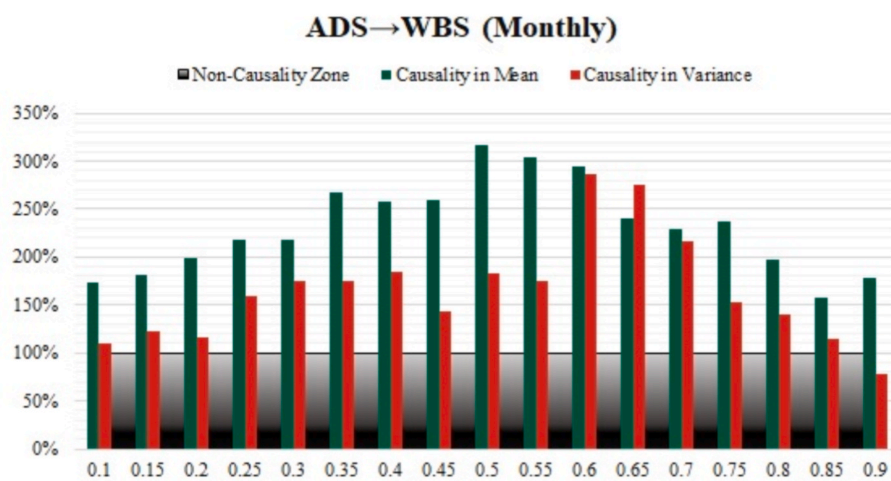

Fig. 3. Causality Analysis for ADS (Monthly Frequency)
Note: This table reports the quantile-based causality results for Aruoba-Diebold-Scotti (ADS) Index vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

distinctive types of distributional statistics. Developed by Firpo et al. [7]; this technique looks beyond traditional mean-focused comparisons and is designed to assess various distributional impacts by yielding partial effects of explanatory variables on any unconditional quantile of the dependent variable. As such, we were able to study distributional statistics, such as mean, variance, quantiles, and high-dimensional fixed effects. Considering the WBS series, the RIF could aid in identifying potential outliers or influential data points that exert considerable impact on the WBS dynamics, allowing for a deeper understanding of the extreme movements or anomalies within the spread. This analysis is particularly crucial in view of the identified evidence of significant structural breaks in the series. In effect, the RIF estimator can account for a robust examination of the entire distribution of the spread, providing means for an evaluation of the factors contributing to the substantial fluctuations in the series. More importantly, the quantile-based approach can help in revealing the influence of factors contributing to lower or upper quantiles of the spread corresponding to periods of large differentials or an otherwise minimal range of the spread.

We are specifically interested in specific distributional measures, such as the interquartile range (IQR), interquartile ratio (IQRATIO), and the variance of WBS. The IQR can be used as a measure of the difference between the maximum and minimum values while revealing some levels of sensitivity to the outliers. Meanwhile, IQRATIO can measure the skewness in data, which helps in identifying whether the spread is symmetric or skewed to one side of the distribution if the upper half of the series has more variability than the lower half. This could suggest that a higher spread due to the greater value of the IQRATIOs is predominantly attributed to the rise of WTI prices, as opposed to the increase in the Brent counterparts. The opposite relationship applies otherwise to negative coefficients. Finally, the variance measure captures the degree of the sample's estimated deviation from the mean value. The core process underlying this estimation approach follows the determination of the impact of an infinitesimally small change or perturbation in the distribution function of a sample F_Y in the direction of H_{yi} to determine the influence of a change on the function of interest ν. Therefore, we could formalize the definition of the IF as shown below:

$$IF\{y_i, \nu(F_Y)\} = \lim_{\varepsilon \to 0} \frac{\nu\left\{(1-\varepsilon)\,F_Y + \varepsilon H_{yi}\right\} - \nu\left(F_y\right)}{\varepsilon} = \frac{\partial \nu\left(F_Y \to H_{yi}\right)}{\partial \varepsilon} \tag{8}$$

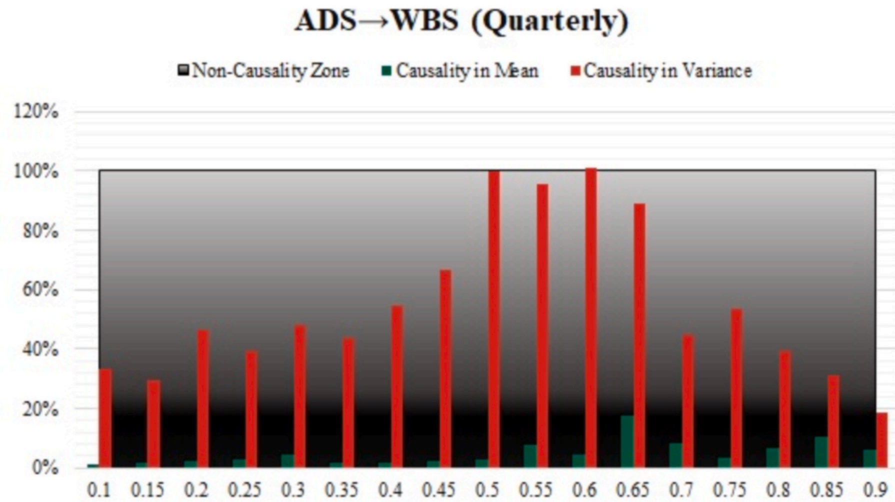

Fig. 4. Causality Analysis for ADS (Quarterly Frequency)
Note: This table reports the quantile-based causality results for Aruoba-Diebold-Scotti (ADS) Index vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

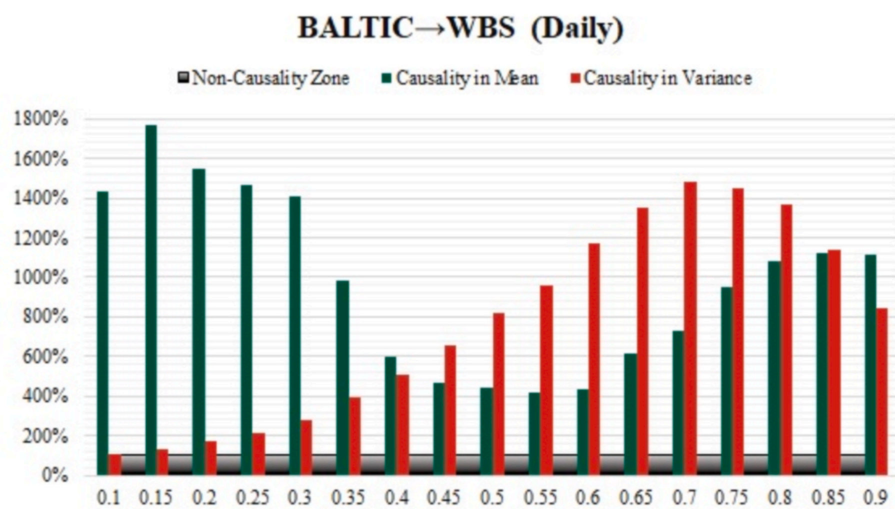

Fig. 5. Causality Analysis for Baltic Dry Index (Daily frequency)
Note: This table reports the quantile-based causality results for Baltic Dry Index (BALTIC) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

where y_i denotes the newly introduced observation in the sample, $v(\bullet)$ is a function that uses all the information contained in Y being a finite population or sample, and F_Y, which is the cumulative distribution function (c.d.f), was specified as follows:

$$F_Y = [\{y, F_Y(y)\} | \, y \in \mathbb{R}\} \tag{9}$$

Here, y represents any real number. This technique is parallel to the so-called *Gateaux derivative method* used to estimate the robust directional derivative of functionals to the data outliers [114]. The IF can also be alternatively interpreted as the influence of the observation y_i on the estimation of the distributional statistic ν. Firpo et al. [7] extended the RIF framework by applying a *recentered* version of Equation (8) based upon a linear approximation or construction of corresponding distributional statistics υ, as in Mises [115]; given the relative contribution or influence of observation y_i:

$$RIF\{y_i, \nu(F_Y)\} = \nu(F_Y) + IF\{y_i, \nu(F_Y)\} \tag{10}$$

Both IF and RIF have a number of fundamental properties: the expected value of IFs constructed using all values of y_i is equal to 0, while the expected value of the RIFs is equal to the distributional statistic itself. Moreover, estimating the sampled variance of IF or the RIF would produce an asymptotic variance of any statistic of interest. Finally, we extended our analysis to reassess the fundamental forces of the WBS using the RIF-type method of the seemingly unrelated regression (RIF-SUR), as proposed in Rios-Avila [11]. Using this framework, we could allow for a generalization of the linear regression approach into several quantile-specific regression equations to examine the differential effect of the antecedents across different quantiles of the WBS in terms of sign and magnitude. In particular, the RIF-SUR specification yields the estimate of unconditional regression while fitting all models declared in heterogeneous quantiles. In this way, we could obtain more robust findings by allowing for the impact of covariates measured on the entire unconditional distribution of the WBS instead of its conditional mean. More to the point, the marginal effect of covariates on the WBS at various points in the distribution was captured.

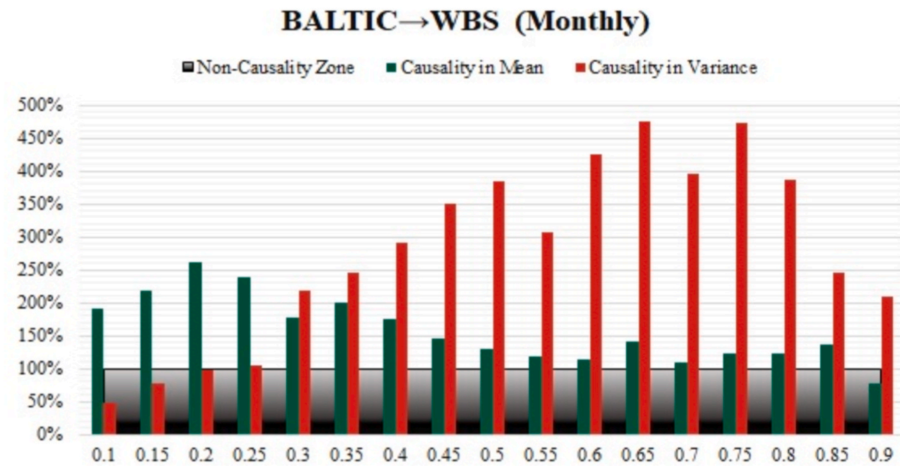

Fig. 6. Causality Analysis for Baltic Dry Index (Monthly frequency)
Note: This table reports the quantile-based causality results for Baltic Dry Index (BALTIC) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

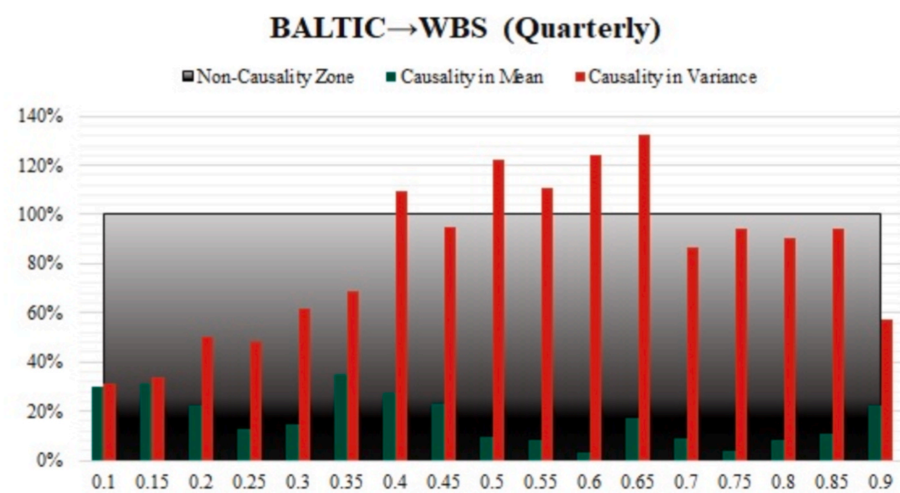

Fig. 7. Causality Analysis for Baltic Dry Index (Quarterly frequency)
Note: This table reports the quantile-based causality results for Baltic Dry Index (BALTIC) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

4.4. Causality in quantiles estimation

The Causality in Quantiles approach is a nonlinear technique used to test causality in mean and variance (Balcilar et al., 2017), which is robust to extreme values and capable of handling nonlinear time-varying dependence. This approach was chosen to investigate causality in this paper due to the long-horizon nature of all variables under consideration, spanning multiple crises and structural breaks. In such cases, linear Granger causality tests are known to suffer from poor specification and have previously yielded unreliable results [116]. The technique was operationalized in this paper by treating WBS as dependent and various macro-antecedents as predictor variables (MP), more formally as shown below:

$$WBS_{t-1} \equiv \left(wbs_{t-1}, \ldots, wbs_{t-p}\right) \tag{11}$$

$$MP_{t-1} \equiv \left(mp_{t-1}, \ldots, mp_{t-p}\right) \tag{12}$$

$$Z_t \equiv (WBS_t, MP_t) \tag{13}$$

The functions pertaining to conditional distribution of $wbs_t|Z_{t-1}$ and WBS_{t-1} can respectively be expressed as $F_{wbs_t|Z_{t-1}}(wbs_t, Z_{t-1})$ and $F_{wbs_t|WBS_{t-1}}(wbs_t, WBS_{t-1})$. At this point, it is possible to represent the following:

$$Q_\theta(Z_{t-1}) \equiv Q_\theta\left(wbs_t|Z_{t-1}\right) \tag{14}$$

$$Q_\theta(WBS_{t-1}) \equiv Q_\theta\left(wbs_t|WBS_{t-1}\right) \tag{15}$$

$$\Rightarrow F_{cof_t|Z_{t-1}}\{Z_{t-1}\} = \theta \tag{16}$$

As such, θ-th quantile non-causality null hypothesis could be formulated as shown below:

$$H_N : P\left\{F_{wbs_t|Z_{t-1}}\{Z_{t-1}\} = \theta\right\} = 1 \tag{17}$$

The alternative hypothesis thus stands at the following:

$$H_A : P\left\{F_{wbs_t|Z_{t-1}}\{Z_{t-1}\} = \theta\right\} < 1 \tag{18}$$

Applying the distance measure proposed by Jeong et al. [117];

$$J = \left\{\varepsilon_t E(Z_{t-1}) f_z(Z_{t-1})\right\} \tag{19}$$

here, ε_t represents the residual term, while $f_z(Z_{t-1})$ is a marginal density function. The regression residual ε_t is a by-product of H_N and can be true

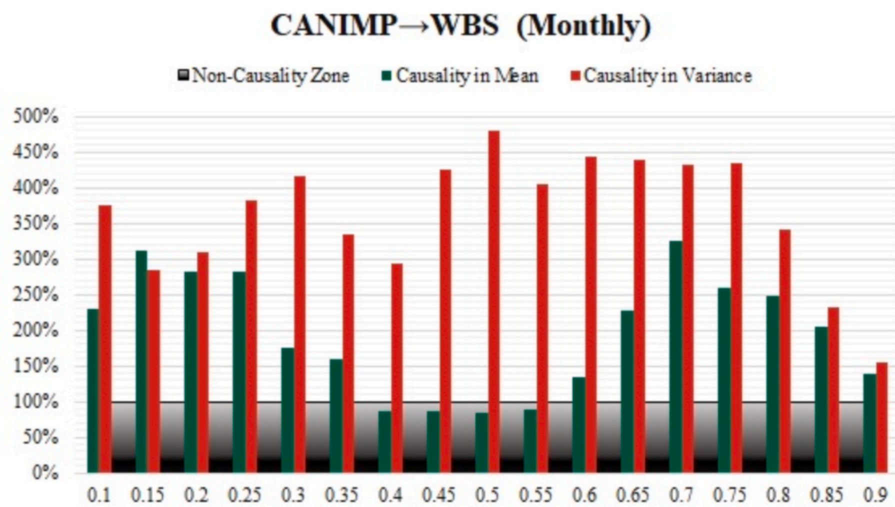

Fig. 8. Causality Analysis for Import of Canadian Oil (Monthly frequency)
Note: This table reports the quantile-based causality results for Import of Canadian Oil (CANIMP) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

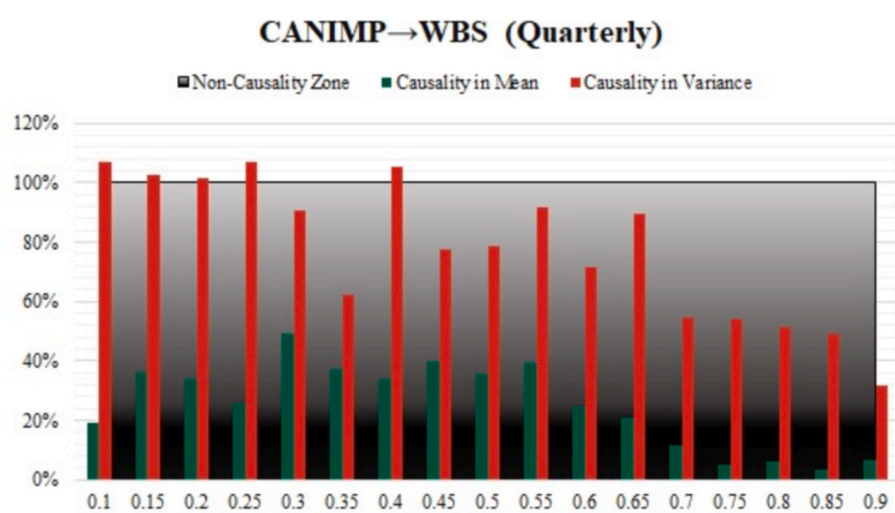

Fig. 9. Causality Analysis for Import of Canadian Oil (Quarterly frequency)
Note: This table reports the quantile-based causality results for Import of Canadian Oil (CANIMP) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

only upon the fulfillment of the following condition:

$$E[1\{Z_{t-1}\}] = \theta \tag{20}$$

The feasible kernel-based sample analog J can be expressed like this:

$$\widehat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1}^{T} K\left(\frac{Z_{t-1}-Z_{s-1}}{h}\right)\widehat{\varepsilon}_t\widehat{\varepsilon}_s \tag{21}$$

in Equation (21), p stands for the lag, T represents the sample size, and h is the bandwidth of kernel function K. The estimation of the regression residual could be expressed as follows:

$$\widehat{\varepsilon}_t = 1\{cof_t \leq Q_\theta(WBS_{t-1})\} - \theta \tag{22}$$

Additionally, adopting Nishiyama et al.'s [118] approach, the higher-order causality in the quantiles could be defined as shown below:

$$H_N : P\left\{F_{cof_t^k|Z_{t-1}}\{Z_{t-1}\} = \theta\right\} = 1;\ \text{where k} = 1, 2, 3\ldots, \text{K} \tag{23}$$

$$H_A : P\left\{F_{wbs_t^k|Z_{t-1}}\{Z_{t-1}\} = \theta\right\} < 1;\ \text{where k} = 1, 2, 3\ldots, \text{K} \tag{24}$$

Upon implementing the full CiQ framework, causality could be ascribed in the following way:

I. Macro-predictor variable Granger-caused WBS in quantile θ for up to k-th moment by using Equation (22) to derive the test statistic of Equation (24) for every value of k.
II. Causality in variance was determined by substituting wbs_t in Equations (23) and (24) with wbs_t^2.

5. Findings

5.1. RIF regression

One of our motivations behind applying the RIF framework was its advantages in revealing the partial effect of the explanatory variables on the unconditional quantile of the dependent variables. We applied the RIF for a range of different statistical distributions by specifying the dependent variable in the forms of IQR, IQRATIO, and variance. Table 5 reports the obtained statistics on the RIF regression using monthly data.

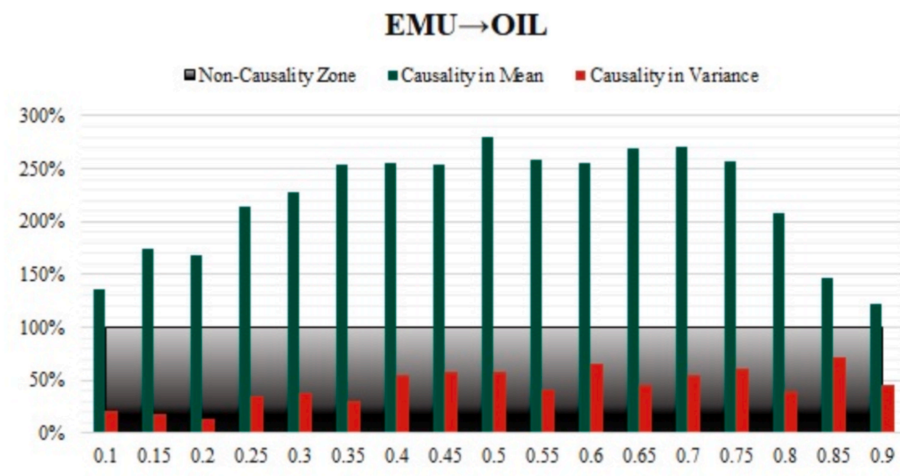

Fig. 10. Causality Analysis for Equity Market Uncertainty Index
Note: This table reports the quantile-based causality results for Eurozone Equity Index (EMU) vs. Brent. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

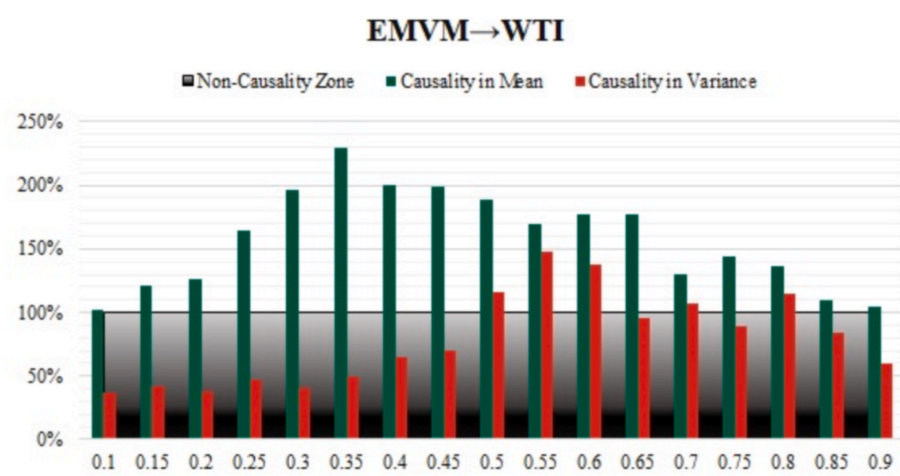

Fig. 11. Causality Analysis for EM Minimum Volatility (EMVM type ETF)
Note: This table reports the quantile-based causality results for EM Minimum Volatility (EMVM) vs. WTI. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

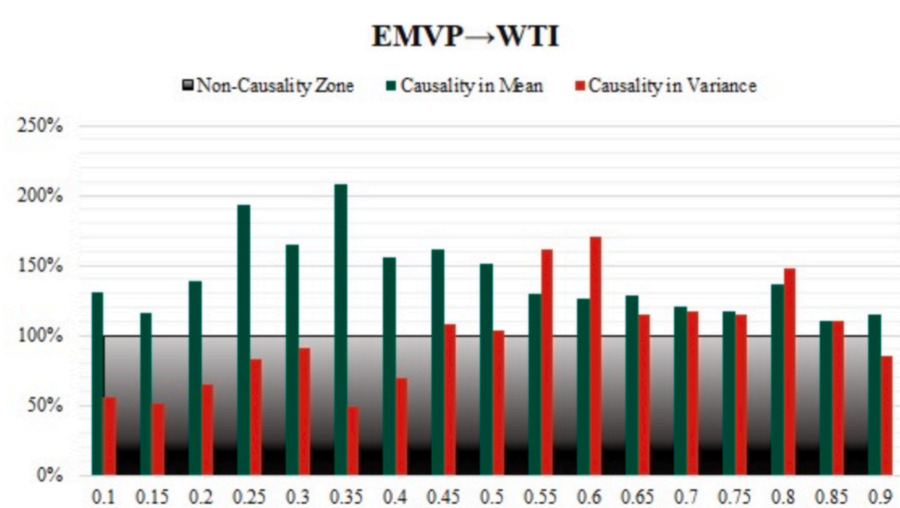

Fig. 12. Causality Analysis for Economic Volatility
Note: This table reports the quantile-based causality results for Economic Volatility (EMVP) vs. WTI. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

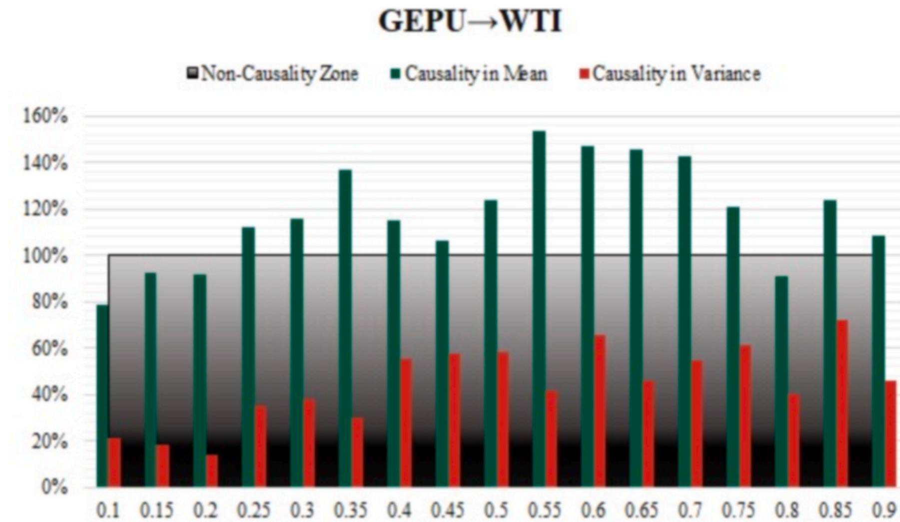

Fig. 13. Causality Analysis for Geopolitical Uncertainty
Note: This table reports the quantile-based causality results for Geopolitical Uncertainty (GEPU) vs. WTI. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

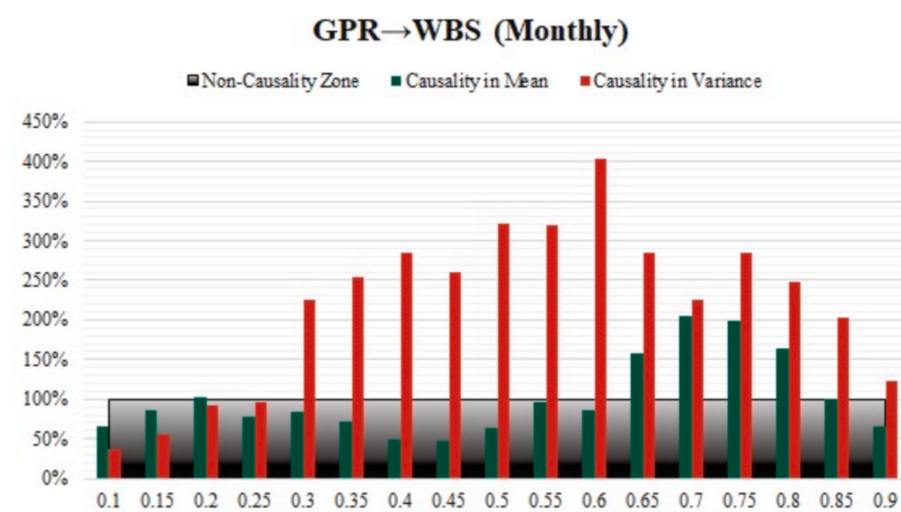

Fig. 14. Causality Analysis for Geopolitical Risk (Monthly frequency)
Note: This table reports the quantile-based causality results for Geopolitical Risk (GPR) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

We reported three forms of standard errors, namely the OLS standard errors (default), the robust standard errors (robust), and bootstrap standard errors (bootstrap). In addition, the average RIF is presented in a separate row titled *average*. In this respect, the term IQRATIO refers to the ratio of the IQR, which is the measure of variability in statistics (defined as the difference between the upper and lower quartiles of the data set) to the median of the data set. It indicates how the spread data are relative to the central value of the data set. The IQRATIO is a useful measure of dispersion when the median is used as a measure of central tendency.

Following the approach employed by Firpo et al. [7]; we reported our obtained test results regarding the estimation of unconditional partial effects (UPEs) of the small changes in the distribution of independent variables. Specifically, the AVERAGE measures reported in the penultimate section of Table 5 were used as a reference point for the UPE interpretation. Correspondingly, all the interpretations were given in relative terms with respect to the current levels of the WBS to ease the comparison of results across different specifications of the WBS. Considering the demand-type variables, the ADS variable was found to have a positive and significant association with the range of the WBS. Our results confirmed that the booming business condition in the US leads to a higher relative WBS IQR of 65% on average (0.330/0.506). Moreover, the positive coefficient of IQRATIO implied that the ratio of the upper 10% of the spread compared to its lower 10% increased by 11.7% (0.138/1.1795). We believe this finding can be attributed to a series of major events, particularly since the advent of the shale oil revolution in the mid-2000s. This led to major infrastructural advancements in hydraulic fracturing and horizontal drilling to ease the extraction process following a surge in US oil production and supply. Moreover, a succession of setbacks, such as the 2008 global financial crisis, followed by Keystone XL pipeline delays, the US oil export ban, and the COVID-19 pandemic, exerted downward pressure on WTI prices. The relatively considerable decline in the price of WTI, followed by its massive supply glut, led to the widened IQR and IQRATIO of the WBS. Our findings also revealed a positive association between the PMI and the oil price spread. The PMI broadly represents a measure of economic activity in the manufacturing sector as well as an indicator of aggregate demand for energy and petroleum products. While the economic

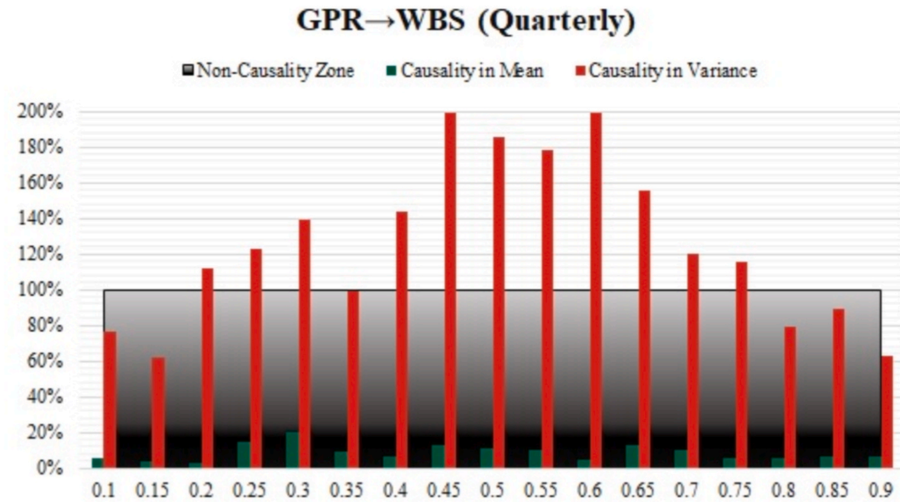

Fig. 15. Causality Analysis for Geopolitical Risk (Quarterly frequency)
Note: This table reports the quantile-based causality results for Geopolitical Risk (GPR) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

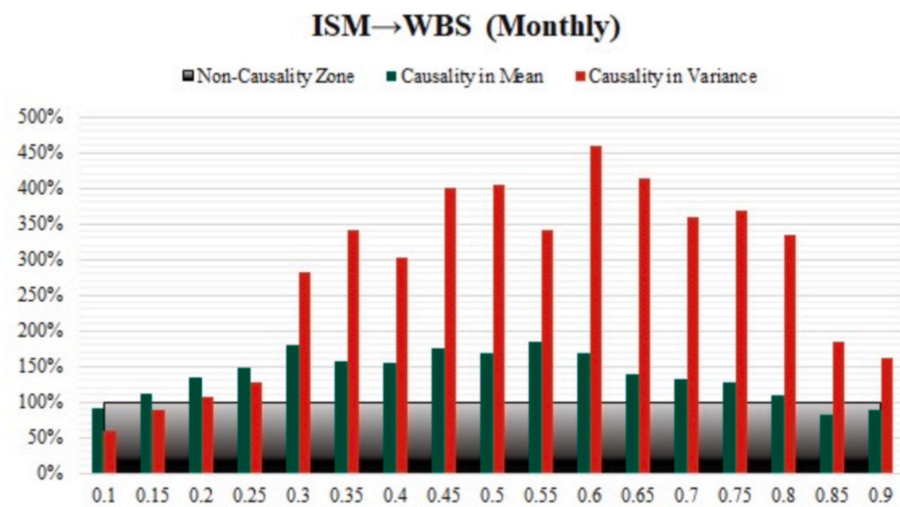

Fig. 16. Causality Analysis for Purchasing Manager Index (Monthly frequency)
Note: This table reports the quantile-based causality results for Purchasing Manager Index (ISM) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

interpretation generally suggests that a greater PMI is associated with higher demand for WTI, we believe that the overall average decline in WTI prices is pertinent to the offsetting impact of notable supply. The scale of this effect was substantial: an increase of 188% and 33% in the range and ratio of the spreads, respectively.

A second class of the proposed explanatory factors included the supply-type variables. We first estimated the degree of association of the PADD oil flow with the WBS. The Brent oil was produced at a geographical location with close proximity to the sea, making it a hassle-free transportation to overseas destinations, whereas the delivery of the WTI oil was subject to significant logistical challenges from the land-locked production hubs through a network of pipelines followed by the overseas shipment. Therefore, we could conceivably hypothesize that the overseas demand for WTI oil will likely dampen at some (specifically crises) periods, given the shipment bottlenecks and transportation obstacles. Correspondingly, we found affirmative evidence suggesting that the flow of the WTI crude oil is, on average, negatively associated with the extent of IQR, IQRATIO, and variance of the WBS. This finding could be in part attributed to the effect of widespread diminishing international demand. It is also noteworthy that despite the transitional shocks and misalignments of the Brent oil price, the policy decisions from OPEC + member countries (13 key oil-producing countries and their 10 partner nations) would trigger higher stability in Brent's prices, unlike the WTI. We found that the rising flow of oil across the PADDs, on average, lowers (i) the range by 89%, (ii) the ratio of top to bottom 10% of the spread by 16%, and (iii) the variance of the spread by about 100%.

Our second proposition concerning the supply-type variables centered around the analysis of the impact of oil rig counts on the degree of dispersion of the WBS. The revolution of the shale oil industry over the last decade has resulted in larger-scale production of low-permeable share, sandstone, and carbonate rock thanks to technological advancements and aggressive capital inflow [119]. It is thus justifiable that a downward pressure on the WTI prices has ensued. Therefore, we hypothesized that the number of operational oil rigs in the US could trigger an impact on the degree of variability of the WBS. We found evidence in this regard, suggesting that the higher number of oil rigs gives rise to a larger volume of production and a consequent high degree of variation of the WBS—a fact that has been more pervasive over the last decade.

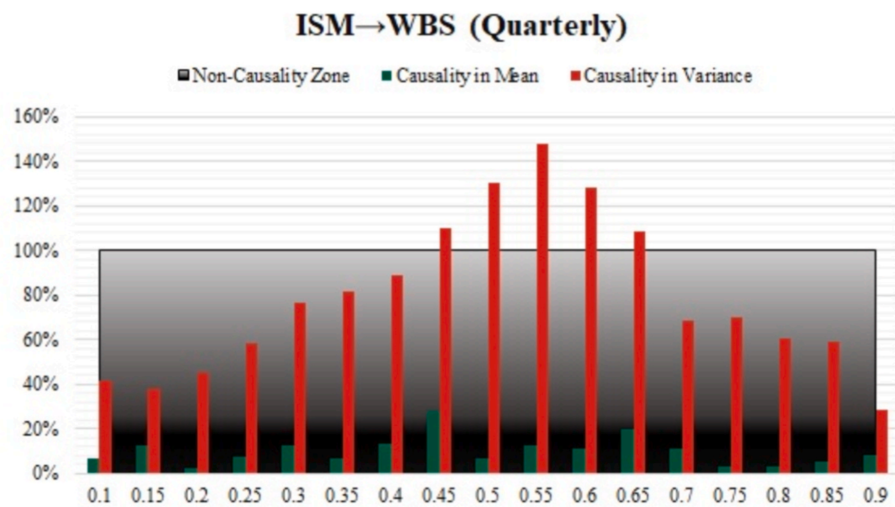

Fig. 17. Causality Analysis for Purchasing Manager Index (Quarterly frequency)
Note: This table reports the quantile-based causality results for Purchasing Manager Index (ISM) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

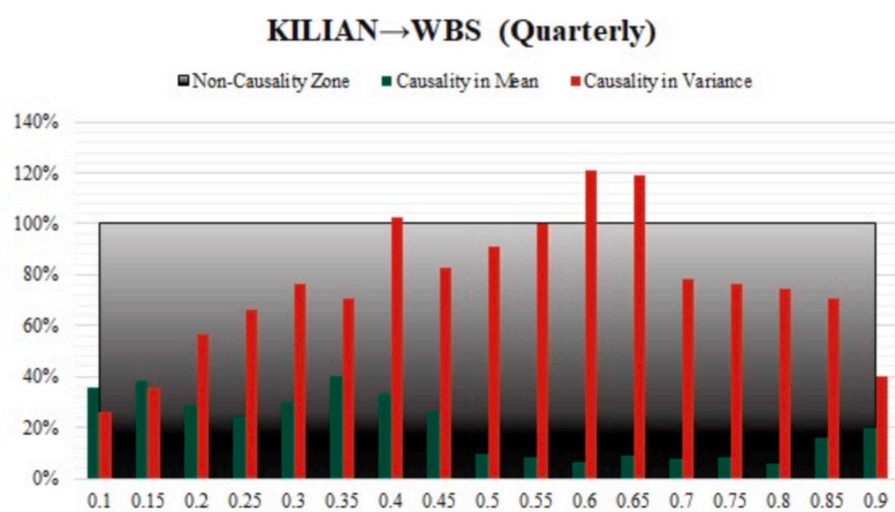

Fig. 18. Causality Analysis for Kilian Index (Quarterly frequency)
Note: This table reports the quantile-based causality results for Kilian index (KILIAN) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

We also found a significant and positive association between Canadian oil imports and the price spread. A notable share of the US oil market is made up of Canadian crude oil, which is a heavy sour oil with a distinct pricing formula, unlike other light sweet oils, such as the US shale oil. The delivery of Canadian oil, however, is very similar to the transportation of the US oil—from the PADD2 trading hub at Cushing via the pipeline routes, barges, or rails. Hence, the increasing inflow of heavy and light crude oils at the Cushing hub would induce demand–supply disequilibria within the local context, thereby stimulating higher variability of the WBS. The obtained test statistics reported in Table 5 also suggested an increasing variability of the oil price spread in response to the surging Canadian oil imports in the USA.

The third category of explanatory factors correlated to the level of prevalent global perception of financial markets and geopolitical uncertainties. Our evidence affirmed a significant and positive influence of financial market uncertainties on the WBS, as proxied by the VIX. Specifically, we found that a higher degree of implied 30-day forward-looking market risk based on the S&P 500 option, bid/ask quotes is associated, on average, with increasing WBS divergence. This finding conforms to theoretical expectations since there are credible suggestions that the growing global uncertainty over global economic recovery would lead to significant variations in crude oil prices, hence a divergent oil price spread [120,121]. More to the point, higher global uncertainty in relation to future financial outlook could escalate concerns about global economic growth and, correspondingly, the oil price variations.

Additionally, we examined the impact of the GPR index. Our findings evidenced an inverse relationship between the GPR and the variations in the WBS. We found proof of an inverse relation of GPR with the WBS variability. We believe one plausible explanation for this might be that in the event of global geopolitical shocks, there is a likely uniform impact on the major oil benchmarks as a result of considerable, widespread oil demand disruptions, thereby inducing lower variability of oil price spread, as especially evident from the obtained coefficient of the GPR (0.130/0.12512), resulting in a 104% decline in variance of the spread. This result is not surprising, since various scholars have previously confirmed both associations and causal influences of geopolitical risk on oil prices. We note, however, that most such studies investigated the major benchmarks separately. Hence, our finding expands existing

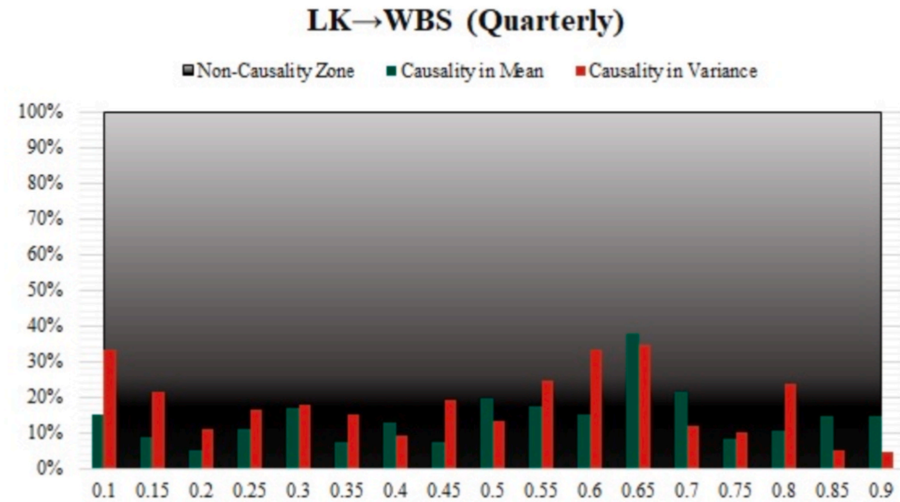

Fig. 19. Causality Analysis for Liner Shipping Index (Quarterly frequency)
Note: This table reports the quantile-based causality results for Lutz Kilian index (LK) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

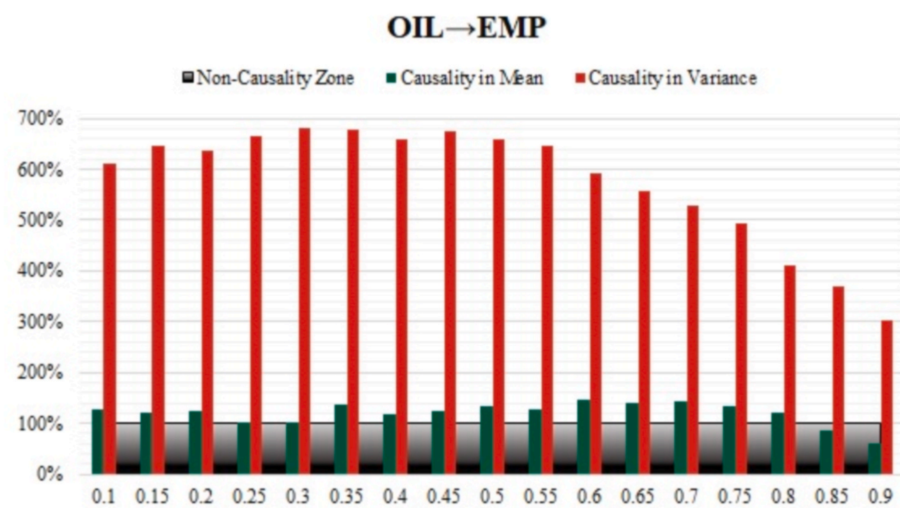

Fig. 20. Causality Analysis for Exchange Market Pressure Index
Note: This table reports the quantile-based causality results for Exchange Market Pressure Index (EMP) vs. Brent. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

knowledge by underlining the pertinence of geopolitical risk for the relative differences of the said benchmarks. Although this finding is naturally important, its utility is limited, as we could not infer causal flow at this point by relying solely on the strength of the association. To illustrate further, though high oil prices (and diverging spreads) can cause geopolitical tensions, for many energy-resource-dependent economies, they can also trigger internal turmoil that can spiral into crises. The commodity bubble preceding the subprime mortgage crisis is one such example. Others have pointed out the mediating role of spare capacity of OPEC producers in this regard [122]. Other studies, operating on a narrower scope, show the salience of geopolitical risk in detecting not only the local price levels but also the liquidity of the financial sector: Su et al. [123] for intra-economy liquidity in Saudi Arabia, Su et al. [124] for Venezuelan inflation, and Su et al. [125] for the wage levels in Russia. The Causality section of this paper covers further information on this issue.

5.2. SURIF regression

We extended our empirical analysis to assess the dynamics of the WBS using the RIF quantile approach. Our motivation for employing this technique stemmed partly from recent debates concerning global oil market integration and efficiency [30,126]. To this effect, we employed a two-step system of SURIF that accounts for the cross-correlation of errors. Table 6 reports statistics pertaining to the factor effects on the lower tail (i.e., 0.20–0.40), the median tail (i.e., 0.50), and the upper tail (0.60–0.80) quantiles of the WBS. We found distinctive patterns of the association of variables across different quantiles. Our obtained test statistics, by and large, provided evidence of sizable and significant coefficients of most variables, namely the PMI, OILRIGS, VIX, and GPR higher quantiles of the WBS. This finding supports the received wisdom in the industry and academic research that the WBS is predominantly fundamental-driven [29,92]. Furthermore, the relatively higher significance of US-centric metrics suggested that the WBS is determined to a greater extent by WTI-specific variables. This observation can be seen as arbitrating an apparent dissensus in the literature about the relative

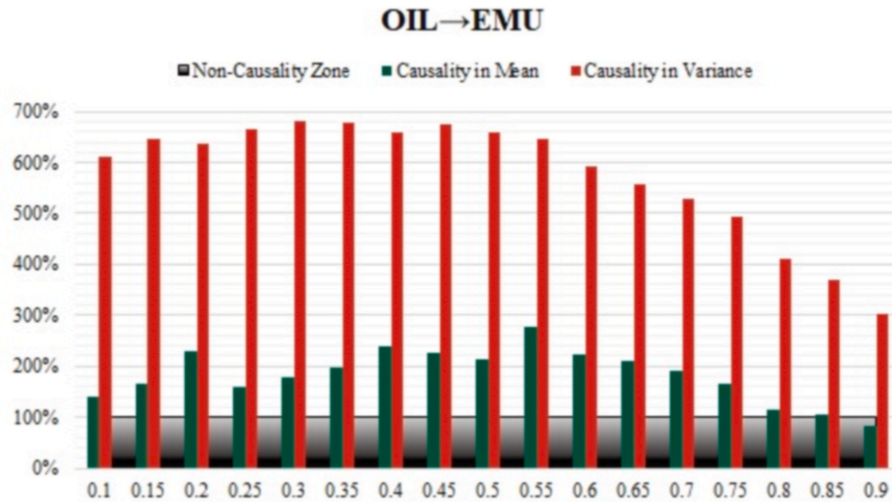

Fig. 21. Causality Analysis for Equity Market Uncertainty
Note: This table reports the quantile-based causality results for Eurozone Equity Index (EMU) vs. Brent. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

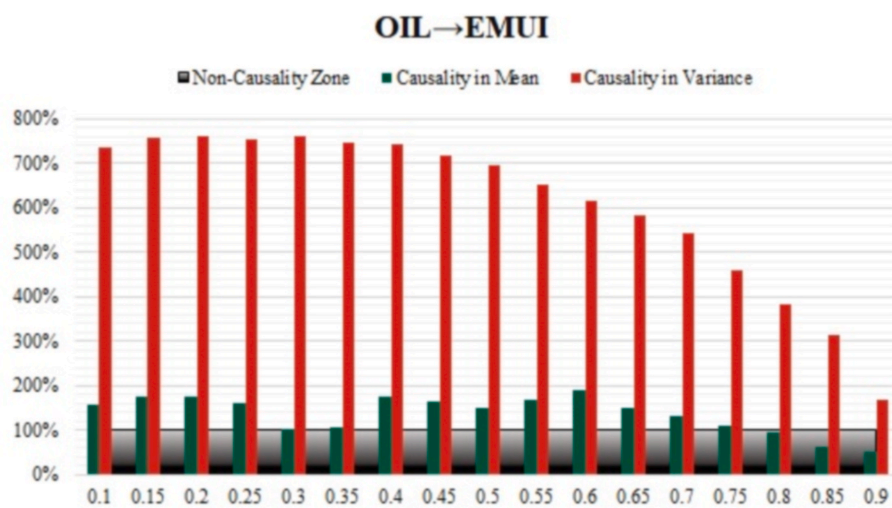

Fig. 22. Causality Analysis for European Union Uncertainty
Note: This table reports the quantile-based causality results for European Economic and Monetary Union Index (EMUI) vs. Brent. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

contribution of the benchmarks on the spread. For instance, based on the technical properties of the two series' decoupling and recoupling, Mastroeni et al. [127] ascribe the leadership to WTI. Contrarily, using a fractional cointegration approach, Caro et al. [34] conclude the exact opposite. Moreover, we found evidence of discordant coefficient signs like those reported in Table 6, specifically with respect to the OILRIGS and CANIMP. That is, the increasing number of operational OILRIGS amid the shale oil revolution led to a declining WBS to a greater extent at lower-tails compared with upper-tail quantiles. We note that the Canadian oil import was also negatively associated with the magnitude of the WBS, with results uncovering a coefficient range of 0.118–0.374 units of decline from the 60th quantile to the 20th quantile, respectively. This finding is partly attributable to the overhang of oil supply in the US to induce the slumping WTI demand and price, followed by a smaller WBS. In addition, at times when the proposed Keystone pipeline via North Dakota came to a standstill due to environmental protests, oil flow from Canada supplemented the US-based shortfall. This came from both the import of oil sands and the extension of certain TransCanada pipeline capacities [128]. Additionally, our evidence postulated a positive and significant association of the GPR with the upper-tail quantile of WBS.

Our empirical analysis dived deeper by estimating the conditional and unconditional quantile regression within a SUR-RIF specification for a chosen basket of variables. This is illustrated in Fig. 1 across the 20th to 80th quantiles of the WBS. The left column in Fig. 1 displays the unconditional estimates, and the right column shows conditional estimates with confidence intervals. The results revealed the complementary strengths of both approaches. On one hand, the unconditional estimates illustrated the varying impacts of covariates across quantiles. Notable patterns included the declining effects of ADS, PADD, and Baltic at lower quantiles. Thus, unconditional estimations uncovered hidden heterogeneity in the relationships, whereas conditional estimates hinted at monotony. Meanwhile, the conditional quantile regression rights to the right side revealed statistically significant effects at some quantiles. We referred to a GPR at q20 as a positive effect. This was not readily apparent from the unconditional plots alone. Together, the unconditional and conditional estimations provided a more comprehensive understanding of how impacts vary across the WBS distribution. For instance, the evolving patterns of variables like VIX, GPR, and Kilian are

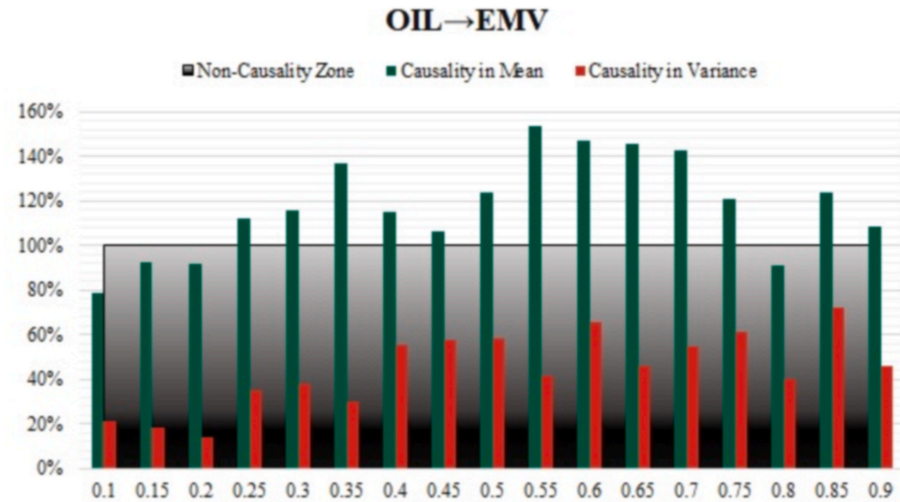

Fig. 23. Causality Analysis for Equity Market Volatility
Note: This table reports the quantile-based causality results for Equity Market Volatility Index (EMV) vs. Brent. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

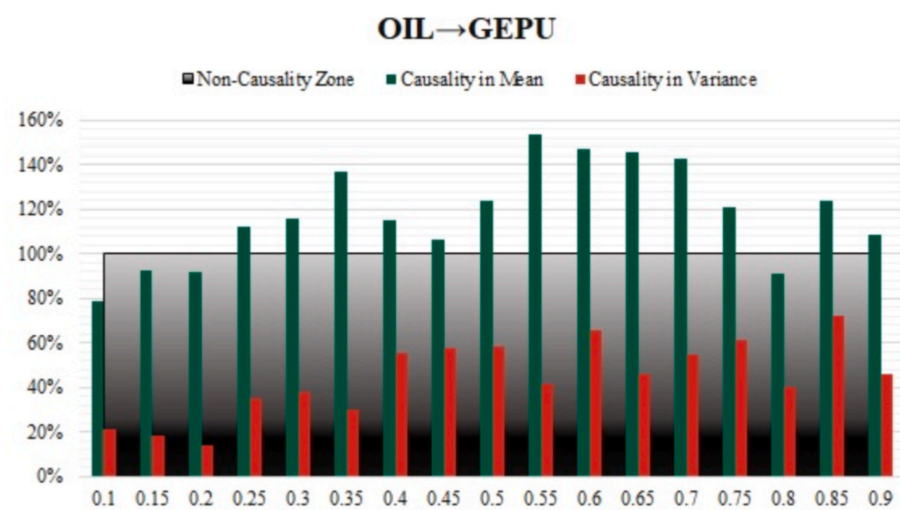

Fig. 24. Causality Analysis for Geopolitical Uncertainty
Note: This table reports the quantile-based causality results for Geopolitical Uncertainty (GEPU) vs. Brent. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

more fully understood by jointly considering the distinctive insights unmasked through both techniques. The quantile-specific results here build upon the useful foundation—albeit mean-centered—by Kaufmann [12]; who revealed the supply–demand and transportation issues pertaining to the spread in question. Our differential—quantile-specific—approach highlighted the divergent forces in high versus low volatility regimes and hinted at non-linearity. In this regard, we missed out on the benefits of the cointegrated regression technique applied by Kaufmann [12]. Future works may consider non-linear cointegrated techniques augmented by the basket of covariates applied by both investigations.

All in all, our findings indicated a more sensible impact of the ADS, PADD, and Baltic variables during periods of lower volatility and market stress. Correspondingly, the relationship can be justified given the stronger role of market participants in response to the short-term variations in the levels of ADS and PADD flows during periods of higher market stability. In contrast, results associated with PMI, OILRIGS, and GPR generally revealed evidence of increasing impact of the variables on the WBS, particularly at lower quantiles. One plausible explanation for this could be analogous to the greater impact of the demand-type variables and geopolitical risks at lower quantiles, resulting in tighter supply and increased differentials for the WBS. Moreover, there is a potential for investors to engage in higher speculative trading activities in the quest for higher price discrepancies stemming from market inefficiencies.

5.3. Causality Analysis

The rationale behind the causality tests was to overcome a known pitfall in statistical and machine learning exercises: correlation vs. causation. The tests done so far proved useful in revealing which macro-fundamental drivers are significant. However, whether those variables are independently useful in predicting the WBS was of practical interest and aided in stress testing our existing results. It is important to note that we mean causal influence in the Granger sense, i.e., past values of one variable reliably predict future values of another. Furthermore, the causality exercise in mean and variances across quantiles helped reveal which distribution segment is most informative. To start, results in

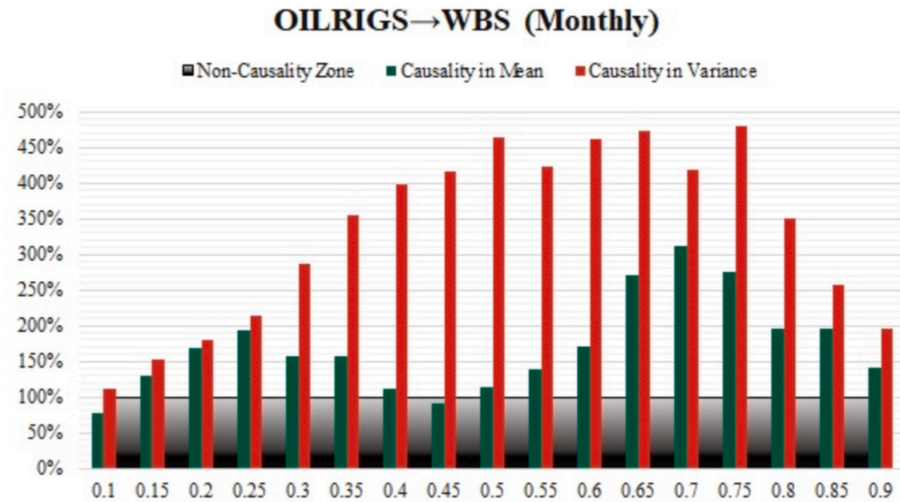

Fig. 25. Causality Analysis for number of operational oil rigs in the US (Monthly frequency)
Note: This table reports the quantile-based causality results for number of operational oil rigs in the US (OILRIGS) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

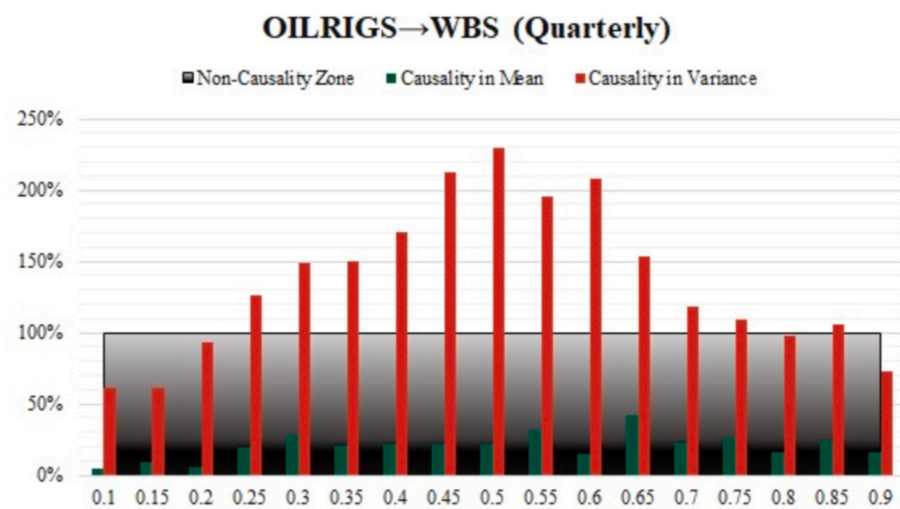

Fig. 26. Causality Analysis for number of operational oil rigs in the US (Quarterly frequency)
Note: This table reports the quantile-based causality results for number of operational oil rigs in the US (OILRIGS) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

Figs. 2–32 show that the business conditions in the US, as proxied by the ADS index, held a causal influence on the WBS on a daily basis. The relationship was significant for the first moment across all quantiles but insignificant for variance at lower quantiles. Qualitatively similar results persisted when looking at a monthly frequency, but the significance disappeared over a very long term: quarterly frequency. While the ADS index is a contemporaneous indicator of business indications, the Baltic Dry Index (BDI) has a broader and more global appeal. It tracks the cost of raw material transportation. The lagged nature of BDI was reflected in the causality results, as the mean values showed less quantile-specific significance at a daily level. Monthly and quarterly frequencies showed similar patterns, with the latter being practically significant. During the RIF portion of this paper, we also utilized the PMI to ensure the robustness of the business conditions. This index provides an alternative look into the state of the US economy by quantifying the economic activities of 300 managers of US firms. In this study, this index registered practically non-significant results over a quarterly frequency, whereas the causality in mean was relevant at mid-low to mid-high quantiles. Importantly, the extreme quantiles were not significant. Consequently, we can interpret the state of the US economy, as proxied by the PMI, to hold predictive ability for the WBS under ordinary circumstances. Other proxies via Kilian and LK indices yielded no significant results.

Switching to the supply side, the flow of imported oil from Canada registered significant results only on the extreme spectrums of the quantiles. That is, the normal (mean/median) circumstances of the WTI–Brent oil spread could not be predicted by oil imports from Canada. This result indicates that extreme inflow or lack of flow from Canada has a significant impact. Therefore, Canada does have a role in determining the WBS. It is worth noting that the significant result above referred only to monthly data, while the quarterly frequency results were insignificant. Daily frequency data were not available. On the supply side, upon consulting literature, we recognized the predictive ability of the number of active US oil rigs. These values generally had causal flows on the WBS at most quantiles. Since the number of active American oil rigs is a strong current indicator of the impending oil supply via the WTI, it is entirely plausible that the results were significant across the board. Comparably less relevant were the PADD flows. This statement,

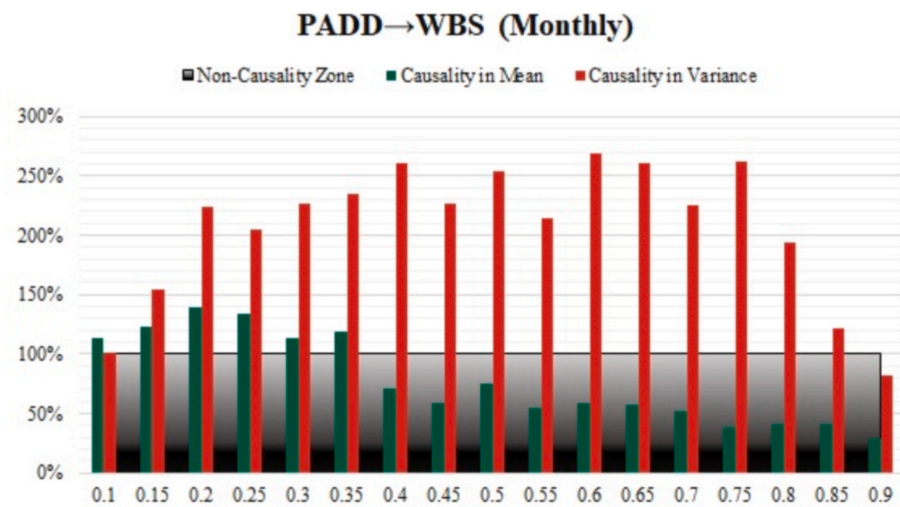

Fig. 27. Causality Analysis for Oil flow from Cushing oil hub in Oklahoma to Gulf coast (Monthly frequency)
Note: This table reports the quantile-based causality results for Oil flow from Cushing oil hub in Oklahoma to Gulf coast (PADD) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

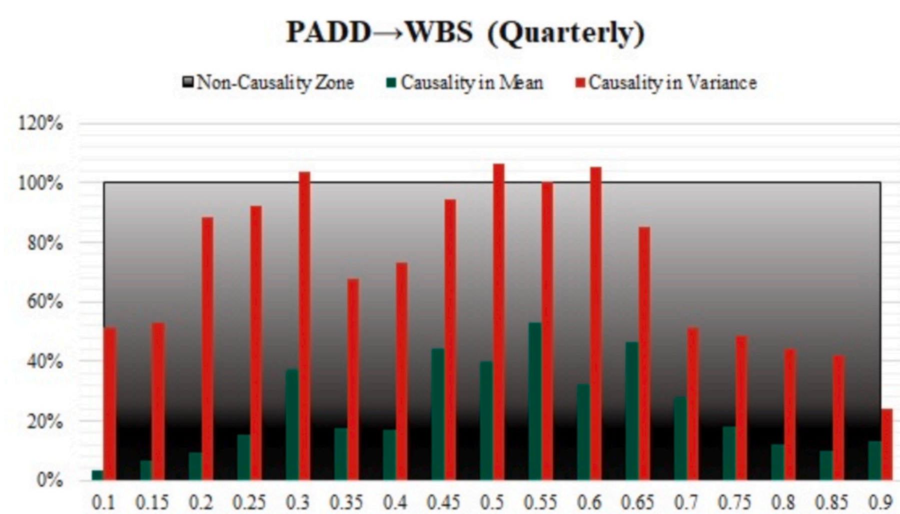

Fig. 28. Causality Analysis for Oil flow from Cushing oil hub in Oklahoma to Gulf coast (Quarterly frequency)
Note: This table reports the quantile-based causality results for Oil flow from Cushing oil hub in Oklahoma to Gulf coast (PADD) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

however, requires some qualification, as at the monthly frequency, the causality in variance was significant for most quantiles. This suggests that fluctuations in oil flows matter more than the nominal value of oil flowing within the pipelines in the US.

Another noteworthy factor in the oil market is the constant threat of geopolitical turmoil. As such, we utilized the GPR index by Caldara and Iacoviello [98]. The results showed that geopolitical uncertainty holds causal influence over the spread at mid- and high-range quantiles for variance while being significant for the first moment only in high quantiles. This suggests that in normal circumstances, geopolitical situations affect the fluctuation of the spread but only matter in predicting the nominal value of the WBS in cases of large divergences. Interestingly, no causality in mean was observed at the quarterly frequency, but causality in variance remained relevant. One explanation for this could be that geopolitical risk is a persistent and pervasive element ever-hanging over the oil market, and, as such, its effect almost never vanishes. We furthermore accounted for the role of global economic uncertainty impacting the spread. Using Ahir et al.'s [129] index, we found this not to be the case. However, the popular VIX (fear) index, which measures the CBOE option, implied forward-looking volatility. Consistent with prior literature, we, too, observed that at both daily and monthly frequencies, VIX holds predictive ability over the WBS for both mean and variance results. The same did not hold for quarterly results.

5.4. Robustness check

In this section, we report the obtained test statistics using alternative proxy variables in place of the PMI. Our rationale for using the PMI centered around its widely known utility as a composite monthly indicator that accounts for manufacturing activities, such as output, employment, new orders, inventories, and vendor deliveries [130]. Moreover, it is commonly regarded as an evaluation benchmark against the performance of key financial markets and the economy as a whole [131]. Although we argue that it is superior to other indices, some studies document its lack of predictive validity and power in judging the qualitative condition of economic activities for a number of reasons, such as false signal transmission, erratic capturing of cyclical swings [132], and poor forecasting power for manufacturing sector's

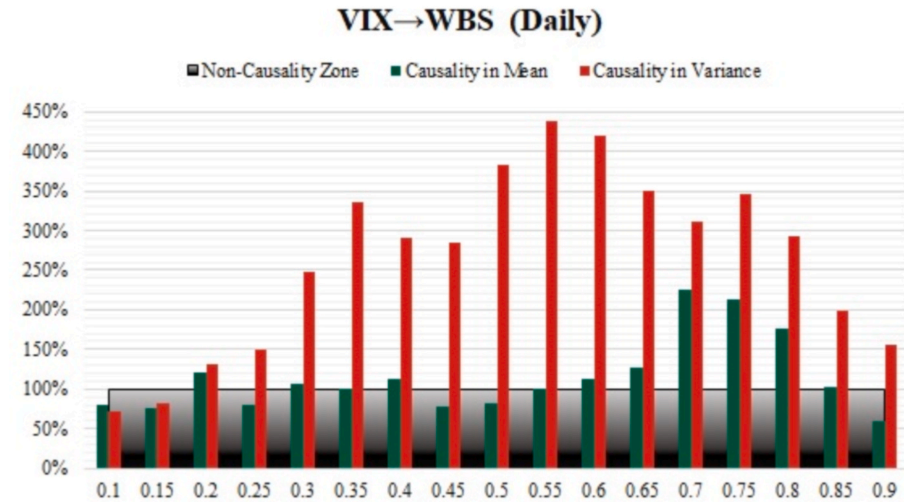

Fig. 29. Causality Analysis for CBOE Volatility Index (Daily frequency)
Note: This table reports the quantile-based causality results for CBOE Volatility Index (VIX) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

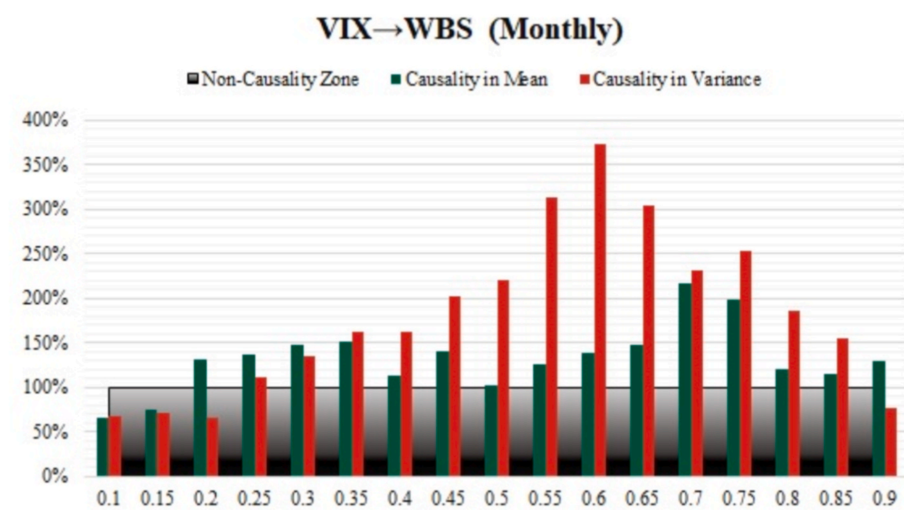

Fig. 30. Causality Analysis for CBOE Volatility Index (Monthly frequency)
Note: This table reports the quantile-based causality results for CBOE Volatility Index (VIX) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

performance and real GDP and hours worked [133]. The empirical literature further provides evidence of other comparable corresponding to and leading proxy indicators (called diffusion indexes) for the determination of economic performance. The predictive power of such indices consisting of key macroeconomic components was found to be, at best, minimal [134]. Hence, we performed a robustness check by employing alternative proxies of the PMI, namely the BDI and Kilian index. The motivation for using these two factors lay in their novelty and pervasiveness in gauging the level of global aggregate economic and business conditions in relation to commodity trading and transportation.

We examined how the BDI, as an indicator of global demand for raw materials, namely dry commodities, links to the range and quantiles of the WBS. The reported test statistics in Table 7 evidenced a negative and significant relationship between the BDI and IQR/IQRATIO of the spread. That is, the higher value of BDI had a diminishing influence on the deviation of the WBS, foreshadowing a narrower range. We found this result intuitive because higher BDI prompts a greater global demand for crude oil, productive capacity, global economic activity, and, consequently, upward pressure on the Brent oil benchmark. Moreover, we also found that during other (specifically unstable economic) episodes as identified by the distinctive quantiles of the WBS (see Table 8), a decreasing BDI would potentially trigger supply gluts in the oil market [135], hence a decreasing price of Brent oil and consequently a higher price spread. Additionally, we employed the Kilian index to evaluate the real global economic activity built upon the single-voyage ocean freight rates for dry bulk commodities used to disentangle demand and supply shocks in the global oil market. We hypothesized that higher freight rates would conceivably promote greater demand for industrial commodities, including iron ore and coal, thus inducing higher demand for Brent oil, leading to a declining spread. Our results suggested no significant evidence of the association with the WBS range, ratios, variance, and quantiles, with an exception being at the lower tail, which negatively implies that a higher Kilian index coincides with a lower price spread. These differences, though minute, are likely due to several criticisms of the Killian index pointed out recently by Hamilton [136]; for particular reasons being (i) lesser resemblance of the index to the actual behavior of the world economic activity, especially since 2009; (ii) deficient identification of the cyclical component by removing a

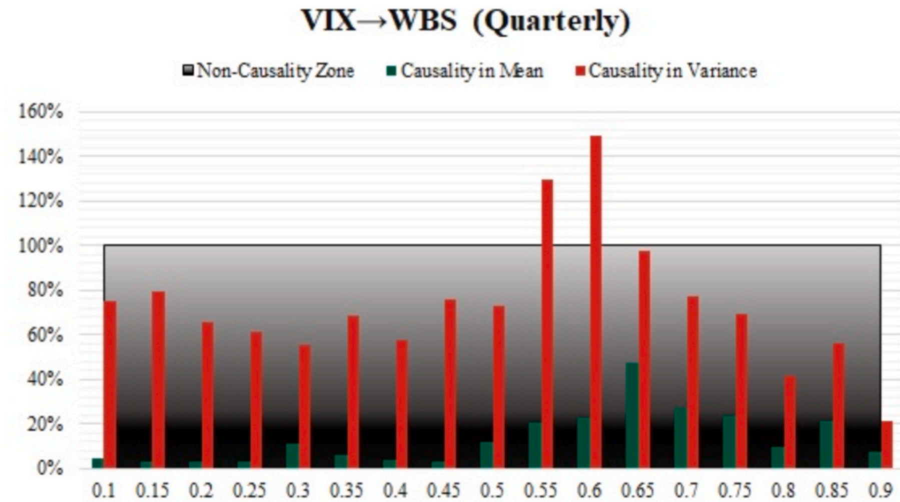

Fig. 31. Causality Analysis for CBOE Volatility Index (Quarterly frequency)
Note: This table reports the quantile-based causality results for CBOE Volatility Index (VIX) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

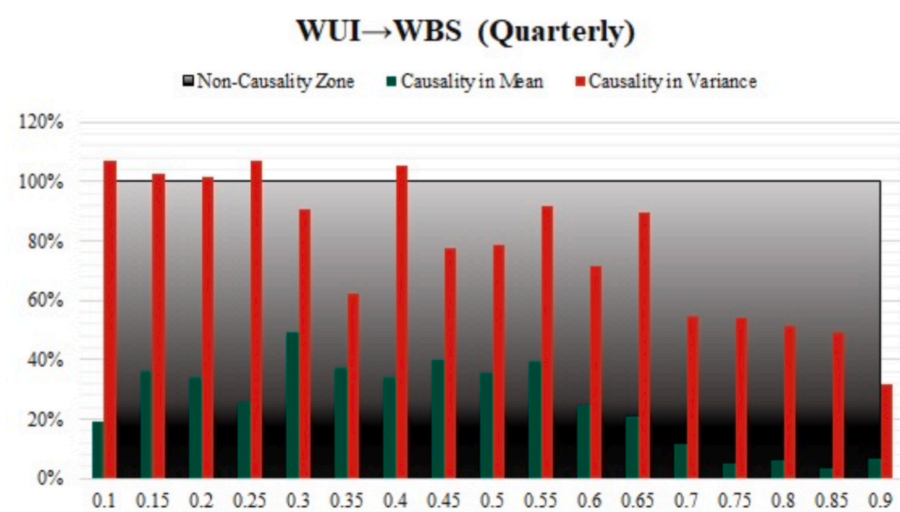

Fig. 32. Causality Analysis for World Uncertainty Index (Quarterly frequency)
Note: This table reports the quantile-based causality results for World Uncertainty Index (WUI) vs. WTI-Brent Spread. The shaded (black) zone indicates the non-causal zone. This means that scores beyond that count as statistically significant results.

deterministic time trend; (iii) the absence of statistically significant association between the index and real GDP growth rates; and (iv) low statistical correlation of the index with future changes in commodity prices. By the same token, Nonejad [137] provides evidence suggesting that the Kilian index, even after its coding-error correction, does not perform any better than the world industrial production index of Baumeister and Hamilton [138].

The robustness of our findings received a further credibility boost through the application of a sophisticated RIF technique. This approach improved upon the ordinary IF by providing robustness to outliers, higher statistical efficiency, bias reduction, improved inference, and enhanced applications in treatment effects analysis. RIF achieved these benefits by reweighting observations, reducing the impact of outliers, and incorporating additional information from the data, leading to more accurate and reliable parameter estimation.

5.5. Country-wise analysis

Notwithstanding the significance of broad sample results, it was also worth verifying whether the WBS is influenced by the volume of oil production in major light-oil exporting countries outside the USA. In particular, we hypothesized that any likely disruption in the production of light sweet oil could trigger a heterogeneous impact on the price of Brent crude oil and, consequently, the WBS. Table 9 provides statistical evidence on our country-level regression equation. We placed special emphasis on the impact of the volume of light oil production on the range of the WBS. Our empirical test results evidenced a positive and significant association between the volume of oil production and the IQR of the price spread in Algeria, Nigeria, and Norway. We particularly found evidence implying that higher oil production in the mentioned countries would lead to a greater overall price discrepancy across the two major benchmarks and, thus, a widened price spread. The case of Libya was, however, counterintuitive, with results registering a significant and negative association between the production level and the range of price spread. One plausible explanation for this is analogous to the influence of a succession of geopolitical events having occurred in Libya to exacerbate the demand and create supply outages of Libyan oil. More notably, the post-2011 political and economic upheaval in Libya

Table 7
RIF Regression using Monthly Data (Robustness Check).

	SPREAD iqr(90 10)	SPREAD iqratio(90 10)	SPREAD variance
ADS	0300.	0.125	0.200
(Default)	(0.246)	(0.103)	(0.178)
(Robust)	(0.103)***	(0.042)***	(0.124)
(Bootstrap)	(1.948)	(0.547)	(0.684)
BALTIC	−0.273	−0.116	0.060
(Default)	(0.168)*	(0.070)*	(0.123)
(Robust)	(0.130)**	(0.054)**	(0.101)
(Bootstrap)	(0.244)	(0.080)	(0.131)
KILIAN	0.150	0.062	−0.116
(Default)	(0.250)	(0.105)	(0.182)
(Robust)	(0.202)	(0.084)	(0.128)
(Bootstrap)	(0.412)	(0.146)	(0.195)
PADD	−0.647	−0.270	−0.140
(Default)	(0.147)***	(0.061)***	(0.106)
(Robust)	(0.164)***	(0.069)***	(0.063)**
(Bootstrap)	(0.393)*	(0.152)*	(0.053)***
OILRIGS	0.961	0.405	0.342
(Default)	(0.106)***	(0.044)***	(0.077)***
(Robust)	(0.145)***	(0.061)***	(0.087)***
(Bootstrap)	(0.464)**	(0.191)**	(0.090)***
CANIMP	1.181	0.494	0.240
(Default)	(0.234)***	(0.097)***	(0.170)
(Robust)	(0.227)***	(0.094)***	(0.081)***
(Bootstrap)	(0.590)**	(0.226)***	(0.076)**
VIX	0.171	0.071	0.268
(Default)	(0.136)	(0.056)**	(0.098)***
(Robust)	(0.132)	(0.055)	(0.191)
(Bootstrap)	(0.185)	(0.061)	(0.187)
GPR	−0.175	−0.074	−0.133
(Default)	(0.084)**	(0.035)*	(0.061)**
(Robust)	(0.065)***	(0.027)***	(0.070)*
(Bootstrap)	(0.128)	(0.051)	(0.067)**
CONS	−7.560	−2.194	−3.128
(Default)	(1.500)***	(0.626)***	(1.085)***
(Robust)	(1.313)***	(0.550)***	(1.477)**
(Bootstrap)	(8.277)	(2.442)	(2.892)

Note: This table presents RIF regression estimates analyzing how explanatory factors affect key moments of the WTI-Brent spread distribution as a robustness check with expanded covariates. Compared to linear models, granular and distributional impacts are visible. For instance, arbitrage and supply factors consistently shift dispersion and skewness. The marginal effects are estimated using default, robust, and bootstrap standard errors.*, **, and *** indicate 10%, 5%, and 1* statistical significance, respectively. Additional of extra and alternative covariates here serves as a robustness check to ensure the validity and reliability of our previous estimations reported in Tables 5 and 6

has seen a marked shift in the foretaste of traders, analysts, and even the oil ministers toward the rehabilitation and sustainability of Libya's oil production to levels commensurate to the pre-crisis period [139]. We also note that despite the several shutdowns of major Libyan oil fields in the periods ensuing the crisis, there was a minimal adjustment or surging price pattern of Brent oil due to the role of certain factors, such as Saudi Arabia's higher volume of production compensating the shortage, lower demands for the Libyan oil due to its refinery maintenance and outages, lower demand for the Libyan oil from the European refiners given their realized weak profit margin of processing, and an overall global economic slowdown. Moreover, the role of non-OPEC crude oil production, particularly those attributed to North America and the Canadian oil sands, resulted in the modulated impact of Libyan oil production on the Brent price, specifically from the onset of the Libyan civil war. Our obtained finding on Libya is also partially consistent with that of Ji and Guo [140]; who provide compelling evidence implying that the role of Libyan civil unrest was, at best, transitory on the oil price changes, hence inferring a negligible influence on the original fundamental balance between oil supply and demand.

Notwithstanding these findings, the Libyan oil sector has been recuperating very recently from the civil war fallout, with its production and export more than doubling to exceed the level of expectation of the country's national oil corporation. However, the effect of such a renewed production surge on the oil price is not so evident, mainly due to the crucial role of the so-called non-OPEC North African countries—which are exempt from the OPEC production cut deal—in the oil price run-up. This would thus call for further research on this topic to verify how Libyan oil production affects global oil benchmarks in general and the WBS in particular.

Table 8
SUR-RIF Regression using Monthly Data on Quantiles (Robustness Check).

	SPREAD 20th Quantile	SPREAD 40th Quantile	SPREAD 60th Quantile	SPREAD 80th Quantile
ADS	0.215	0.006	−0.008	0.005
(Default)	(0.115)*	(0.027)	(0.028)	(0.028)
(Bootstrap)	(0.740)	(0.250)	(0.114)	(0.153)
BALTIC	0.273	−0.032	0.033	0.046
(Default)	(0.079)***	(0.019)*	(0.019)*	(0.019)**
(Bootstrap)	(0.124)**	(0.040)	(0.023)	(0.017)***
KILIAN	−0.255	0.050	−0.008	−0.014
(Default)	(0.117)**	(0.028)	(0.029)	(0.028)
(Bootstrap)	(0.230)	(0.056)	(0.028)	(0.020)
PADD	0.138	−0.035	0.016	0.001
(Default)	(0.068)**	(0.016)**	(0.017)	(0.017)
(Bootstrap)	(0.105)	(0.021)*	(0.016)	(0.015)
OILRIGS	−0.497	−0.080	−0.051	−0.038
(Robust)	(0.049)***	(0.012)***	(0.012)***	(0.012)***
(Bootstrap)	(0.101)***	(0.026)***	(0.011)***	(0.011)***
CANIMP	−0.555	−0.183	−0.155	−0.042
(Default)	(0.109)***	(0.026)***	(0.027)***	(0.026)*
(Bootstrap)	(0.130)***	(0.030)***	(0.040)***	(0.027)
VIX	−0.003	0.002	−0.010	0.017
(Default)	(0.063)	(0.015)	(0.015)	(0.015)*
(Bootstrap)	(0.078)	(0.024)	(0.018)	(0.017)*
GPR	−0.002	0.011	0.012	0.022
(Default)	(0.040)	(0.009)	(0.010)	(0.010)**
(Bootstrap)	(0.047)	(0.010)	(0.010)	(0.012)*
CONS	7.504	5.371	4.434	3.420
(Default)	(0.689)***	(0.166)***	(0.172)***	(0.168)***
(Bootstrap)	(2.698)***	(1.036)***	(0.476)***	(0.575)***

Note: This table presents Seemingly Unrelated Regression estimates of RIF models analyzing how explanatory factors differentially affect quantiles of the WTI-Brent spread distribution. More granular distributional impacts are visible in this table compared to ordinary linear models. For instance, the arbitrage and supply factors have larger effects on the left tail while financial variables mostly shift the right tail. The marginal effects are estimated using default, robust, and bootstrap standard errors.*, **, and *** indicate 10%, 5%, and 1* statistical significance, respectively.

6. Conclusion

We examined the role of the key determinants of the WBS using an unconditional quantile regression technique. To that end, we investigated the partial effect of a set of explanatory factors broadly known as the demand- and supply-type factors, as well as the global market's perception and geopolitical uncertainties on the unconditional quantile of the WBS. Correspondingly, the salience of our adopted testing framework points to the relative potency and robustness of our results, considering the impact of covariates on the entire unconditional distribution of the WBS instead of its conditional mean. Our findings were clearly indicative of a positive statistical concordance among the demand-type variables, namely the US business condition, the PMI, and the WBS. Taken together, our findings are in agreement with the general economic interpretations reflecting the COVID-19 pandemic's induced demand shocks for WTI oil. The second major finding correlated to the role of the supply-type factors, namely the flow of the WTI oil, oil-rig counts, and Canadian oil imports, in determining the WBS. Our findings generally verified a significant negative association of the supply-type factors with regard to the WBS, with implications pointing to the collective consequences of the diminishing international demand following the outbreak of COVID-19, the policy decisions made by the OPEC + member countries, higher volume of production, and rising

Table 9
RIF quantiles, country level test-results.

	Spread iqr (90 10)	Spread iqr (90 10)	Spread iqr (90 10)	Spread iqr (90 10)	Spread iqr (90 10)	Spread iqr (90 10)	Spread iqr (90 10)	Spread iqr (90 10)
	Algeria	Angola	Egypt	Libya	Nigeria	Norway	Russia	UK
PROD	0.518	0.331	−2.017	−46.303	3.361	−0.103	2.504	−1.272
	(0.355)	(0.285)	(0.819)**	(14.012)***	(0.603)***	(0.540)	(0.665)***	(0.532)**
ADS	0.291	0.239	0.336	0.328	0.338	0.274	0.260	5.796
	(0.269)	(0.271)	(0.268)	(0.265)	(0.257)	(0.271)	(0.263)	(4.216)
PMI	0.517	0.680	0.624	0.706	0.032	0.688	0.475	−0.551
	(0.599)	(0.587)	(0.583)	(0.578)	(0.573)	(0.589)	(0.578)	(1.145)
PADD	−0.293	−0.351	−0.412	−0.721	0.234	−0.472	−0.184	−0.718
	(0.185)	(0.173)**	(0.146)***	(0.164)***	(0.187)	(0.159)***	(0.160)	(0.240)***
OILRIGS	0.936	0.950	1.050	1.026	0.750	0.997	0.910	1.173
	(0.126)***	(0.127)***	(0.115)***	(0.114)***	(0.120)***	(0.134)***	(0.116)***	(0.214)***
CANIMP	0.238	0.082	−0.766	0.573	0.784	0.460	−0.740	−0.512
	(0.395)	(0.503)	(0.622)	(0.348)*	(0.341)**	(0.411)	(0.477)	(0.747)
VIX	0.358	0.329	0.317	0.341	0.287	0.357	0.351	0.499
	(0.138)**	(0.140)**	(0.138)**	(0.136)**	(0.132)**	(0.139)**	(0.135)**	(0.204)**
GPR	−0.150	−0.130	−0.172	−0.184	−0.158	−0.160	−0.172	−0.146
	(0.112)	(0.115)	(0.111)	(0.110)*	(0.107)	(0.112)	(0.110)	(0.162)
CONS	−5.182	−4.823	−9.059	−6.424	−1.009	−8.738	5.289	−18.414
	(4.026)	(4.700)	(3.083)***	(3.151)*	(3.289)	(3.261)***	(4.847)	(12.735)
AVERAGE	0.54342	0.54342	0.54342	0.54342	0.54342	0.54342	0.54342	0.54342
N	319	319	319	319	319	319	319	300

Note: This table presents the results of RIF regressions analyzing the differential effects of market factors on the WTI-Brent spread across quantiles of the conditional spread distribution for major oil exporting countries. The disaggregated and distributional insights from RIF quantify varying effects of production, inventories, and other variables on spread behavior in each nation. For example, higher production coincides with widening the spread in Russia and Nigeria but contracts in Libya.

Canadian oil import. Likewise, the prevalent global perception of financial markets and the geopolitical uncertainties were found to have a statistically significant relationship with the WBS quantiles, in line with the theoretical expectations of Bakas and Triantafyllou [120]; Lyu et al. [121]; and Su et al. [125]. Additionally, our results survived multiple robustness checks by considering the system of SURIF, alternative proxy variables, and country-wise analysis. Dividing the series according to change points measured via changes in the mean and persistence of the spread series suggested that the spread experiences separate regimes before and after late 2010. This is consistent with the findings of the papers highlighting the role of the shale oil revolution in traditional benchmarks, such as WTI and Brent. Further analysis via causality in quantiles suggested that variables representing economic conditions in the US have causal influences on the WBS with much more regularity than various macro-fundamental variables, most notably the state of fear, risk aversion, and uncertainty in financial markets.

Our findings contribute to energy economics, energy finance, and financial markets in various ways. We considered demand- and supply-type factors, global market perception, and geopolitical uncertainties. We updated prior findings on the positive association between demand variables and negative associations with supply variables. We are also among a few to highlight this salience of market perception and geopolitical uncertainties.

We generated several insights with real-life implications for energy firms, traders, investors, and policymakers. First, the significance of the demand side-related results implies that those factors deserve attention to mitigate risk, forestall crises, and maximize profits. Exploiting the WTI–Brent differential relies heavily on the demand factors. However, supply-side indicators are not entirely without utility. For instance, oil rig counts, intra-US pipeline flows, and Canadian import volume offered valuable insights into when spread shrinks. Failure to account for these factors can affect investment returns. Meanwhile, given the importance of timing entry and exit points into financial markets, our structural break point exercise contributes to stakeholders who monitor and anticipate market fluctuations for either trading strategies or policy intervention decisions.

Our findings and analyses contain actionable insights for shaping energy policies and guiding investment decisions in the global oil market. For instance, optimizing infrastructure and addressing supply-side factors—as with the Keystone XL pipeline closedown—can mitigate price disparities and help reestablish equilibrium prices for either oil benchmark. On the financial side, we found spread traders more responsive to fundamentals than sentiments. This implies that regulators possess discretion in crafting targeted measures to intervene if systemic risk concerns escalate in the oil market or the global economy, akin to the CFTC's schemes to combat the risk of financial crisis in the earlier decade. Further managerial and policy implications of our findings include a forewarning to firms with exposure to the energy sector demanding side factors, such as business conditions and manufacturing activity in the US, which are essential to anticipate fluctuations in the spread. Moreover, oil producers can stand to benefit from their production and storage decisions by monitoring supply-side indicators. The shrinkage of the spread in this regard can act as a leading indicator, as our RIF regression results imply. US-based policymakers may also want to consider infrastructure improvements to better connect the hinterland of the US with coastal and international markets if they wish to stabilize the benchmark price equilibrium discovery process.

Before we conclude, a delineation of the shortcomings of this research is warranted. The framework we employed relies on assumptions and models, which may have fallen short of encompassing in entirety the complexity of the WBS phenomenon—especially since this is a spread that is factored by many moving pieces of concurrent economic, political, and geological origins. Specifically, forces of demand and supply in the global oil markets are widely shaped by numerous dynamic and multifaceted phenomena, stemming particularly from geopolitical tensions, regulatory changes in the energy market, the overall state of the economies, and fluctuations in global oil production and consumption. It is worth noting that the interplay of these variables could potentially add more complexity to the modeling of the WBS spread. Scope constraints inhibited us from employing more complex models containing additional potential variables that could capture the geopolitical, economic, and even geological factors influencing the WBS. Preliminary attempts to do so were met with disappointing statistical power. Future research may improve on our foundation by employing sophisticated modeling techniques, such as machine learning algorithms or dynamic modeling approaches, which capture the complex interactions between many endogenous variables. Moreover, despite our efforts to proxy financial sentiments, our study did not explicitly address the behavioral tendencies of market participants. A disaggregated approach incorporating financialization, the influence of index traders, and speculative interest via Commitment of Traders reports can be useful future extensions to overcome this shortcoming. This is on top of the possibility that specific theoretical or conceptual frameworks may have constrained the argument presented in this manuscript. Thus, care must be afforded in replicating or transferring it to other contexts—e.g., crush spread or other futures market spreads.

CRediT authorship contribution statement

Imtiaz Sifat: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Alireza Zarei:** Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Abdollah Ah Mand:** Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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