

Thresholds and Delays: Gulf Weather Effects on WTI Crude Oil Prices

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Abstract

This study examines how short-term atmospheric variability propagates into an economically sensitive system, using West Texas Intermediate (WTI) crude oil prices as a response variable to marine weather conditions in the Gulf of Mexico. Employing distributed lag non-linear models (DLNM), we quantify simultaneous threshold-type and delayed effects of daily meteorological fluctuations, capturing nonlinear, asymmetric, and multi-day climate–economy interactions. The analysis covers trading days from 2015 to 2024 and integrates WTI spot prices with observed marine weather variables—precipitation, near-surface air temperature, sea-level pressure, and wind speed—from NOAA/NDBC Station 42001, representative of mid-Gulf boundary-layer conditions. Results reveal fast and predominantly short-lived atmospheric influences, with the strongest responses occurring within 0–5 days and generally dissipating by 15–20 days. Precipitation exhibits a pronounced nonlinear threshold behavior, where light rainfall is associated with marginal price increases, while heavier precipitation reverses the effect, producing stronger negative responses. Temperature effects are mainly negative in the short term, with only transient positive anomalies that vanish after the first week. Sea-level pressure impacts are weak, oscillatory, and sensitive to specification. In contrast, wind speed shows a robust and statistically significant cumulative effect over 0–20 days, indicating that wind-related disruptions in marine and offshore environments play a dominant role in short-term system responses. The findings highlight the importance of boundary-layer meteorological processes and nonlinear lag structures in transmitting weather variability into applied systems. The study demonstrates the value of advanced climate-related statistical modeling for understanding short-term climate impacts, with implications for applied climatology, and climate-sensitive risk assessment

Keywords

WTI Crude Oil, Lagged Impacts, Distributed Lag Non Linear Model, Weather Variables.



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Introduction

The most significant industry in the global economy today is oil. Since 1983, oil has been the primary focus of economists due to the well-established effect that oil prices have had on the US economy following World War II. Despite its evolving character, oil has also played a crucial role in the global economy (Katias et al., 2019). Crude oil prices are susceptible to a variety of elements, including military, political, financial, and diplomatic forces, resulting in price fluctuations that are random, abrupt, and chaotic (Dong et al., 2024).

An extensive body of empirical work connects tropical cyclones to damage to Gulf of Mexico infrastructure, shut-ins, and crude and refined product price movements. Case and panel data on Hurricanes Gustav and Ike illustrate damage to platforms, lost production, and statistically significant downstream price impacts; and more generally, extreme weather contributes to greater volatility in offshore production and can move the prices of refined products relative to crude. These studies all identify short-lived, but economically important impacts that diminish as facilities come back online and supply chains normalize (Kaiser & Yu, 2010). Based on 1950–2003 Gulf data, first-order regressions indicate that tropical storms and hurricanes are the only events that can close large numbers of offshore facilities at once, and storm physical attributes account for a large share of the production volatility that results (Kaiser, 2008).

Even in the absence of a tropical storm, day-to-day weather changes, including temperature, wind, sea-level pressure, and precipitation, can influence energy markets due to heating and cooling demand, as well as marine and port operations. The interconnectedness of the US commodity markets is heterogeneously time-scale dependent and influenced by weather conditions (D. Zhang et al., 2023).

The weather's impact on various financial markets, commodities, and the economic growth of a country. Many researchers have analyzed the impact of weather on various fields. Panetsidou & Synapis, (2025) examined the effects of weather alerts on the stock market, Crofils et al., (2025) evaluated the effect of weather on agricultural production, the impact of weather on electricity price (Mosquera-López et al., 2024), electricity demand (Hor et al., 2005), and electricity consumption (Kang & Reiner, 2022).

The oil and gas industry faces problems from a changing climate and an increase in extreme weather events (Cruz & Krausmann, 2013). Extreme weather conditions, including hurricanes, high winds, lightning, flooding, storm surges, and extreme temperatures, present additional difficulties for the oil supply system from upstream to downstream (Katopodis & Sfetsos, 2019). Zha et al., (2025) studies the influence of very high temperature weather data on the prediction of oil futures prices, but there are little research has been done on the dynamic link between the prices of carbon, weather, and crude oil (Li et al., 2023). Motivated by this gap, we analyse how weather affects crude oil prices using daily observations from the Gulf of Mexico Station 42001.

Against this backdrop, we formulate two testable research questions to quantify how regional Gulf weather (around Station 42001) transmits into WTI price dynamics.

RQ 1: Are WTI responses to weather nonlinear, and which variable dominates at 0–5 vs. 10–20 days?

RQ 2: Over 0–20 days, does wind stay positive while precip/temp fade and pressure remains weak?

Literature Review

Crude oil, one of the most important industrial and energy raw materials for the global economy, is used to produce a wide range of petroleum products (Yan et al., 2024). The significance of crude oil volatility cannot be overemphasized, given its influence on the economy and geopolitics (Yu et al., 2023). Oil price volatility indicates the extent of increasing or decreasing oil prices over time. Crude oil price is highly sensitive to changes in the supply-demand balance and the global macroeconomic and geopolitical environment (Demirbas et al., 2017).

The global oil market is becoming more complex and uncertain as a result of oil-related events (Ji & Guo, 2015). Supply and demand for crude oil have seasonally fluctuated and were affected by weather, natural disasters, geopolitical tension, and crude oil prices have been influenced by these factors (Shen et al., 2024). Oil market players are more attuned to climate risks, manifested through regular extremes in weather (Zha et al., 2025).

Many researchers have researched the weather's impact on commodity prices. Lau et al., (2023) Studies how increasing weather risk affects commodity prices. Mosquera-López et al., (2024) employed a distributed lag non-linear model (DLNM) to study the impact of temperature, wind, solar radiation, and precipitation on the wholesale electricity prices in six European countries. Through predictive modeling and STL decomposition, Zhu et al., (2023) documents that El Niño (SOI) influenced climate risk are associated with a reduction in gold price volatility; its impact is condition-specific, and the inclusion of SOI's seasonal pattern enhances the accuracy of volatility predictions. Employing a new Granger causality test on monthly data from 1982 to 2020, the paper establishes that global temperature anomalies (HadCRUT4) Granger-cause commodity futures prices in agriculture, energy, industrial, and precious metals (Taşkın et al., 2021).

Applying a time-varying FAVAR (with stochastic-volatility-in-mean and endogenous regime switching) based on panel data Nam, (2021) reveals that in El Niño years, the uncertain climate contributes to upward inflationary pressure on agricultural, non-energy, and energy commodities. Individuals are making economic choices related to the weather on a daily basis, and this impacts the revenues of firms in many different areas of the economy

(Parnaudeau & Bertrand, 2018). A multi-factor GARCH-MIDAS framework (with Lasso-adaptive selection) outperforms single-factor models in volatility forecasting, underscoring supply demand as the primary long-run driver of crude oil price volatility, with inventories, the U.S. dollar, and geopolitical risk having comparable secondary effects, and alternative energy a relatively minor one (Zhao, 2022).

A modeling approach called DLNM can depict both delayed effects and non-linear exposure-response dependencies at the same time (Gasparrini et al., 2010). We employed a distributed lag non-linear model (DLNM) to analyse the impact of the weather at station 42001 on the WTI crude oil price, as weather shocks can induce nonlinear (e.g., thresholds around storms) and lagged (production/transport disruptions developing during several days) price movements. DLNM's cross-basis allows us to model the shape of the exposure-response function and the lag structure simultaneously, resulting in cumulative and lag-specific estimates - typically unobserved using standard linear or single-lag models. The approach is mature and reproducible, with a dedicated and widely documented R implementation (Gasparrini et al., 2017). Finally, DLNMs have been applied to weather energy price links (electricity), supporting their relevance for commodity pricing contexts like crude oil (Mosquera-López et al., 2024).

A recent health-climate paper in a Dow decision reinforces our choice of DLNM by demonstrating that the effects of weather are nonlinear and delayed, and that lag modeling of exposure and of outcome is important (C.-Y. Guo et al., 2021). Many used DLNM and GAM on 440 U.S. counties and found COVID-19 cases were higher in very cold or very hot weather, but lower at moderate temperatures and when humidity and sunlight were higher. Gao et al., (2023) applied a DLNM to 2014-2018 data from Hulunbuir, China, and observed that heat elevates deaths immediately, while cold enhances deaths with a time lag of a few days, particularly among elderly people and women.

Crude oil prices are positively predicted by extreme weather attention (EWA) (Xu et al., 2023). Since crude oil is one of the commodities that has been heavily financialized, millions of investors from around the world participate in the vibrant global market (R. Guo et al., 2022). Every nation in the world has some degree of economic activity tied to the price of crude oil, as changes in crude oil prices normally influence the prices of other goods and services (Adeniyi et al., 2022).

Ocean temperatures, particularly in the Indian and Pacific and increasingly so in recent years, have been a significant predictor of the price of crude oil, with forecastability being transmitted through market risk, investor attention, and (more recently) oil-fundamental channels (He et al., 2024). The issue of climate change risk from carbon emissions has recently been in the spotlight in the crude oil market as investors search for activity on this matter that may have an impact on crude oil prices (Lin et al., 2024).

We adopt a distributed lag non-linear model (DLNM) as it allows us to represent threshold-type, non-linear weather effects and their multi-day lag pattern through a single cross-basis, providing a more accurate estimation of both lag-specific and cumulative effects of weather on WTI price dynamics than linear or single-lag models.

Material and Methods

This paper studies the effect of daily weather on WTI crude oil prices with distributed lag non-linear models (DLNMs) that allow to consider both nonlinear exposure response relationships (e.g. thresholds around storms) and lagged effects simultaneously within one cross-basis object. We consider precipitation, temperature, sea-level pressure, and wind speed as predictor variables at a Gulf of Mexico marine station (42001) for WTI dynamics and present the exposure-response, lag-response, and cumulative effects.

Data Collection and Preprocessing

We construct a daily sample for the years 2015-2024 based on the WTI spot prices (DCOILWTICO) obtained from FRED and the weather data taken from Visual Crossing for station 42001. The sample is limited to trading days only: we make all series consistent with the NYMEX trading calendar, remove weekends and holidays, and assign the same-day weather to the trading day. None of the weather variables (precipitation, temperature, sea-level pressure, wind speed) are missing values during the window of the study. WTI Although there are some missing observations in prices, we fill these by linear interpolation in the trading-day calendar in order to maintain a continuous time series that is used to construct lags.

Box-Cox Transformation

Before estimation, we applied the Box-Cox transformation to stabilize variance and improve the normality of the crude oil price series. This transformation is particularly useful for data with skewness or heteroskedasticity and is defined as:

$$(y)^{(\lambda)} = f(x) = \begin{cases} \frac{y^\lambda - 1}{\lambda}, & \lambda \neq 0 \\ \log(y), & \lambda = 0 \end{cases} \quad (1)$$

The optimal λ parameter was selected using log-likelihood maximization.

Stationarity and Time Series Diagnostics

Before estimation, stationarity of the crude oil price series was verified using the Augmented Dickey-Fuller (ADF) test, which examines whether a time series has a unit root. The test equation is given by:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^p \delta_i \Delta y_{t-i} + \varepsilon_t \quad (2)$$

Where:

$\Delta y_t = y_t - y_{t-1}$	is the first difference of the series.
α	is a constant (drift).
βt	is a trend term
γ	tests for the presence of a unit root
δ_i	are coefficients for lagged differences.
p	is the number of lags.
ε_t	is white noise.

We also employed the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) to examine the residual structure of the time series. The ACF at lag k is defined as

$$\rho_k = \frac{\sum_{t=k+1}^T (y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^T (y_t - \bar{y})^2} \quad (3)$$

Where:

ρ_k	is the autocorrelation at lag k ,
y_t	is the value at time t ,
$\bar{y}$	is the mean of the series,
T	is the total number of observations.

while PACF isolates the direct effect of lag k after removing the effect of shorter lags. PACF at lag k is derived from:

$$y_t = \alpha + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_k y_{t-k} + \varepsilon_t \quad (4)$$

Where:

ϕ_k	is the partial autocorrelation at lag k
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These diagnostics were used to assess residual dependencies and inform model specification.

Distributed Lag Nonlinear Model (DLNM)

The core of the analysis utilizes the DLNM framework introduced by Gasparrini, (2011). This approach models the nonlinear exposure-response relationships between the dependent variable (crude oil prices) and meteorological predictors, accounting for their lagged impacts. The model was fitted using a GLM with a Gaussian distribution and identity link function. Natural cubic splines were used to model the exposure-response and lag-response relationships, with 3-4 degrees of freedom and a maximum lag of 20 days.

The general form of the model is expressed as:

$$g(\mu_t) = \alpha + \sum_{j=1}^J s_j(x_{tj}; \beta_j), \quad (5)$$

Where,

$g(\mu_t)$	Link function representing the expected value of crude oil prices
α	Intercept term.
x_{tj}	Predictor variables, including lagged meteorological factors.
$s_j(x_{tj}; \beta_j)$	Smoothing functions capturing nonlinear relationships.

To accommodate lagged effects, cross-basis functions were constructed. This involved the transformation of predictors into a multidimensional space where both temporal lags and nonlinear relationships could be explored. Specifically, we extended the model as:

$$s(x_{tj}; \beta) = Z_t \cdot \beta \quad (6)$$

Where,

Z_t	is a matrix of basis variables derived from transformations of the predictors
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The lag structure was incorporated using distributed lag models (DLMs):

$$s(x_{tj}; \eta) = q_t^T \cdot C_n \quad (7)$$

Where,

C	Basis matrix capturing the temporal lag structure.
q_t^T	Vector of lagged values for each predictor

The DLNM generalizes this by incorporating cross-basis functions that jointly model nonlinear and lagged effects:

$$s(x_{tj}; \eta) = \sum_{j=1}^{\theta_x} \sum_{k=1}^{\theta_l} r_{tj}^T \cdot c_k \eta_{jk}, \quad (8)$$

Where,

 r_{tj}^T

Transformed vector for predictor j at time t

 c_k

Basis coefficients capturing the lagged impacts.

Results

Weather Variables and Their Lagged Impacts on WTI Price in the Czech Republic

Figure 1 shows an unprecedented nonlinear and thresholded reaction of WTI prices to precipitation for small values (around 0-1.1 units). The estimated impact is positive, but it changes sign after a threshold around 1.2, becoming negative and increasing in size with further increases in precipitation. The suppression of the response under high rainfall was more than twice that of the positive effect under low rainfall, indicative of a skewed sensitivity. In time, the effect is focused at short lags (0-5 days) and declines gradually to a small effect at ~15-20 days, consistent with a rapid market correction. The near-vertical lines indicate that the primary driving factor is the precipitation level, and the lag only alters the intensity of the effect, not its direction. In other words, WTI is fast and nonlinear: drizzles lead to small price increases, while downpours cause even more dramatic price plunges, with effects dissipating within two to three weeks.

The sea-level map of pressure presents a non-monotone banded pattern for the WTI prices. Prices are higher at moderate pressures (around 1003-1011 hPa) with the maximum values at short lags (0-5 d), fall slightly at about ~1017-1020 hPa, and then they increase again at a thinner band around ~1023-1030 hPa. At the ends, the effect becomes slightly negative so at very low pressure (<~996 hPa) and very positive at ~1031-1032 hPa, with the magnitude of the deteriorations increasing with pressure. Over the full range of regimes, the effect decays with time and is found to be largely insignificant by ~15-20 days. The almost vertical contours illustrate that it is really the pressure level that drives this and that lag only scales the intensity, but not the sign pattern.

The Temperature panel in Figure 1 indicates a predominantly negative relationship between temperature and WTI that is strongest at cooler levels (~10-30°) and short lags, then gradually weakens with time. Two localized positive bands interrupt this pattern: (i) a late-onset ridge around ~35-45° that emerges at longer lags (~12-20 days), suggesting a delayed, modest uplift; and (ii) a brief near-term bump near ~70-80° that appears only at very short lags (0-3 days) before fading to neutral or slightly negative. Beyond ~55-60°, effects are mostly weakly negative across lags, implying any heat-driven demand or supply signal is transitory. The contours are almost vertical, indicating that the temperature level is the dominant driver, while lag mainly dampens or momentarily amplifies the impact but does not alter its sign pattern.

The wind-speed plate shows a definitely non-linear time evolution effect on WTI. At very low speeds (~3-6), the effect is mildly negative, but transient. There is a positive impact of moderate winds (~8-15) that increases at longer lags (~10-20 days), and it reaches a maximum close to ~10-12 m/s. We observe a neutral trough at about ~18-22, and then the sequence reverses: high winds (>~23) have a negative impact on prices at the short-run (0-6 days), apparently due to immediate risks of disruption, but then reverse to a strong positive effect by weeks 2-3, with the largest gains residing at the very highest speeds.

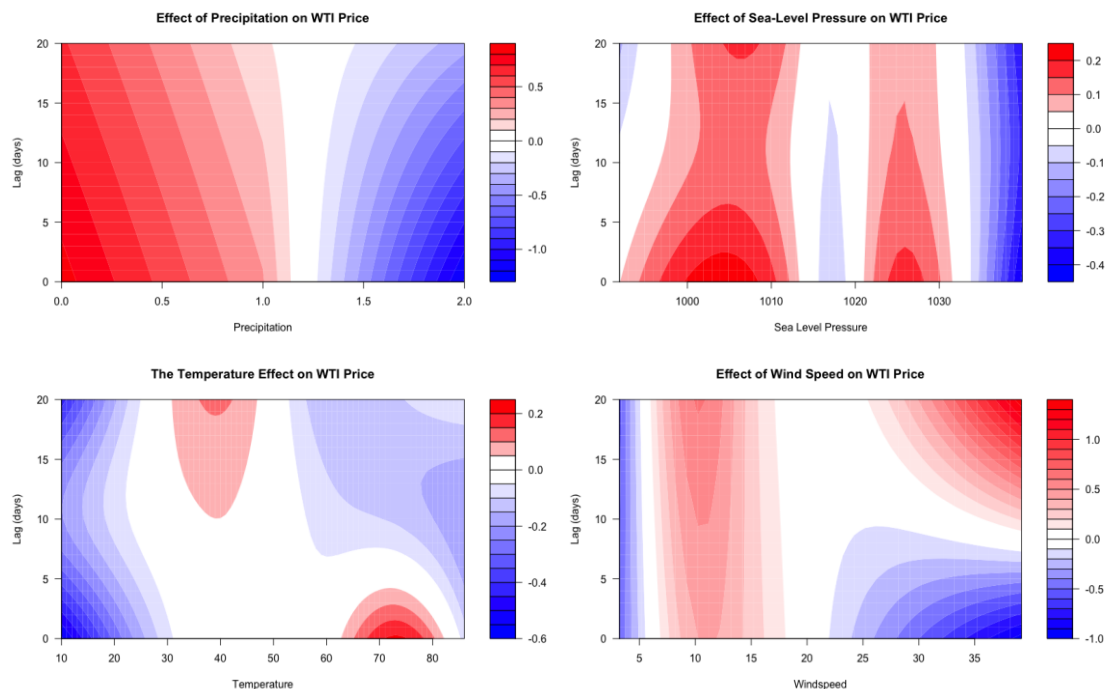


Figure 1: Effects of Weather Variables on WTI Prices

Cumulative effects of weather variables on WTI Price

Looking at Figure 2, we can see that precipitation tends to push up WTI prices, but this effect gets weaker over time. Right away, the cumulative impact is around 0.30, but it drops off pretty steadily to about 0.12 by the 20th day. The gray area tells us there's a lot of uncertainty, and it gets wider as we look further out. It even touches or crosses zero near the end, which means the whole effect might disappear in about three weeks. Statistically speaking, rainfall shocks initially cause WTI to rise, but those gains decrease steadily and become statistically insignificant by the late teens. This is typical for short-term price movements followed by a return to the average.

A somewhat positive but weak and unclear cumulative effect of sea-level pressure on WTI is depicted in Figure 2. Around 0.2 is where the curve starts at contemporaneous/very short delays. It has largely leveled out by days 12–16, settling down to ~ 0.070 – 0.10 . While the point estimate stays slightly above zero throughout, the interval spans substantial positive and negative values by day 20. The confidence band is vast and overlaps zero at nearly all horizons, notably expanding at the beginning and again after around day 16. Together, the results suggest statistically weak, tiny, front-loaded net benefits that soon stifle any pressure-driven impulse and offer little cumulative push after two weeks.

Figure 2's cumulative temperature response shows a little, time-varying, net negative effect on WTI. Beginning below zero (~ -0.3 at extremely short lags), the curve then drifts modestly downward again to around -0.15 to -0.2 by day 20 before heading back toward zero and reaching its least-negative point around days 10–12 (about -0.08 to -0.1). Significant uncertainty exists since the gray band overlaps 0 over the majority of horizons, is broad early on, narrows at the mid-horizon, then widens again late. This makes the negative effect statistically fragile. To put it briefly, temperature shocks have a tendency to initially pull WTI down. By week two, the drag has decreased to almost nil, and any remaining negative effects are small and difficult to quantify.

Over the entire 0–20 day horizon, Figure 2's wind-speed cumulative response is impressively constant and continuously positive. The point estimate, which indicates a tiny but sustained net elevation in WTI after wind-speed shocks, begins at about 0.26 at contemporaneous lags, declines only slightly toward ~ 0.25 by days 10–15, and stays close to 0.25 at day 20. The band remains completely above zero, indicating that the positive cumulative effect is strong and does not fade away within three weeks, even if uncertainty is highest at the endpoints and narrowest around the mid-horizons. Practically speaking, wind-related disturbances cause WTI to experience a slight, long-lasting upward pressure as opposed to a brief bump that eventually disappears.

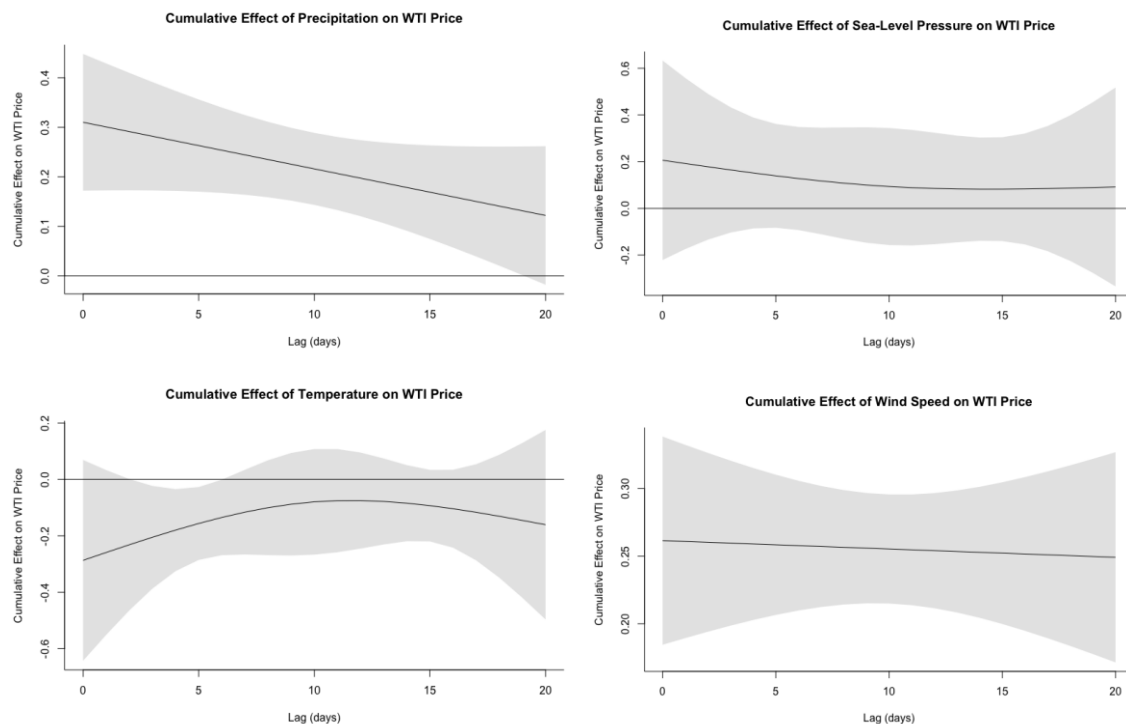


Figure 2: Cumulative Effects of Weather Variables on WTI Prices

Table 1 shows that More negative test values favor stationarity. Our ADF statistic is about -2.63 , which is in the range of usual decision cutoffs: it will typically not reject a unit root at the 5% level with a constant (drift) added to it, but will under more lenient levels or with a zero-mean specification. This is more or less borderline evidence that the series is at best weakly stationary. To be cautious, we present results in both levels (for long-run interpretation) and in returns (for short-run dynamics), and check robustness to alternative ADF specifications (lag lengths, with/without trend)

Table 1: Descriptive Statistics and ADF Test Results

Metric	Value
Min	8.2098270
Mean	20.527760
Max	31.011160
Sds	3.4977870
Skewness	0.1658793
Kurtosis	3.0775090
t.ADF	-2.6301310
t.ADF (drift)	-2.6301310

Discussion

RQ1: Are WTI responses to weather nonlinear, and which variable dominates at 0–5 vs. 10–20 days?

Our findings reveal that WTI has quick, non-linear, and threshold-based reactions to weather conditions. Rainfall shows the most evident threshold: light showers (about 0-1.1) link to small price hikes, while heavier downpours (over 1.2) flip this trend, causing sharp drops. These effects peak within 0-5 days and fade out by 15-20 days. Sea-level pressure creates a banded non-monotonic pattern. Mid-range pressures match with short-term gains, while low and high pressures lead to negative outcomes. These impacts also lessen over two to three weeks.

Temperature is negative for the most part, strongest at colder levels ($\approx 10-30^\circ$) and short lags, interrupted by two slender positive pockets (a late band around $35-45^\circ$ and a near-term bump around $70-80^\circ$). Wind speed is clearly both state and time dependent: very-low winds are slightly negative; moderate winds ($\approx 8-15$) become positive and grow in the 10-20-day lags; strong winds ($> \approx 23$) are negative in the 1st week but after that turn positive very strongly at the 2-3 weeks. Striking in all the panels are the near verticality of the contours, indicating that the sign is determined by the levels of, while the lag determines the magnitude of, confirming that there are nonlinear, threshold effects within the 0-20 day window and that wind is the variable that most evidently switches dominance from short to medium lags.

RQ1: Over 0–20 days, does wind stay positive while precip/temp fade and pressure remains weak?

Over time, wind has provided the largest and most consistent positive influence on WTI: The response begins at about 0.26 and has remained at approximately 0.25 over day 20, with all of the uncertainty bands staying above zero. In contrast, there was a net positive for precipitation early in the horizon that decayed to about 0.12 from an initial 0.30 by day 20 and crossed into negative territory, indicating mean reversion. For temperature, the net effect was slightly negative with an approximate initial value of -0.3 that improved to approximately -0.1 between days 10-12 before eventually trending downward to an approximate -0.15 to -0.2; however, temperature had wider confidence intervals than the other variables, which sometimes included values equal to zero. The sea level pressure variable provided a modestly positive but fragile effect, beginning at approximately 0.2, declining to approximately 0.07-0.10, and crossing into zero across most of the horizons considered. Therefore, over 0-20 days, only wind exhibited a consistently positive cumulative effect; the effects of precipitation and temperature faded rapidly towards zero; and the pressure effect was weak and also fading.

As such, these cumulative effects are generally consistent with short-term adjustments to market conditions as well as other factors. The rapid dissipation of both precipitation and temperature likely reflects the temporary nature of their impacts via either supply/demand frictional effects or behavioral/logistical effects that dissipate within a few days. In addition, the variability in the response of sea level pressure likely reflects the different meteorological regimes and associated market narratives and therefore limits the value of this variable as a stand-alone predictor of WTI price movements. The persistence of the cumulative effect of wind over the very short term as a result of operational disruptions/transport constraints that continue to exist (e.g., offshore exposure, shipping delays) supports this conclusion.

Conclusion

Evidence suggests that weather shocks influence WTI in a timely, nonlinear, and apparently threshold-like manner, while time (lag) mainly stretches the magnitude of the impact rather than changing its direction. The near-vertical contouring across figures emphasizes that the size of each weather variable is the primary driver, and that markets learn the information rapidly—most signals are strongest in the first few days and fade thereafter. Precipitation has the steepest threshold: light rain ($\sim 0-1.1$) raises prices, but heavy rain ($> \sim 1.2$) turns the effect around negatively, with the negative side of the effect dominating the positive one. The cumulative curve starts near 0.30 and drifts towards ~ 0.12 by day 20, with uncertainty spreading out and going through very close to zero, which indicates that the initial lift provided by precipitation diminishes within 2-3 weeks. This is in line with transitory logistics or sentiment effects (e.g., short-run supply frictions or demand expectations) that revert as physical flows normalize. Suggest that various meteorological regimes are mapped into different market narratives. Sea-level pressure produces a banded non-monotonic response to two moderate positive ridges

separated by a weak negative trough-shaped, suggesting different meteorological regimes map into different market narratives. But its cumulative effect is small and fragile: it starts at around 0.2, drifts down to about 0.07-0.10 by the mid-teens, and the confidence interval includes zero for most horizons. In practice, pressure is an unreliable signal by itself once we consider more than a week or so.

Mostly negative for temperature, strongest at the lower end of the lag spectrum with two narrow positive pockets (late-onset around 35-45°, near-term at 70-80°), it starts near -0.3 and rebounds toward ~-0.1 by days 10-12, then drifts slightly more negative (~-0.15 to -0.2 by day 20). These broad uncertainty bands make this net drag statistically tentative; however, that shape does imply that shocks to temperature weigh on prices early and fade to neutrality by the second week. Though high winds press the prices in the ultra-short term, they turn positive in the second and third weeks. The cumulative return is positive and stable-roughly 0.26 at initiation and ~0.25 on day 20-with the uncertainty band above zero. This would indicate that wind-driven perturbations leave a net positive mark on WTI over a three-week horizon, thus rendering wind the most persistent and tradeable of all weather signals analyzed. Implications. For forecasting and trading, weather effects on WTI are short-horizon, nonlinear, and state-dependent. Signals are strongest within the first week, and efficacy depends on where today's conditions sit relative to thresholds (e.g., heavy vs. light precipitation; moderate vs. extreme winds). If one were to prioritize, wind speed offers the clearest, robust positive cumulative edge, while precipitation and temperature provide transient, mean-reverting cues, and sea-level pressure adds limited standalone value. Any systematic strategy should therefore model nonlinearities explicitly (splines, GAMs, tree ensembles), weight recent lags more heavily, and guard against regime shifts by monitoring uncertainty bands and recalibrating as seasons or infrastructure conditions change. Confidence intervals widen at longer horizons, and several cumulative paths overlap zero, so results should be used probabilistically, not deterministically.

Future work could interact with weather seasonality and regional exposure (production vs. refining vs. demand centers), test asymmetry and extreme-event tails explicitly, and evaluate out-of-sample performance versus benchmarks. Overall, the evidence supports the view that weather matters for WTI chiefly in the near term, with wind-related shocks offering the most persistent bullish bias over a 20-day window.

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