International Journal of Education Studies and Social Science Research

Volume: 01, Issue: 02 March - April 2026

OIL PRICE ESTIMATION BASED ON CHANGES IN DOLLAR-DENOMINATED ETFS: A MULTI-INSTRUMENT REGRESSION APPROACH (2025-2026)

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Received: 21/03/2026 Accepted: 29/03/2026 Published: 03/04/2026

ABSTRACT

This paper provides a rigorous econometric estimation of West Texas Intermediate (WTI) crude oil spot prices by analyzing the price action of liquid, dollar-denominated Exchange-Traded Funds (ETFs). Utilizing a high-frequency weekly dataset spanning March 2025 to March 2026, the study employs a series of linear regression models to ascertain the "Theoretical Spot Price" of crude oil. By treating WTI futures as the dependent variable and a basket of ETFs—including USO, BNO, USL, DBO, XLE, and XOP—as independent variables, we quantify the degree to which financialized energy assets leadingly reflect physical market fundamentals. The primary finding reveals a significant divergence between the actual spot price (96.09) and the model's theoretical estimate of 99.10 for the week ending March 15, 2026. This $99.10 figure, derived specifically from the United States 12 Month Oil Fund (USL) regression, indicates an "Undervalued Spot" condition of 3.1%. The model achieved a statistical significance (p-value) of 0.031 (3.1%), suggesting that the ETF basket provides a robust explanatory framework for pricing discovery during periods of high volatility. The results suggest that institutional investors can utilize the "laddered" futures exposure of USL and the "optimum yield" strategies of DBO to mitigate contango-induced tracking errors and identify alpha-generating price lags in the physical market.

Keywords: WTI Crude Oil, ETFs, Regression Analysis.

1.0 INTRODUCTION

The global oil market serves as the primary pulse of industrial macroeconomics, yet the inherent volatility of West Texas Intermediate (WTI) continues to challenge traditional forecasting methods. In contemporary markets, the "financialization" of commodities has elevated the role of liquid, dollar-denominated instruments as essential barometers for price discovery (Girardi, 2015; Maitra et al., 2023). For institutional strategists, the ability to estimate underlying commodity values through accessible financial proxies like ETFs is no longer a luxury but a strategic necessity (Ayoub & Qadan, 2024).

This research addresses the problem of WTI price estimation amidst the supply-side shocks and geopolitical shifts observed in the 2025-2026 cycle. By leveraging the sensitivity of energy-related financial instruments, we construct a predictive framework that bridges the gap between the spot market and derivative-based funds (Shao et al., 2021; Ogol et al., 2025). The following sections detail the technical characteristics of the instruments utilized, the econometric methodology of the regression, a full-scale analysis of the 52-week dataset, and an interpretation of the resulting $99.10 theoretical price.

2.0 GENERAL OBJECTIVE

To estimate the theoretical spot price of WTI crude oil by analyzing the price movements of a basket of dollar-denominated ETFs through multi-instrument regression models in order to provide a statistically robust framework for forecasting and identifying undervalued or overvalued conditions in the oil market during 2025–2026.

3.0 SPECIFIC OBJECTIVES

The research aims to collect and organize weekly price data for WTI futures and selected ETFs (USO, BNO, USL, DBO, XLE, XOP) from March 2025 to March 2026, and to construct linear regression models linking WTI spot prices with the movements of these ETFs as explanatory variables. It seeks to evaluate the predictive accuracy of each ETF model to identify the instrument with the strongest explanatory power, calculate the theoretical WTI spot price, and compare it with the actual market price to detect undervaluation or overvaluation. Furthermore, the study analyzes the statistical significance of the model results using R^2 and p-values to ensure reliable forecasting and interprets the findings within the broader context of financialized commodity markets, considering supply-side shocks as well as contango and backwardation effects.

4.0 THEORETICAL FRAMEWORK

Selecting the appropriate independent variables in modeling WTI crude oil prices requires a thorough understanding of how different financial instruments capture specific dimensions of energy market exposure. Financialized commodity markets are complex, and price movements reflect a combination of fundamental supply-demand dynamics, investor sentiment, and structural market factors such as contango and backwardation. Not all instruments respond equally to these factors; therefore, the choice of ETFs as explanatory variables must account for the type of exposure each provides. Direct futures trackers and equity-based energy funds offer different perspectives: futures trackers closely follow the underlying commodity and its price dynamics, while equity-based ETFs reflect corporate performance and broader market sentiment. This differentiation is critical, as it allows the regression model to account for both commodity-specific risks and broader market beta, providing a comprehensive analytical framework that bridges the physical and financial sides of the oil market (Da et al., 2024; Babalos et al., 2026).

WTI crude oil futures serve as the global benchmark for light, sweet crude, representing the foundational "ground truth" for the energy complex. As standardized contracts for future delivery, they are central to global price discovery and widely used as reference points in both physical and financial markets. Despite their importance, WTI futures are subject to structural pressures such as contango, backwardation, and rollover costs, which can create short-term distortions in observed prices. Contango, for instance, occurs when future prices exceed the spot price, creating potential tracking errors for ETFs that roll over front-month contracts. Backwardation, conversely, occurs when the spot price exceeds future prices, often reflecting immediate supply tightness. In this research, WTI futures are treated as the dependent variable (Y) in the regression framework, providing a benchmark against which the explanatory power of different ETFs is measured (Mohamad, 2025; Anatolyev et al., 2021). Their inclusion ensures that the model reflects real market outcomes while allowing for the identification of theoretical price levels that may differ from the observed market prices.

Among the ETFs analyzed, the United States Oil Fund (USO) tracks the daily price movements of front-month WTI futures. Its high liquidity and broad adoption by traders make it an important instrument for capturing short-term market sentiment. However, USO's reliance on single-month contracts makes it particularly vulnerable to structural decay in contango markets, as the fund must roll contracts from one month to the next. This rollover process incurs costs that can lead to significant tracking error relative to the underlying WTI futures (Cortazar et al., 2024; Clayton, 2015; Ben-David et al., 2023). By including USO in the regression, the model captures immediate, high-frequency signals of investor behavior and short-term supply-demand expectations, although the potential for tracking error must be carefully accounted for in interpretation.

The United States Brent Oil Fund (BNO) offers exposure to Brent crude, the North Sea benchmark, providing a complementary perspective to WTI-focused instruments. Including BNO allows the model to incorporate the Brent-WTI spread, which reflects global supply conditions relative to North American markets. Divergences between WTI and Brent can signal regional logistical constraints, geopolitical tensions, or differences in storage and transportation availability (Bai & Koong, 2018; Zhang & Wu, 2018). By integrating BNO into the regression framework, the study captures the influence of global market dynamics on domestic pricing, enhancing the robustness of theoretical price estimation.

The United States 12 Month Oil Fund (USL) employs a laddered futures strategy, holding contracts across 12 consecutive months. This approach mitigates the negative effects of contango that affect front-month trackers and smooths out short-term volatility, allowing USL to capture the structural trend of the oil curve over time (Sobati & Koy, 2026; Berk, 2016). Historically USL has demonstrated strong predictive alignment with observed WTI price movements, making it the most reliable instrument for estimating the theoretical spot price. Similarly, the Invesco DB Oil Fund (DBO) utilizes an "optimum yield" strategy, selecting futures contracts with the highest implied roll yield to minimize costs and improve tracking efficiency during periods of market rotation (Yap et al., 2022; Halkos & Tsirivis, 2019; Baffes & Etienne, 2024). Both USL and DBO highlight the importance of considering multi-month futures structures when forecasting crude prices, particularly in periods of market stress or rapid price changes.

Equity-based ETFs provide additional insight into the oil market by reflecting the broader financial environment in which energy firms operate. The Energy Select Sector SPDR ETF (XLE) focuses on S&P 500 energy companies and is influenced by corporate fundamentals such as balance sheet health, dividends, and operational performance, as well as overall market sentiment (Kammoun & Mrissa, 2026; Martí-Ballester, 2025). By introducing this sector-specific "equity risk" into the model, XLE accounts for factors that may decouple from direct commodity movements, such as investor perception of profitability or risk appetite. Similarly, the SPDR S&P Oil & Gas Exploration & Production ETF (XOP) targets upstream companies that are highly sensitive to crude price fluctuations, serving as a high-beta proxy for speculative activity in the energy sector (Chang et al., 2025; Jiang et al., 2024). XOP captures the amplified effects of price volatility on firms directly exposed to exploration and production cycles, complementing the more stable signals provided by USL or DBO.

By combining these instruments into a multi-instrument regression framework, the study captures short-term and long-term market signals, integrates commodity-specific, equity-related, and structural factors, and provides a statistically robust methodology for estimating the theoretical WTI spot price. This approach allows for a detailed assessment of potential undervaluation or overvaluation in the market, offering valuable insights for institutional investors seeking to optimize hedging, speculative, or investment strategies in financialized energy markets. Overall, the framework demonstrates how integrating diverse financial proxies can bridge the gap between observed market prices and fundamental valuations, improving both forecasting accuracy and strategic decision-making.

5.0 METHODOLOGY

The estimation logic rests on a linear regression model designed to solve for WTI (Y) using the various ETFs as independent variables (X). In an efficient market, the price of the derivative should reflect the underlying commodity; however, structural factors like contango create price leads and lags that our model seeks to exploit (Singh et al., 2024; Tessmann et al., 2022).

The model utilizes a linear regression line (y = mx + b). Unlike basic linear analysis, this econometric approach accounts for the relationship between known historical values (March 2025 – March 2026) to estimate a new Y based on the current levels of the ETF basket. We focus on the coefficient of determination (R^2) and the p-value to validate the model's reliability (Yang et al., 2022).

Observations were taken weekly over a 52-week period. This timeframe allows us to filter out high-frequency "noise" while maintaining enough granularity to capture the impact of geopolitical shocks and rollover effects (Qin & Gao, 2025; Opoku et al., 2025). The use of regression is justified as it provides a mathematical basis for identifying "theoretical fair value" in a market prone to emotional overreaction and speculation (Razmi & Razmi, 2023; Shao et al., 2024).

6.0 RESULTS OBTAINED

The dataset (Table 1) illustrates a period of relative stability followed by a massive breakout in the first quarter of 2026. The surge in March 2026, where WTI jumped from $87 to $96 in a fortnight, represents a structural shift that tested the tracking capacity of every ETF in the basket.

Table 1: Weekly Price Data for WTI and Associated ETFs (2025-2026)

Date	WTI (Y)	USO (X1)	BNO (X2)	USL (X3)	DBO (X4)	XLE (X5)	XOP (X6)
23/03/2025	68.90	74.77	30.18	37.16	13.97	46.22	130.68
30/03/2025	61.99	67.92	27.60	34.06	12.81	39.38	106.71
06/04/2025	61.50	66.46	26.97	33.24	12.49	39.44	107.57
13/04/2025	64.68	69.48	28.19	34.53	12.97	40.75	111.93
20/04/2025	62.33	69.03	27.90	34.42	12.93	41.19	113.38
27/04/2025	58.29	64.01	26.08	32.37	12.16	40.99	114.95
04/05/2025	61.02	66.61	27.04	33.40	12.55	41.22	118.84
11/05/2025	62.49	68.10	27.67	33.94	12.76	42.74	125.45
18/05/2025	60.93	67.99	27.54	33.92	12.71	40.99	120.84
25/05/2025	60.79	67.15	26.93	33.13	12.40	40.76	119.55
01/06/2025	64.58	71.38	28.52	34.64	13.10	41.71	123.23
08/06/2025	72.98	80.22	31.86	37.63	14.32	44.05	132.78
15/06/2025	74.93	83.12	33.12	38.84	14.79	44.49	134.55
22/06/2025	64.07	73.28	29.11	35.06	13.20	42.65	127.20
29/06/2025	67.00	75.19	30.08	35.80	13.51	43.51	129.17
06/07/2025	68.45	77.29	30.95	36.76	13.89	44.56	133.07
13/07/2025	67.34	75.93	30.40	36.46	13.75	42.98	129.41
20/07/2025	64.34	74.85	30.03	36.11	13.61	43.55	128.02
27/07/2025	67.33	77.46	30.94	36.60	13.91	42.79	123.70
03/08/2025	63.88	73.30	29.55	35.40	13.32	42.47	122.99

10/08/2025	62.80	72.80	29.45	35.26	13.24	42.78	124.52
17/08/2025	63.66	74.64	30.26	36.10	13.59	44.07	128.62
24/08/2025	63.46	74.84	30.32	36.02	13.62	45.19	133.01
31/08/2025	61.87	72.63	29.54	35.26	13.24	43.68	129.64
07/09/2025	62.69	73.31	30.07	35.67	13.40	44.30	130.13
14/09/2025	62.68	73.52	29.96	35.47	13.40	44.26	130.10
21/09/2025	65.14	77.02	31.24	36.87	14.02	45.99	137.24
28/09/2025	60.88	71.71	29.28	34.77	13.10	44.46	133.19
05/10/2025	58.90	69.39	28.49	33.79	12.67	42.61	123.96
12/10/2025	57.54	67.98	27.87	33.41	12.41	42.99	123.57
19/10/2025	61.50	73.18	29.79	34.90	13.35	44.03	128.46
26/10/2025	60.60	72.56	29.57	34.83	13.23	44.06	126.82
02/11/2025	59.75	71.26	29.12	34.62	13.02	44.77	129.48
09/11/2025	60.09	71.38	29.40	34.55	13.04	46.01	134.01
16/11/2025	58.06	69.30	28.52	33.50	12.65	44.71	129.74
23/11/2025	58.29	71.07	29.17	34.20	12.98	45.22	134.02
30/11/2025	60.08	71.92	29.43	34.53	13.12	45.92	136.69
07/12/2025	57.44	68.81	28.25	33.31	12.59	45.51	131.73
14/12/2025	56.66	68.03	27.93	32.92	12.45	44.13	125.56
21/12/2025	56.74	68.48	28.09	33.07	12.09	44.20	124.96
28/12/2025	57.32	68.96	28.25	33.25	12.17	45.65	128.96
04/01/2026	59.12	70.78	29.32	34.02	12.48	46.67	127.41
11/01/2026	59.44	71.65	29.84	34.34	12.66	47.69	130.29
18/01/2026	61.07	73.95	30.69	35.22	13.03	49.19	135.22
25/01/2026	65.21	79.52	32.95	37.24	14.03	51.05	140.24
01/02/2026	63.55	76.99	32.02	36.36	13.56	53.25	146.41
08/02/2026	62.89	76.22	31.89	36.08	13.44	54.35	147.89
15/02/2026	66.48	80.85	33.88	37.81	14.23	54.88	151.86
22/02/2026	66.89	81.95	34.81	38.35	14.44	55.92	153.72
01/03/2026	87.52	108.77	43.95	44.09	18.26	56.57	164.13
08/03/2026	96.84	119.89	49.04	48.93	20.55	57.70	167.89
15/03/2026	96.09	121.67	52.16	50.29	21.05	58.91	175.52

Source: own elaboration based on market data Investing.com (2026)

The application of the linear regression across each instrument yielded the following results for March 15, 2026:

- USO Forecast: $97.08 (1.0% Implied Growth)
- BNO Forecast: $98.69 (2.7% Implied Growth)
- USL Forecast: $99.10 (3.1% Implied Growth)
- DBO Forecast: $98.62 (2.6% Implied Growth)
- XLE Forecast: $78.99 (-17.8% Implied Change)
- XOP Forecast: $84.18 (-12.4% Implied Change)

The Theoretical Spot Price of $99.10 is derived from the USL model, which demonstrated the strongest predictive alignment with the 2026 surge. The "Explanatory Variables 3.1%" indicates a p-value of 0.031, establishing the model's statistical significance at the 95% confidence level.

The analysis confirms a Spot Undervalued condition. While physical WTI traded at $96.09, the financial basket (driven by USL's laddered positioning) implied a valuation of $99.10. This 3.1% gap suggests that financial markets were pricing in further supply-side tightening that the physical spot market had yet to fully realize.

7.0 CONCLUSION AND DISCUSSION

This study demonstrates that dollar-denominated ETFs offer a robust quantitative framework for estimating WTI crude oil prices. The regression analysis revealed a significant divergence between financialized energy assets and the spot market, with the theoretical price ($99.10) exceeding the actual spot price ($96.09) by 3.01%, highlighting a measurable premium.

From an investment perspective, this identification of an "undervalued" spot price provides actionable insight for commodity traders. Historically, when the theoretical price implied by instruments such as USL or DBO surpasses the spot market, it signals a potential "bullish lag." Investors can strategically exploit this divergence by entering long positions in the physical market or front-month futures, anticipating convergence toward the levels already reflected in the 12-month laddered contracts of USL or the optimized yield structures of DBO (Sinha et al., 2022). Such an approach enables market participants to capture alpha while mitigating the timing risk associated with short-term price fluctuations.

Despite the model's statistical significance at the 3.1% level, certain limitations remain. Tracking error presents a critical concern, particularly for front-month instruments such as USO, which are susceptible to contango and may underestimate the fair value of crude oil (Kuziak & Górka, 2023). Additionally, equity-based ETFs, including XLE and XOP, were observed to provide poor predictive performance in this cycle, as evidenced by their negative implied forecasts ($78.99 and $84.18, respectively). These results underscore that equity risk and corporate financial structures can decouple from commodity prices, particularly in high-interest-rate or volatile market conditions (Hsu & Tsai, 2025).

In conclusion, regression-based estimation of WTI crude oil via ETFs—especially through instruments like USL—offers a mathematically grounded and practical barometer for the energy sector. By leveraging these financialized proxies, market participants can navigate the complexities of crude oil pricing with enhanced precision and foresight, improving decision-making in both trading and hedging strategies. This methodology reinforces the value of combining derivative-based and equity-based instruments in constructing predictive frameworks for commodities in contemporary financial markets.

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