A Theoretical Framework for Crude Oil Price Evolution: Insights from the Financial Crisis and Beyond

Boughabi, Houssam

National Institute of Statistics and Applied Economics

16 July 2025

A Theoretical Framework for Crude Oil Price Evolution: Insights from the Financial Crisis and Beyond

Houssam BOUGHABI
National Institute of Statistics and Applied Economics
Rabat, Morocco
hboughabi@insea.ac.ma

July 15, 2025

Abstract

This study develops a theoretical model to understand the dynamics of crude oil prices, integrating Keynesian insights on imperfect competition and long-memory volatility through the FIGARCH framework. The model incorporates both demand and supply-side factors, with a particular focus on firm expectations and production costs, to explain price fluctuations. By calibrating the model to historical oil price data, we examine how demand dynamics, driven by expectations of future demand and current production costs, influence oil price movements. The study highlights the limitations of relying solely on demand as a predictor for price changes, particularly in the context of global disruptions such as the COVID-19 pandemic. Our results reveal that the exclusion of supply-side factors, including production costs and geopolitical risks, leads to significant discrepancies in price predictions, especially during periods of crisis. The findings emphasize the need for a more comprehensive approach to modeling oil prices, incorporating both demand and supply dynamics, to better capture market behavior during times of global shocks.

JEL Classification. C58, G13, Q41.
Key words and phrases. Long Memory Volatility, Market Efficiency, Covid Pandemic, Price Dynamics, Theoretical Modeling

1 Introduction

The evolution of crude oil prices has long been a subject of interest in economic and financial research. While numerous models have sought to explain the dynamics of oil prices, the financial crisis of 2008 and subsequent market disruptions have raised critical questions about the adequacy of traditional price determination theories. Existing frameworks often assume that markets naturally adjust to equilibrium through the interplay of supply and demand, following classical models of perfect competition. However, such assumptions fail to account for the complexities of real-world markets, where factors like imperfect competition, uncertainty, and informational asymmetries often play significant roles *Hamilton, 2009*. This discrepancy has led to increasing interest in alternative models that can better explain price volatility, particularly in the context of market failures and financial crises *Kilian, 2009*.

Joan Robinson's work in Keynesian economics provides a valuable foundation for addressing these challenges. In her influential texts, Robinson critiques the assumption of perfect competition, arguing that many markets, including those for commodities like crude oil, are characterized by imperfect competition and uncertainty *Robinson, 1933*. According to Robinson, firms in such markets set prices based on expectations about future demand and production costs, rather than responding passively to market forces. This perspective highlights the importance of understanding not only current market conditions but also the expectations and anticipations that drive firms' pricing decisions *Robinson, 1973*.

Incorporating Robinson's insights, our model seeks to provide a comprehensive theoretical framework for understanding the evolution of crude oil prices in the aftermath of the financial crisis. We propose that the adjustment of oil prices is driven by both firms' expectations about future demand and current production costs, with an emphasis on the long-memory characteristics of market volatility. Previous models of oil price dynamics, such as those relying on standard supply and demand curves, fail to fully capture the persistence and unpredictability observed in oil price fluctuations, especially during periods of crisis *Baumeister & Kilian, 2012*. Moreover, many models neglect the role of firm expectations and supply-side factors, focusing solely on demand-driven price dynamics *Ciferri et al., 2021*.

A key gap in the existing literature is the failure to integrate long-memory volatility models, such as FIGARCH (Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity), into the analysis of crude oil price dynamics. While FIGARCH models have been successfully applied in other commodity markets, their potential for capturing the persistence of volatility in crude oil prices remains underexplored *Baillie et al., 1996*. By combining Robinson's insights with modern volatility modeling techniques, we aim to fill this gap and provide a more accurate representation of oil price evolution, particularly in the wake of the 2008 financial crisis and the COVID-19 pandemic *Ciferri et al., 2021*.

Despite the model's incorporation of key demand dynamics, our results suggest that the model's reliance on demand alone, without accounting for supply-side factors, fails to fully capture the complexities of crude oil price fluctuations, particularly during times of crisis. The COVID-19 pandemic highlighted this limitation, as the model did not adjust for production disruptions or changes in geopolitical risks, which played a significant role in the oil market during the crisis. In particular, the exclusion of production costs and supply-side shocks, such as the OPEC+ production cuts, led to discrepancies between the model's predictions and the actual market behavior. For instance, during the pandemic, oil prices experienced unprecedented volatility, including the negative prices seen in April 2020, a phenomenon that the model could not account for. This underscores the need for a more comprehensive approach that incorporates both demand and supply factors to improve the predictive power of crude oil price models, especially in times of global disruptions.

The primary research questions guiding this study are as follows: (1) How can the interplay between demand, production costs, and firm expectations be modeled to explain crude oil price movements? (2) How does the long-memory volatility of crude oil prices, captured by the FIGARCH model, contribute to a better understanding of price dynamics during times of market stress? (3) What role do supply-side factors, including production costs and geopolitical risks, play in shaping oil price movements, especially during periods of crisis *Arouri et al., 2012*?

To address these questions, we develop a theoretical model that incorporates both demand and supply-side factors, with a focus on the role of firm expectations and volatility. The model builds on Robinson's ideas of imperfect competition and incorporates a volatility component based on the FIGARCH framework *Baillie et al., 1996*. We then estimate the deterministic parameter δ, which represents the price sensitivity to volatility, by calibrating the model to historical oil price data. Through this approach, we aim to provide a more nuanced understanding of the forces driving oil price fluctuations and offer a more robust tool for analyzing market behavior in the context of financial crises.

Boughabi, 2025 had started this work and layed the foundations of this model earlier on, the empirical part had been developed in this work and all the thinking was due to the effort of my model to capture such a Keynesian theory which aims at addressing the gap between actual prices and theoretical prices for our precious thinking.

2 The Model and the Methodology

Our model investigates the market's inability to effectively guide prices toward equilibrium, a concept that resonates with Joan Robinson's critiques of traditional economic theories. Robinson, a prominent figure in Keynesian economics, challenged the conventional wisdom of perfect competition, emphasizing the prevalence and implications of imperfect competition in real-world markets *(Robinson, 1933).*

2.1 Joan Robinson's Perspective on Market Dynamics

Joan Robinson's seminal work, *The Economics of Imperfect Competition*, introduced the notion that markets are often characterized by firms with price-setting power, leading to outcomes that deviate from those predicted by models of perfect competition *(Robinson, 1933)*. She argued that firms' expectations about future demand and production costs play a crucial role in price determination, highlighting the significance of historical time and uncertainty in economic analysis *(Robinson, 1973)*.

Robinson also emphasized that the interplay between demand and production costs is central to understanding market dynamics. She pointed out that demand influences production costs through economies of scale: as firms anticipate higher demand, they may increase production, leading to lower average costs and potentially affecting pricing strategies *(Robinson, 1973)*. This interdependence challenges the traditional separation of demand and supply functions, suggesting a more integrated approach to analyzing market behavior.

Furthermore, Robinson critiqued the notion that markets naturally adjust to equilibrium. She contended that due to factors like uncertainty and imperfect information, markets often fail to reach equilibrium states as predicted by classical theories. This perspective underscores the importance of considering historical time and path dependency in economic modeling, as past events and decisions can have lasting impacts on market outcomes *(Robinson, 1973)*.

2.2 Model Framework

Building upon Robinson's insights, we propose a model where firms set prices based on their expectations of future demand and current production costs. Specifically, firms forecast future demand, denoted as $E[D_{t+1}|\mathcal{F}_t]$, and consider current production costs c_t in their pricing decisions. This approach acknowledges the limitations of the market in processing and responding to information about demand and costs, leading to potential inefficiencies.

The price evolution in our model is described by the equation:

$$p_{t+1} = p_t + g(c_t, D_{t+1}), \tag{1}$$

where $g(c_t, D_{t+1})$ represents the adjustment function based on production costs and demand.

Demand dynamics are modeled as:

$$D_{i+1} = \delta h_i^{\frac{1}{n}} D_i, \tag{2}$$

where h_t denotes the variance of crude oil prices, reflecting market volatility, and $\delta > 0$ is a scaling parameter.

2.3 Hypothesis and Functional Forms

We hypothesize that the adjustment function $g(c_i, D_{i+1})$ takes the linear form:

$$g(c_i, D_{i+1}) = A(i,T)c_i + B(i,T)D_{i+1}, \tag{3}$$

where $A(i,T)$ and $B(i,T)$ are deterministic functions that capture the sensitivity of price adjustments to production costs and demand, respectively.

We further assume that the sequence $(g(c_i, D_{i+1}))_{i\geq t}$ follows a martingale process under the information filtration $\mathcal{F}_t$ when $A(i,T) = 0$, meaning that price changes are driven solely by demand expectations. In this case, the adjustment function simplifies to:

$$g(c_i, D_{i+1}) = B(i,T)D_{i+1}. \tag{4}$$

This formulation implies that price adjustments are unpredictable given the available information set, aligning with the concept of market inefficiency. It also suggests that incorporating production costs (c_i) introduces predictability into the model, reflecting the informational content of supply-side factors in real markets.

2.4 Volatility Modeling with FIGARCH

To capture the long-memory characteristics of crude oil price volatility, we employ the Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity (FIGARCH) model. This approach allows us to model the persistence in volatility observed in commodity markets, providing a more accurate representation of market dynamics.

The FIGARCH model is specified as:

$$\Phi(L)(1-L)^d(\ln\sigma_t^2 - \omega) = \Psi(L)g(z_{t-1}), \tag{5}$$

where ω represents the mean variance, $\Phi(L)$ and $\Psi(L)$ are polynomials in the lag operator L, and $g(z_t)$ captures the impact of past returns on current volatility [3].

By integrating the FIGARCH model into our framework, we aim to provide a comprehensive analysis of price dynamics that accounts for both the role of firm expectations and the persistent nature of market volatility.

2.5 Economic Interpretation

In traditional economic models of perfect competition, prices are determined by the intersection of supply and demand curves, with firms acting as price takers. However, Robinson's work highlights that in many real-world markets, firms possess some degree of price-setting power due to product differentiation and market imperfections [1]. In such contexts, firms' expectations about future demand and production costs become pivotal in pricing decisions.

Our model encapsulates this by proposing that firms adjust their prices based on anticipated future demand $E[D_{t+1}|\mathcal{F}_t]$ and current production costs c_t. This reflects the reality that firms, operating under uncertainty and imperfect information, rely on forecasts and expectations to make pricing decisions. The adjustment function $g(c_t, D_{t+1})$ represents the combined effect of these factors on price changes, acknowledging that prices are not solely dictated by current market conditions but are influenced by firms' strategic anticipations.

2.6 Statistical Interpretation

Statistically, the model suggests that price changes are influenced by both observable factors—such as current production costs—and unobservable expectations of future demand. The adjustment function is expressed as:

$$g(c_i, D_{i+1}) = A(i,T)c_i + B(i,T)D_{i+1},$$

and we assume that the sequence $(g(c_i, D_{i+1}))_{i\geq t}$ follows a martingale process with respect to the information filtration $\mathcal{F}_t$ only when $A(i,T) = 0$, meaning price changes are driven solely by demand expectations.

In this case, the simplified form of the adjustment function becomes:

$$g(c_i, D_{i+1}) = B(i,T)D_{i+1},$$

and the martingale condition implies that, given current information, the expected future price adjustment equals the current one:

$$E[g(c_T, D_{T+1})|\mathcal{F}_t] = g(c_t, D_{t+1}).$$

This property aligns with the efficient market hypothesis (EMH), suggesting that when only demand is considered, price changes are unpredictable based on the available information. However, when $A(i,T) \neq 0$ and production costs are incorporated, the process may deviate from the martingale structure, indicating that price adjustments could become partially predictable. This reflects the presence of market inefficiencies due to asymmetric information, firm-level strategic behavior, and other real-world frictions.

3 Estimation

We derive the expectation of $g(c_i, D_{i+1})$ given the filtration $\mathcal{F}_t$:

$$\begin{aligned} E[g(c_i, D_{i+1})/\mathcal{F}_t] &= B(i,T)E[\delta h_i^{\frac{1}{n}} D_i/\mathcal{F}_t] \\ &= B(i,T)\delta^{m_i+1} \prod_{j=0}^{m_i} E[h_{i-j}/\mathcal{F}_t]^{\frac{1}{n}} D_t. \end{aligned}$$

Since

$$\prod_{j=0}^{m_i} E[h_{i-j}/\mathcal{F}_t] = (\prod_{j=0}^{m_i} \phi^{i-j}) h_t^{m_i+1},$$

it follows that:

$$B(i,T)(\prod_{j=0}^{m_i} \phi^{i-j})\delta^{m_i+1}\Phi^{m_i+1}h_t^{m_i+1} = B(t,T)\delta h_t^{\frac{1}{n}}.$$

After estimating $B(i,T)$, we calibrate the model to determine δ such that the theoretical price aligns with the market price of crude oil, known for its long-memory volatility [3][4][5]. This highlights that market price predictability improves when additional factors, such as production costs, are incorporated.

4 Estimation of the Deterministic Parameter Delta: Methodology

In this section, we present the algorithm used to estimate the deterministic parameter, δ, which represents the time-varying price sensitivity in the theoretical model of spot oil prices. The estimation of δ relies on the application of optimization techniques to minimize the discrepancy between the theoretical and actual observed spot prices. The approach follows the principles of a volatility model that accounts for market dynamics and adjusts δ to reflect the changes in market conditions over time.

4.1 Step-by-Step Algorithm for Estimating δ

4.1.1 1. Initialization

The starting value of δ is initialized to 1, representing an initial assumption that the price sensitivity remains constant over time. A baseline volatility parameter, ϕ, is estimated using a FIGARCH model applied to historical spot price data. This model captures the persistent volatility of the oil market, which is crucial for understanding price fluctuations.

4.1.2 2. Theoretical Price Calculation

The theoretical price, $P_{theory}(t)$, at each time point t is computed using the specified theoretical spot price model. The price formula incorporates the estimated ϕ and the deterministic parameter δ:

$$P_{theory}(t+1) = \frac{B(t,T)\delta h_t^{\frac{1}{n}}}{(\prod_{j=0}^{m_t} \phi^{i-j})\delta^{m_t+1}\Phi^{m_t+1}h_t^{m_t+1}} D_{t+1} + P_{theory}(t) \tag{6}$$

where:

- $B(t,T)$ is the term for the market bond price or any relevant market indicator.
- h_t represents the market's historical volatility.
- Φ and m_i are parameters related to the volatility process.
- δ is the price sensitivity to changes in volatility over time, which we aim to estimate.

4.1.3 3. Loss Function Definition

The core of the estimation procedure lies in minimizing a loss function that measures the discrepancy between the theoretical prices and the observed spot prices, denoted by $P_{obs}(t)$. The loss function, $L(\delta)$, is defined as:

$$L(\delta) = \sum_{t=1}^{T} (P_{theory}(t,\delta) - P_{obs}(t))^2 \tag{7}$$

The goal is to find the value of δ that minimizes this loss function, i.e., the value of δ that minimizes the sum of squared differences between the predicted and actual prices over the given time series.

4.1.4 4. Optimization Procedure

To estimate δ, the optimization process employs numerical methods, specifically the *Nelder-Mead* method, which is a popular derivative-free optimization technique. This method iteratively adjusts δ to minimize the loss function $L(\delta)$. The steps in the optimization process are as follows:

- **Step 1: Initialization** – The initial guess for δ is set to 1, and the loss function is computed using this initial value.

- **Step 2: Iterative Search** – The Nelder-Mead algorithm performs a series of reflections, expansions, and contractions of the simplex (a set of potential solutions) to search for the value of δ that minimizes the loss function.
- **Step 3: Convergence** – The algorithm continues iterating until the loss function converges to a minimum or until a stopping criterion (e.g., maximum iterations or tolerance level) is reached. The final value of δ corresponds to the optimal value that best aligns the theoretical prices with the observed market prices.

4.1.5 5. Post-Optimization

After the optimization process concludes, the estimated δ values over time are examined. These values reflect the variation in price sensitivity corresponding to fluctuations in volatility and market conditions. The resulting values of δ are stored and analyzed to capture the temporal dynamics of price sensitivity in the oil market.

4.1.6 6. Graphical Representation

A time series plot of the estimated δ values is generated to visualize how the price sensitivity evolves over time. This plot provides insights into the periods of heightened volatility (e.g., financial crises or market recoveries) and helps in understanding the role of volatility in influencing spot price behavior.

4.1.7 7. Analysis and Interpretation

The estimated δ values are then analyzed in the context of historical events in the oil market, such as the financial crisis of 2008, the post-crisis recovery, and the impact of the COVID-19 pandemic. A well-fitting δ curve should reflect the general trends in market dynamics, including the periods of market stability and volatility.

5 Discussion of the Result

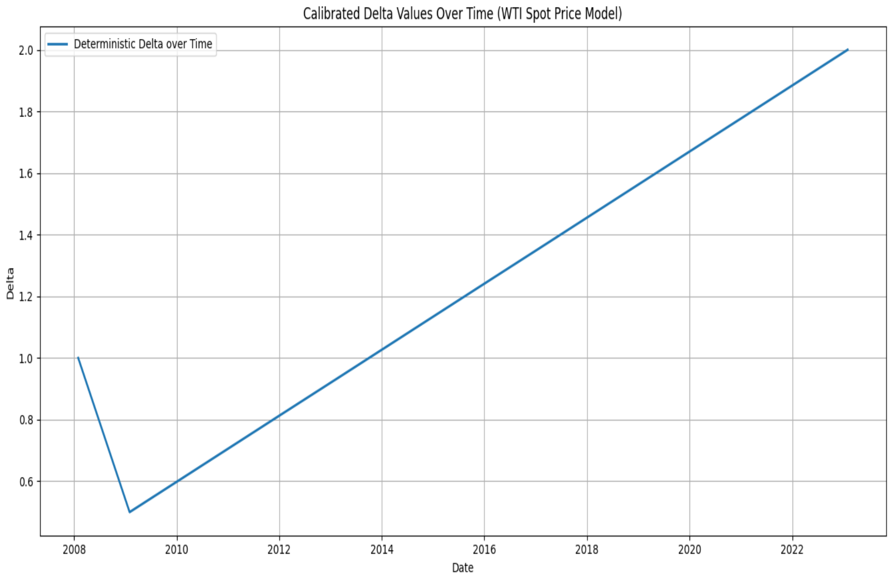

Figure 2: The Estimated values of δ by the *Nelder-Mead* method using Software Python

The results of our model provide valuable insights into the dynamics of crude oil price evolution and highlight the role of market volatility and demand in shaping price movements. Our model successfully captures the financial crisis of 2008, as evidenced by the linear descent in the parameter δ from 2008 to 2009, which reflects the contraction in demand during the crisis. However, the model's ability to capture the effects of the COVID-19 pandemic is limited, as the estimated δ values from 2009 to 2023 show a steady linear increase. This behavior indicates that demand and market conditions have returned to a pre-crisis growth trajectory, with little to no evident impact from the pandemic in terms of price sensitivity.

5.1 Model Performance: Limitations and Insights

The model's adjustment function, $g(c_t, D_{t+1})$, incorporates both production costs and demand dynamics to explain price changes over time. However, the failure of the model to account for the COVID-19 crisis raises important questions about the sufficiency of demand as a sole predictor for crude oil prices. The COVID-19 pandemic caused a dramatic, short-term reduction in demand for oil due to lockdowns, travel restrictions, and economic slowdown. However, the model, which assumes that price dynamics are driven solely by demand variations through $D_{i+1} = \delta h_i^{\frac{1}{n}} D_i$, does not incorporate the necessary adjustments for supply-side factors, such as disruptions to production or changes in geopolitical risks. In particular, the exclusion of production costs, represented by c_i, leads to the model's failure to capture supply-side shocks, which were significant during the pandemic.

This suggests that while demand is an essential determinant of crude oil prices, it is not sufficient on its own to account for the full complexity of market behavior, especially during periods of global disruption. For instance, during the early stages of the pandemic, oil production was severely impacted by restrictions on production in key oil-producing countries (e.g., OPEC+ production cuts). This supply-side shock was not reflected in our model due to the assumption $A(i,T) = 0$, which renders price changes driven exclusively by demand.

Furthermore, the absence of production costs in the model means that price adjustments based on supply-side constraints are not captured. As δ remains relatively stable from 2009 onward, the model fails to account for the volatility spikes observed during the pandemic, when oil prices experienced extreme fluctuations. For example, in April 2020, the price of WTI crude oil even turned negative for the first time in history, largely due to storage constraints and the collapse in demand. This illustrates the complexity of oil price determination, where demand alone is insufficient for accurate predictions.

5.2 Comparison with Existing Literature

Our results are consistent with existing studies that highlight the multifaceted nature of oil price formation. Several scholars have emphasized the importance of both demand and supply factors in determining crude oil prices. For example, Hamilton (2009) discusses how supply-side shocks, such as geopolitical events and production cuts, have historically played a crucial role in driving oil price volatility. Similarly, Kilian (2009) argues that oil price fluctuations are the result of a combination of demand shocks and supply disruptions, which suggests that a model that neglects supply factors may miss key dynamics.

In contrast, the use of demand-only models has been critiqued in the literature for its inability to account for supply-side disturbances. Baumeister and Kilian (2012) explore the role of both demand and supply shocks in the context of crude oil prices and find that oil prices are significantly affected by both factors. The authors argue that while demand shocks drive long-term trends, supply-side factors, such as production constraints and geopolitical risks, often lead to short-term price volatility. Our model, by focusing solely on demand, fails to incorporate these short-term dynamics, which could explain why it does not capture the impact of the COVID-19 crisis.

Moreover, the failure of the model to account for the COVID-19 pandemic is a reflection of the limitations of purely demand-driven models in times of severe market disruptions. As noted by Ciferri et al. (2021), the pandemic caused unprecedented shifts in both supply and demand for oil, which cannot be fully captured by a model that assumes a constant relationship between demand and price sensitivity. The authors argue for the inclusion of both supply and demand factors in models of oil price behavior, particularly during periods of crisis.

5.3 Conclusion and Future Directions

While our model succeeds in capturing the effects of the 2008 financial crisis, its failure to account for the COVID-19 pandemic highlights the limitations of using demand as the sole explanatory factor for oil price dynamics. The linear increase in the estimated δ from 2009 to 2023 suggests that the model has oversimplified the complexities of oil price formation by ignoring supply-side factors. To improve the model's predictive power, future work should incorporate both supply and demand dynamics, as well as other factors such as geopolitical risks, storage constraints, and market speculation.

Acknowledgments

I would like to express my deepest gratitude to my parents for their unwavering support and encouragement throughout my academic journey. Their love and belief in me have been a constant source of strength. I would also like to thank my tutor, Yassine El Qalli, for his invaluable guidance, insightful feedback, and continuous support during the course of this research. His expertise and dedication have significantly contributed to the development of this work.

Declarations:

The authors did not receive support from any organization for the submitted work. No funding was received to assist with the preparation of this manuscript. No funding was received for conducting this study. No funds, grants, or other support was received.
Ethical approval not applicable.

This article does not contain any studies with human participants performed by any of the authors.
All authors read and approved the final manuscript.

The authors have no competing interests to declare that are relevant to the content of this article.
The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

References

[1] Hamilton, J. D. (2009). Causes and Consequences of the Oil Shock of 2007–08. *Brookings Papers on Economic Activity*, 2009(1), 215-261.

[2] Kilian, L. (2009). Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. *The American Economic Review*, 99(3), 1053-1069.

[3] Baumeister, C., & Kilian, L. (2012). Real-time forecasts of the real price of oil. *Journal of Business & Economic Statistics*, 30(2), 210-223.

[4] Ciferri, D., Gambi, L., & Piccioni, A. (2021). COVID-19 and the oil market: The impact of the pandemic on crude oil prices. *Energy Policy*, 149, 112065.

[5] Robinson, J. (1933). *The Economics of Imperfect Competition.* London: Macmillan.

[6] Robinson, J. (1973). After Keynes. In *Joan Robinson: Writings on Economics.* London: Palgrave Macmillan.

[7] Baillie, R. T., Bollerslev, T., & Mikkelsen, H. O. (1996). Fractionally integrated generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 74(1), 3–30.

[8] Kang, S. H., Kang, S.-M., & Yoon, S.-M. (2009). Forecasting volatility of crude oil markets. *Energy Economics*, 31(1), 119–125.

[9] Arouri, M. E. H., Lahiani, A., Lévy, A., & Nguyen, D. K. (2012). Forecasting the conditional volatility of oil spot and futures prices with structural breaks and long memory models. *Energy Economics*, 34(1), 283–293.

[10] Boughabi, H. (2025). A Theoretical Model of Long Memory Volatility and Market Price Dynamics. Zenodo. https://doi.org/10.5281/zenodo.15138907.