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An Introduction to Commodity Volatility Trading

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ABSTRACT

This paper surveys volatility-trading strategies commonly employed by professional commodity traders and market makers. It explains how many of these strategies arise from hedging imbalances across option strikes and maturities. The importance of the real optionality embedded in physical commodity assets — and the need to hedge the associated risks — has contributed to the rapid growth and increasing complexity of commodity derivatives markets.

Commodity volatility-trading strategies can be grouped broadly into three categories: short-term gamma trading, volatility-smile arbitrage, and trading in over-the-counter exotic options. Gamma trading seeks to harvest the volatility risk premium embedded in short-dated commodity options, with performance depending critically on the choice of hedging strategy. Volatility-smile arbitrage relies on pricing models that capture commodity-specific features; the paper presents one such model. Model choice also affects the valuation of exotic options, as illustrated by a binary option whose payoff resembles that of contracts traded in prediction markets.

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Volatility Trading and Hedging-Driven Imbalances

As explained in CQL's "Introduction to Market Participants and Behavioral Trading in Commodities," commodity markets are shaped by the real optionality embedded in many physical assets.¹ Producers and asset owners typically hold this optionality and may benefit from market volatility, whereas for commodity consumers it often represents a liability, leaving them naturally short volatility. It is therefore not surprising that both groups use financial options with comparable risk profiles to manage the nonlinear effects of commodity price movements on their businesses.

Unlike futures, which allow traders to take a view primarily on the mean of the future price distribution, options offer greater flexibility by allowing them to trade the shape of the entire distribution. Hedging imbalances between buyers and sellers in futures markets are therefore relatively easy to correct: apparent mispricing attracts additional speculators, helping to restore equilibrium. Options markets, by contrast, are far more granular. Imbalances can arise across different parts of the probability distribution, driven by mismatches in end-user supply and demand for options with specific strikes and maturities.

These imbalances are far more difficult to correct because the highly customized needs of producers and consumers rarely offset one another precisely. Speculators also cannot respond quickly to perceived opportunities because barriers to entry in commodity options markets are substantially higher. Trading commodity volatility requires significant upfront investment in specialized option-pricing and data infrastructure that cannot be readily adapted from financial markets. Perhaps more importantly, critical information about fundamental and hedging flows is closely guarded by a relatively small group of professional physical traders and over-the-counter derivatives dealers, leaving only limited information about these flows available to the public.

Commodity volatility trading can be broadly divided into three categories. The first encompasses strategies that seek to harvest the volatility risk premium (VRP) embedded in short-dated commodity options, an approach commonly known as gamma trading. The second consists of volatility-arbitrage, or vega-trading, strategies in which traders take the opposite side of short-term hedging imbalances and warehouse the resulting positions until they can rebalance exposures across specific strikes and maturities. The third includes over-the-counter (OTC) and exotic options. These include digital options, which are rapidly gaining popularity because of their similarity to prediction-market contracts, as well as

¹ See Bouchouev (2026).

average-price and spread options, whose payoffs naturally arise from the ownership of physical assets such as storage facilities, pipelines, and refineries.

The Volatility Risk Premium and Gamma Trading

The volatility risk premium can be understood as an extension of the risk premium commonly associated with insurance. Commodity options resemble insurance contracts, with the option's strike price serving a role similar to an insurance policy's deductible. Because an insurer assumes the possibility of a large, asymmetric loss, it generally expects compensation for bearing that risk, and insurance products are therefore typically sold at a premium to their fair value. Similarly, selling commodity options is expected to be profitable because the option seller must be compensated for assuming substantial asymmetric risk.

Commodity options differ from traditional insurance contracts, however, particularly in how their fair value is determined. Insurers generally price policies using actuarial methods: they estimate the average hypothetical payouts that similar contracts would have generated historically and then add a risk premium as compensation for bearing the risk. Professional commodity traders, by contrast, value options based on the cost of dynamically replicating their payoffs through a strategy known as delta hedging. These two valuation methods can produce substantially different fair values, creating trading opportunities among market participants who approach option pricing from different perspectives.²

Over the long run, the actuarial values of many commodity options tend to exceed their volatility-based values. Under the actuarial approach, option values rise during episodes of strong momentum and market breakouts, which widen the range of futures prices and can generate substantial losses for unhedged option sellers. By contrast, such large directional moves have a more limited effect on delta-hedged short-option positions because gains on the futures hedge offset part of the losses on the options.

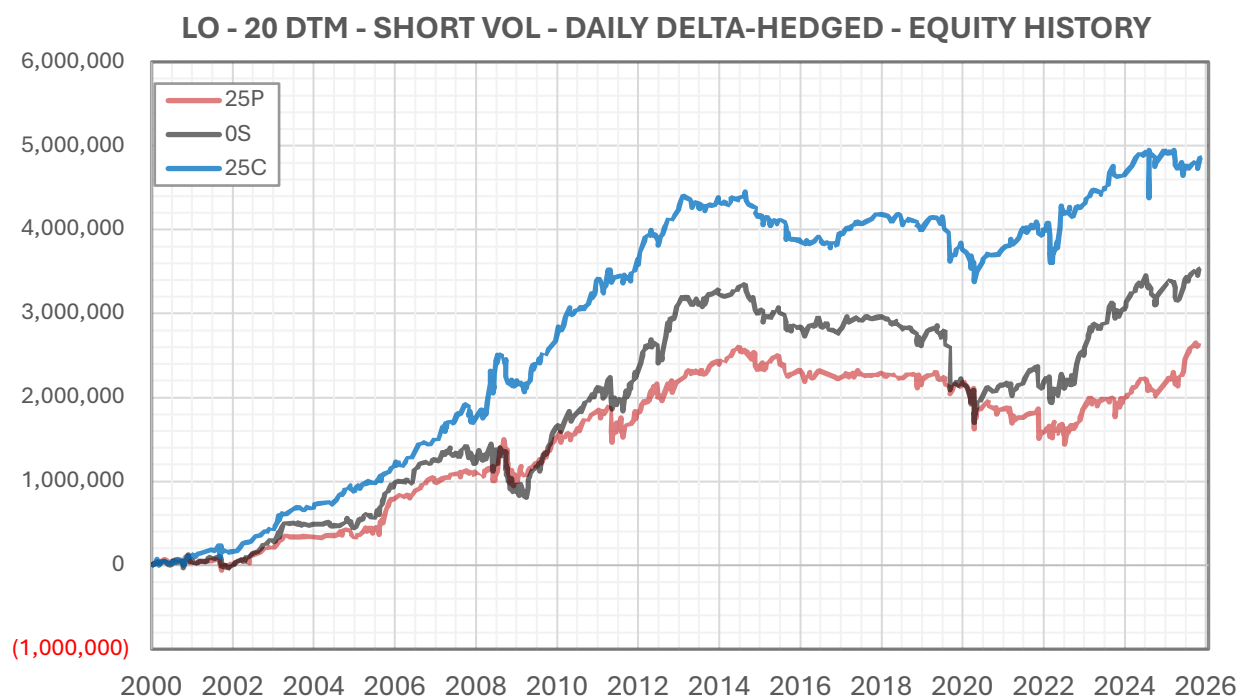
Commodity end users therefore tend to evaluate options through an actuarial lens that reflects the price risks and profitability of their underlying businesses. Because actuarial valuations are generally higher, these users may view commodity options as reasonably priced. Volatility dealers, by contrast, manage risk through delta hedging and rely on volatility-based valuations, under which the same options may appear expensive. Selling these options and dynamically hedging the resulting exposure can therefore present dealers with an attractive opportunity to earn what is known as the volatility risk premium.

² See Bouchouev (2023), Chapter 9.

The existence of a volatility risk premium in commodity markets has likely been recognized by practitioners since the earliest days of commodity options trading. The topic has also received considerable attention in the academic literature.³

To illustrate the VRP from a market practitioner's perspective, Figure 1 presents the strategy's historical performance using the methodology developed by Bouchouev and Johnson (2022).

Figure 1. Historical performance of the VRP strategy



Source: Bouchouev and Johnson (2022) with results extended by the authors through 2025.

In this strategy, the volatility dealer systematically sells 50 WTI zero-delta straddles, along with 100 25-delta puts and 25-delta calls, all with 20 days to expiration, and delta-hedges the positions daily using the industry-standard Black (1976) model. It is important to emphasize that daily hedging with Black-model deltas is only one of several techniques employed by professional volatility traders. Each technique produces a different hedging cost and, consequently, a different return profile for the VRP strategy.

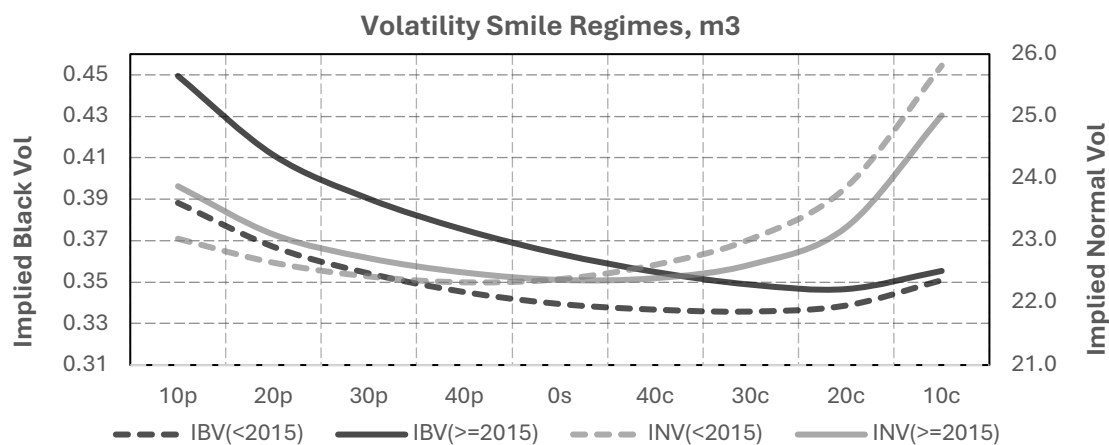
³ See, Doran and Ronn (2006, 2008), Trolle and Schwartz (2010), Kang and Pan (2015), Prokopczuk et al. (2017), Ellwanger (2017), Christoffersen and Pan (2018), Bouchouev and Johnson (2022), and Jacobs and Li (2023), among others.

Volatility-Smile Arbitrage and Vega Trading

As noted above, volatility arbitrage and vega trading differ fundamentally from strategies that harvest a structural, long-term risk premium. Instead, they seek to exploit short-term mispricings created by end-user hedging flows. Dealers can earn a liquidity premium or acquire options at a discount to prevailing market prices by taking the other side of these flows, but they may need time to unwind unwanted exposures across strikes and maturities. Although the liquidity premium on the initial transaction is recognized immediately, subsequent hedging costs can erode profitability over time. Because a typical volatility market-making portfolio may contain dozens or even hundreds of strikes, the success of volatility arbitrage ultimately depends on the choice of pricing model. The model enables market makers to assess whether an option is relatively cheap or expensive and to hedge the portfolio consistently.

The one-parameter Black (1976) model, which assumes a lognormal price distribution, is not well suited to this purpose. In practice, matching market prices requires traders to assign different implied Black volatilities (IBVs) to different strikes, producing the pattern known as the volatility smile and revealing the limitations of the model's lognormal assumption. The two darker lines in Figure 2 show the average historical IBV smiles for the oil market over two periods. Moneyness is expressed in delta terms, consistent with how professional volatility traders typically monitor the smile. The periods lie on either side of the regime breakpoint identified in Bouchouev (2023), which was associated with significant behavioral changes among major market participants. The steeper IBV smile in the later period indicates a further departure from the lognormal distribution assumed by the Black model.

Figure 2. Implied volatility smiles under lognormal and normal models



Source: Bouchouev, Johnson, and Sun (2026).

As Figure 2 shows, out-of-the-money puts tend to trade at higher IBVs than out-of-the-money calls. This does not imply that oil puts are structurally more expensive than oil calls. Rather, it indicates that oil prices do not follow the simple lognormal distribution assumed by the Black (1976) model. The market instead appears to follow an unknown distribution with a substantially heavier left tail than the lognormal distribution.

Many commodity traders instead favor the simple and widely used model developed by Bachelier (1900). By assuming a normal distribution, the model partly addresses the problem by eliminating the artificial skew introduced by the lognormal assumption. Some traders joke that applying a lognormal model to commodities is like prescribing corrective lenses for astigmatism to someone who does not have it: the result is inevitably distorted vision. When the Bachelier formula is inverted across different levels of moneyness to calculate implied normal volatility (INV), the resulting volatility smile is considerably more symmetric. As Figure 2 shows, the INV smile in the current regime is nearly parabolic.

Removing the artificial skew introduced by the lognormal assumption is a clear improvement. Nevertheless, the nonlinear shape of the INV smile still requires dealers to use higher normal volatilities to match market prices for both out-of-the-money puts and calls. This suggests that the normal distribution fails to capture the fat tails characteristic of commodity price distributions. In short, the one-parameter Black and Bachelier models are too simple to represent the richer dynamics of the oil market. A more advanced model is therefore needed to price and hedge a volatility portfolio effectively — and selecting such a model lies at the heart of volatility arbitrage.

Our purpose is not to survey the many option-pricing methodologies used in financial markets to arbitrage the volatility smile.⁴ Commodities also have numerous specialized so-called reduced-form term-structure models, but these models serve a different purpose and have limited applicability to smile arbitrage.⁵ They typically contain too many parameters, making it difficult to maintain stable parameter estimates over time — a critical requirement for arbitrageurs.

Volatility market makers generally prefer models with only a few intuitive parameters. One such framework is the SABR model, which has four parameters governing the initial volatility

⁴ See, for example, Gatheral (2006), Derman and Miller (2016), and references therein, for various approaches to modeling volatility smile in financial markets.

⁵ See Trolle and Schwartz (2009), Chiarella et al. (2013), Trolle (2014), Cortazar et al. (2017), Schneider and Tavin (2018), Kang et al. (2020), Crosby and Frau (2022), Alfeus et al. (2024), among others.

level, the volatility of volatility, the exponent that shapes the skewness of the price distribution, and the correlation between prices and stochastic volatility.⁶

Like many option-pricing frameworks, the SABR model was originally developed for financial markets, where the assumption of an asymmetric price distribution is often more appropriate than it is for commodities. Prices of many commodities, including oil, fluctuate cyclically in response to recurring shifts in the supply of and demand for physical products, producing pronounced booms and busts of broadly similar magnitude. Compared with financial assets, commodity prices therefore tend to exhibit more symmetric behavior, while experiencing larger and more frequent moves in both directions than either normal or lognormal distributions imply.

For example, oil futures prices fell below zero in 2020, immediately invalidating many conventional option-pricing models developed for financial markets.⁷ Prices in other commodity markets can also turn negative. Examples include natural gas at locations affected by transportation bottlenecks and electricity in markets where growing solar generation coincides with limited battery-storage capacity. Commodity markets are also prone to extreme price movements that can be substantially larger than those typically observed in financial markets.

To demonstrate the value of a commodity-specific framework, we present a practical and intuitive alternative: the quadratic normal model (QNM) developed by Bouchouev (2023). The QNM assumes that the underlying futures price follows a diffusion process with quadratic local volatility. For many commodities, volatility tends to be lower when futures prices remain within a fundamentally normal range, but rises rapidly as prices move away from that range in either direction. The model is motivated by the approximately parabolic shape of the INV smile shown in Figure 2. It yields a simple pricing formula that extends the Bachelier normal model to account for skewness and kurtosis.

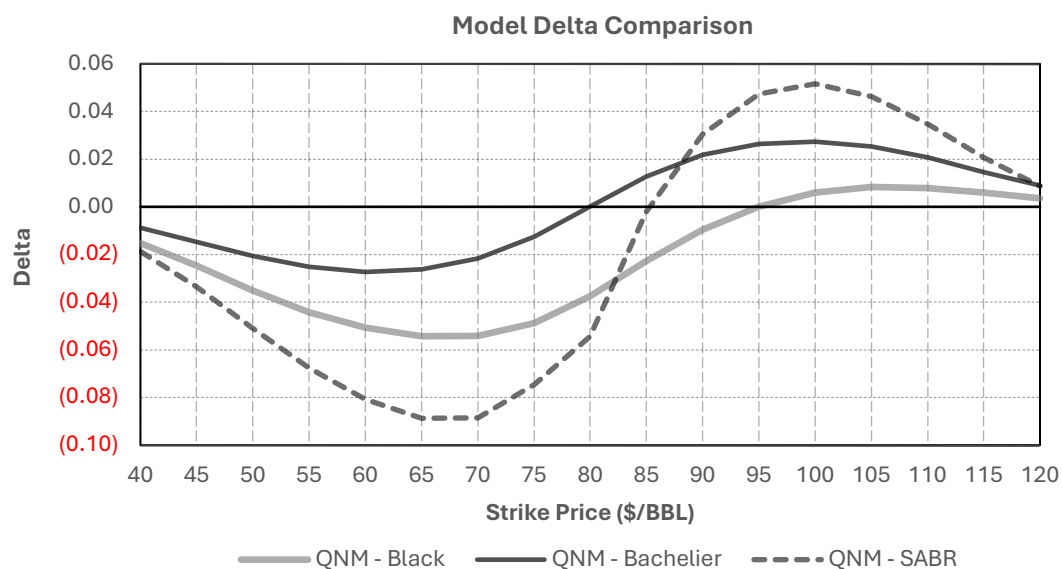
The QNM has three parameters that broadly correspond to the variance, skewness, and kurtosis of the underlying price distribution. These parameters can be calibrated directly to the market prices of three benchmark commodity option structures: an at-the-money (ATM) straddle; a producer's costless collar, in which the cost of an out-of-the-money put is offset by the premium received from selling an equally valued out-of-the-money call; and an out-of-the-money strangle.

⁶ See Hagan et al. (2002).

⁷ Bouchouev (2023, Chapter 3) provides a detailed account of this episode, in which financial squeeze on certain market participants led to negative oil prices.

SABR and QNM can fit market prices with comparable accuracy, yet they imply markedly different hedging dynamics. Figure 3 compares their hedge deltas across a range of strikes and, for completeness, includes those produced by the Black and Bachelier models. Although all four models are calibrated to the same option prices, they generate substantially different hedge ratios. No single model performs consistently better across all market conditions. For a detailed discussion of the models' calibration to the oil market over a 25-year period, as well as the advantages and limitations of these hedging approaches under different market regimes, see Bouchouev, Johnson, and Sun (2026).

Figure 3. Hedge deltas implied by the Bachelier, Black, SABR, and QNM models



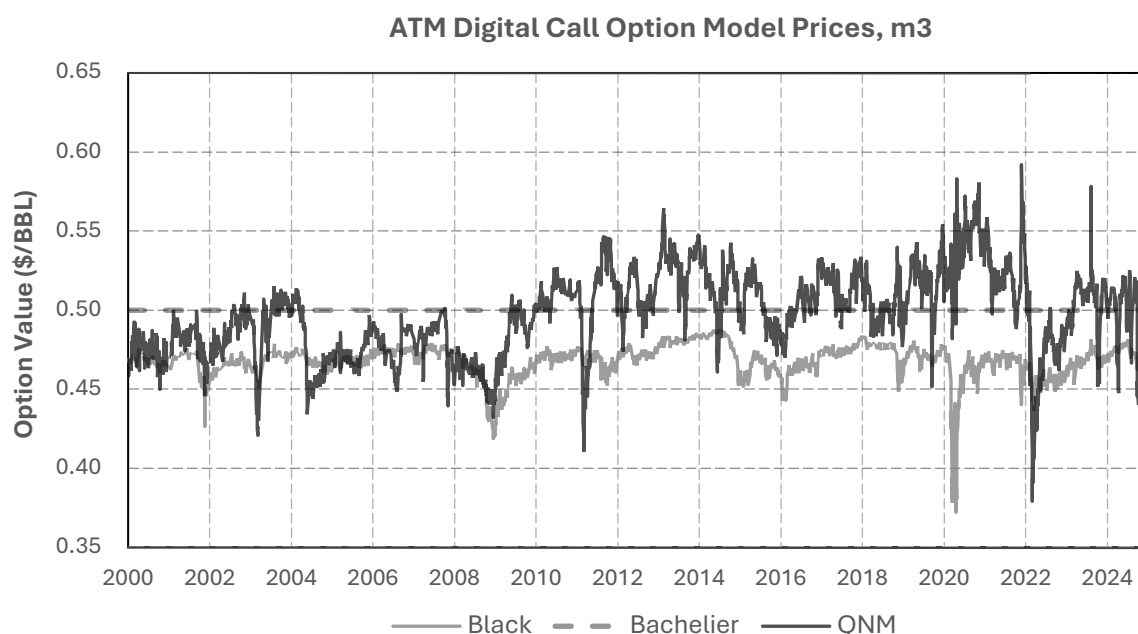
Source: Bouchouev, Johnson, and Sun (2026).

Pricing and Trading Exotic Options

To illustrate how model selection affects the pricing of exotic or nonstandard commodity options, consider a simple digital, or binary, option. At expiration, a digital call pays one dollar if the futures price is above the strike, while a digital put pays one dollar if the futures price is below the strike; otherwise, each pays zero. These options are gaining popularity alongside the rapid growth of prediction-market contracts, which share the same all-or-nothing payoff structure.

Figure 4 compares the time series of model-implied values for an at-the-money (ATM) binary oil option under the lognormal (Black), normal (Bachelier), and QNM frameworks, assuming a zero interest rate for simplicity. The SABR model is omitted because its binary-option values are virtually identical to those produced by the QNM. Unlike delta hedging, this comparison depends only on the terminal price distribution, and SABR and QNM produce similarly accurate fits to the volatility smile.

Figure 4. Binary-option values under the normal, lognormal, and QNM frameworks



Source: Bouchouev, Johnson, and Sun (2026).

Under the normal (Bachelier) distribution, an at-the-money (ATM) binary option with a \$1 payoff is always worth 0.50. Intuitively, this is the fair price of a coin-flip wager when the underlying distribution is symmetric. Under the asymmetric lognormal distribution assumed by the Black model, however, the value of the same option is always below 0.50. Commodity option markets follow neither a normal nor a lognormal distribution, and their dynamics evolve over time. As a result, a price that is fair for a binary option today may not be fair tomorrow. This changing fair value is reflected in vanilla option prices and, therefore, in the shape of the volatility smile. The QNM illustrates how dynamic binary-option pricing can be: the model is calibrated daily to market prices of vanilla options, after which the corresponding binary-option value is obtained from an analytical formula.⁸

⁸ For QNM-based binary-option pricing and further discussion, see Bouchouev, Johnson, and Sun (2026).

As Figure 4 shows, the QNM-implied fair value of a binary option can be either above or below 0.50, depending on the shape of the volatility smile and whether the oil market assigns greater futures-price risk to the upside or the downside. This value also represents the cost of replicating the exotic option with a portfolio of vanilla options. An exotic-option trader need not determine whether the vanilla options themselves are fairly priced: if the replication cost is below the binary option's market price, the difference represents an arbitrage opportunity.

This example shows that even the value of a simple binary option depends heavily on the assumed stochastic process for the underlying commodity futures price. The effect of this assumption can be even greater for more complex commodity derivatives: options on spreads between futures with different maturities (time options), between prices of the same commodity at different locations (spatial options), and between prices of different commodities (quality options). Together, these three forms of optionality are central to the commodity ecosystem.

Many other exotic commodity options are actively traded over the counter. Their pricing and hedging are highly sensitive to model choice, a topic we intend to explore in greater depth in future CQL publications on volatility trading.

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