Volatility, Contango, and Crude Oil Inventories: A Complex Relationship

The Changing Nature of World Oil Markets

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The general theory of storage suggests that the level of inventories is a key factor in determining the basis over time. The basis is the difference between the price of oil in the futures market and the price of oil in the spot market. As an indicator of future price movements, the basis follows a different dynamic when inventories are in scarce supply or in surplus, implying that there are different market states that reflect different underlying crude oil market conditions. We apply a Markov regime switching model to analyze this complex relationship, using a spread option value of storage metric to represent market structure, which enables us to draw preliminary conclusions on how to potentially impact oil-market-price stability via precise inventory decisions.

Introduction: Exploring the Relationship Between Inventories and Market Structure in the Oil Market

Given the volatile nature of global oil markets and their sensitivity to geopolitical and economic shocks, at any given time there may be a "well balanced" oil market, or surpluses or shortages of crude oil supplies. In this dynamic environment, even the suggestion of changes to crude oil demand, supply, or inventories can trigger a price reaction and a subsequent rebalancing of world oil markets.

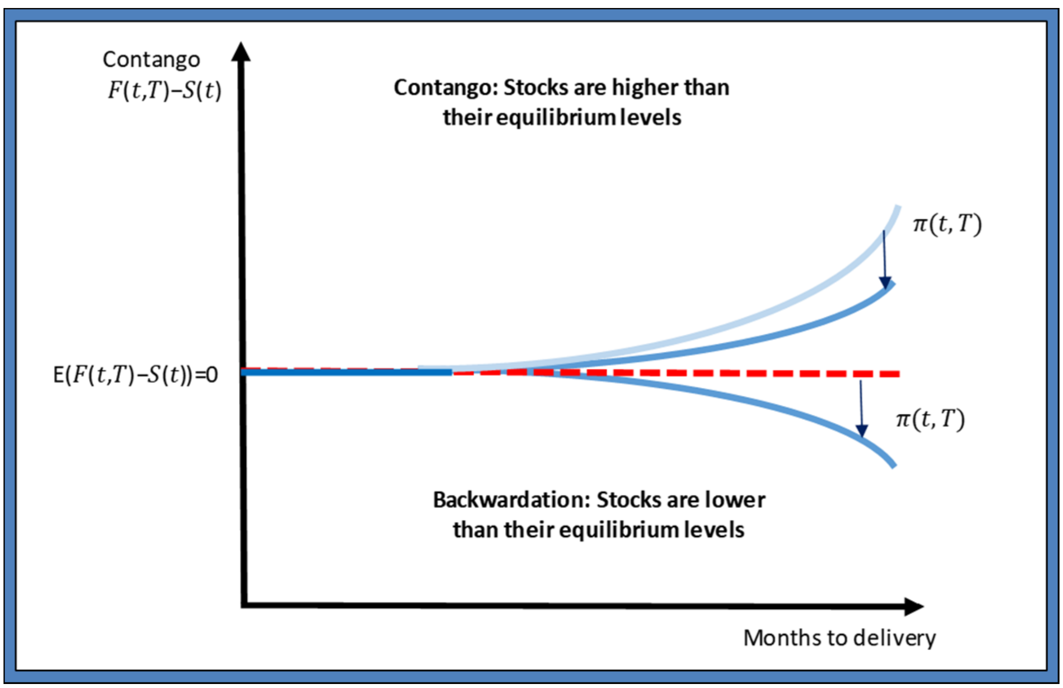
Under normal market conditions, when the crude oil market is balanced, prices are generally in a state of contango. The price that futures trade above the spot price accounts for the costs of storing a commodity, including warehousing costs, the costs of foregone interest, and a convenience yield on inventories (Fama and French, 1987). When this is not the case, and futures prices trade below the spot price, the market is said to be in backwardation. Firms hold minimal or just-in-time inventories, and they tend to increase production to meet demand (Working, 1933; Brennan, 1958; Telser, 1958).

Conventional storage theory predicts a positive relationship between inventories and the basis (defined here as the difference between the futures price and the spot price) or cost of carry, or a negative relationship between the marginal convenience yield and inventories. The relationship is dynamic and changes according to the conditions in world oil markets. The convenience yield falls with inventory levels but at a decreasing rate. When stocks are scarce, the marginal convenience yield will likely be higher than the convenience yield, and the basis will be negative (backwardation). As the level of inventories rises, the convenience yield falls to levels below the cost of carry, and the basis becomes positive (contango) (Fattouh, 2009; Pindyck, 2004).

An alternative theory suggests that the basis can be explained in terms of a risk premium and a forecast of future oil prices (Bailey and Chan, 1993). The risk premium, π(t,T), reflects all of the systematic factors affecting futures prices, including demand and supply shocks, political risk, and net hedging pressure (Hicks, 1939).

Figure 1 illustrates the risk premium theory of storage. When the difference between the futures price and the spot price, F(t,T) - S(t), is higher than the best industry forecasts of the forward price, E(F(t,T)-S(t)), plus a measure of compensation for the risk of holding a barrel of crude oil or a futures contract, π(t,T), then it will pay to buy a barrel of crude (on the physical or futures market) and sell it forward, and stocks will be above their equilibrium levels. The purchase of spot oil and the sale of futures will reduce the level of contango, F(t,T) - S(t), until the market returns to equilibrium (Bailey and Chan, 1993; Fama and French, 1987). Backwardation is explained by the fact that a buyer of futures contracts will earn a positive risk premium when futures prices are trading below the spot price.

Figure 1
The Risk Premium Theory of Storage



Source: Considine *et al.* (2020b).

The theory can be extended to include the implications of hedging against commodity price risk and storage costs. Hedging against the costs of crude oil promotes upward price bias in a futures market, while hedging against rising storage costs promotes downward price bias in a futures market (Hirshleifer, 1989).

Larson (1994) suggests a nonlinear formulation of the theory, positing that the basis or shadow price of inventories is convex in inventories: "Just as the price of a call option contains a premium based on price variability, so the shadow price of inventories contains a dispersion premium associated with the unplanned component of inventories. When inventory levels are low, the value of the premium increases to the point where inventories will be held even in the face of a fully anticipated fall in price."

Conventional storage theory has been criticized for being a product of pure econometric analysis, rather than traditional economic theory and competitive optimization models. An alternative rational expectations approach models the convenience yield as an embedded timing option. An economic agent that has a long position in crude oil can decide to store the commodity, in which case it will be priced as an ordinary asset, and the forward price will reflect the total cost of storage. Alternatively, the agent can decide to consume it or sell it in the spot market. In this case, the commodity is priced as a consumption good, and the forward price will reflect the convenience yield (Routledge *et al.*, 2000; Deaton and Laroque, 1992).

Several studies have shown that an options-based approach to storage valuation models is superior to the traditional cost of carry and convenience yield models (Omura and West 2015). These studies model the convenience yield as a financial call option that has value in market settings subject to supply shocks (Milonas and Thomadakis, 1997; Heinkel *et al.*, 1990). The positive value of the option, which increases with volatility, can provide an explanation for backwardation in futures contract prices (Heaney, 2002; Sorensen, 2002).

Most of these studies are based on a calendar-style spread option. Considine *et al.* (2020b) proposes an alternative: a spread option-based formulation that adds a locational dimension to the theory and is based on the prices of crude oil at different locations, factoring in costs of storage and transportation, and the time required to transport oil between them. The uniqueness of the locational spread option approach is that one can thereby measure the added value to "long distance" crude oil producers and marketers, who are in competition with other crude suppliers, of being able to sell spot crude from a storage facility near to a main market (Considine *et al.*, 2020a.) This alternative formulation appears to improve the accuracy and precision of models that define the quantitative relationship between market structure and inventories (Considine *et al.*, 2020b).

Each of these formulations suggests that the level of inventories is a key factor in determining the basis over time. The shadow price of inventories, or the basis, is expected to follow a different dynamic when inventories are in scarce supply, suggesting a number of different "price regimes" reflecting different underlying conditions in crude oil markets. Fattouh (2009) investigates this assertion and finds two distinct market regimes. One is characterized by low price volatility when the market is in contango, and an alternative regime is characterized by high volatility when the market is in backwardation. The approach adopts Markov switching modeling, which can be extended to include seasonality and jumps in the pricing process for futures with different maturities (Leonhardt *et al.*, 2017).

In a more recent study, Koy (2017) uses a Markov switching autoregressive model to investigate the recession and growth periods of oil futures markets. The study finds that oil futures prices follow a nonlinear pattern that can be divided into three distinct return regimes.

While past studies suggest that there is, in fact, a well-defined quantitative relationship between the level of inventories and the basis, the exact nature of this relationship is unclear and would appear to change at different times, depending on the market structure at the time of the forecast. This study aims to address the following questions:

- What are the characteristics that determine which market state we are in? Is there more than one market state, or regime, governing potential changes in crude oil inventories? Is there a stable path between different market states?
- How high or low must crude oil inventories be before the markets can be deemed stable?

To answer these questions, we examine the dynamic relationship between the market structure and inventories, using the locational spread option approach. The market structure is modeled as a Markov regime switching (MRS) process, which allows us to identify the number of regimes that govern the dynamics of world oil inventories. We also test whether the level of crude oil stocks has any implications for the probability of world oil markets being in, and remaining in, one of three distinct market-structure regimes.

Methodology and Data

<u>Data and Sources</u>

This section describes the data used in the analysis, and the construction of key variables, including a simple measure of contango, inventories and the locational spread option values. We estimate these variables daily for Rotterdam, and for competing crudes delivered to eight major international storage hubs located at major seaports. They include Fujairah in the United Arab Emirates, Jamnagar (India), Kagoshima (Japan), Louisiana Offshore Oil Port (LOOP in the United States), Ningbo (China), Saldanha Bay (South Africa), Singapore Port (Singapore) and Ulsan (South Korea). For LOOP, where the daily storage rates are available, we add the monthly storage rate on a particular day to the delivery costs.

The daily nine- and two-month futures values for the Brent benchmark, which were sourced from the Bloomberg Terminal, were used for the contango variable.

The daily inventory data is based on the daily floating tank top storage volumes in Rotterdam from September 18, 2013 to January 25, 2019; this data was provided by Orbital Insight. The Savitzky-Golay filter was used to smooth the noise introduced by the satellite data gathering procedure and maximize the signal-to-noise ratio (Press *et al.*, 1996). We will refer to the resulting time series as the Savitzky-Golay smoothed inventories (Inv). (This time series is illustrated in Figure 2 on the next page.)

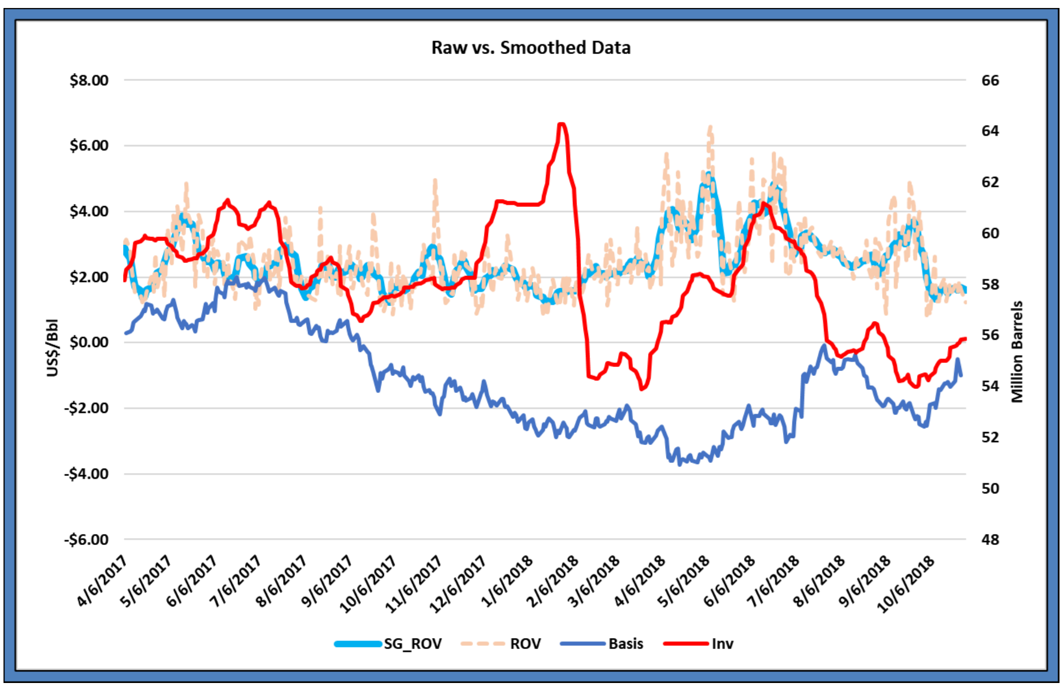
The spread option value (ROV) was obtained from KAPSARC and reported daily for Rotterdam, according to the methodology outlined in Considine *et al.* (2020a) and Considine *et al.* (2020b). Once again, the Savitzky-Golay filter was used to smooth these data and maximize the signal-to-noise ratio (Press *et al.*, 1996). (This time series, SG_ROV, is also shown in Figure 2.)

The spot prices for all the crudes used in the analysis were taken from the Bloomberg Terminal and the shipping costs from Clarksons Research. We applied various national central banks' interest rates, effective on a particular day of the estimation period from December 21, 2015 to January 25, 2019, as a proxy for the cost of capital. These rates were taken from the websites of relevant national central banks and from Triami Media BV. For the Netherlands, we used a one-year zero-coupon bond rate, and for Japan, we used the Japanese yen Libor rate. Both of these datasets were taken from the Bloomberg. The expiry date chosen for the spread options was one month from the date of valuation.

The shipping costs were calculated using the weekly spot freight rates taken from Clarksons Research for crude oil tankers on matching or similar routes. The resulting weekly shipping costs in dollars per barrel ($/b) were interpolated to obtain daily values using a cubic spline multiplicative procedure from EViews. For the cost of carry calculations, we used the same proxies of capital cost to estimate the convenience yield.

This analysis' time series from April 6, 2017 to November 29, 2018 for inventories, the basis, and spread option values are illustrated in Figure 2, which includes both raw and smoothed datasets.

Figure 2
Inventories, the Basis, and Spread Options Values



Sources: Orbital Insights, Bloomberg, and KAPSARC calculations.

A detailed explanation of the smoothing filters, as well as summary statistics and the unit root tests for the variables used in this study, is covered in Considine and Aldayel (2020).

Methodology

To determine the relationship between the market structure and inventories, we postulate the following regression equation of the market structure, as measured by the spread option value (the dependent variable) on inventories and seasonal dummies, using daily data from March 10, 2014 to November 30, 2018.

The regression equation follows the work done by Omura and West (2015), Kucher and Kurov (2014), Fattouh (2009), and Considine *et al.* (2020b), and is represented as:

$$MS_t = \alpha_o + \beta_1 \Delta Inv_t + \sum_i^N \left(\gamma_{i_t} * D_{i_t}\right) + \varepsilon_t \qquad (1)$$

where:
$MS_t \equiv$ Market structure as defined by the spread option value,
$\Delta Inv_t \equiv$ Rotterdam inventories as reported by Orbital Insight,
$D_{i_t} \equiv$ A vector of dummy variables, including monthly seasonal dummy variables and a dummy variable for 2014 to 2015, to accommodate the evolution of the data collection process from Orbital Insights, and
$\alpha_o, \beta_1, \gamma_{i_t} \equiv$ Estimated parameters.

The regression was estimated for the different market states or regimes using the Markov regime switching model. Markov switching models are used to describe situations where the behavior of the variables, or stochastic processes, change from one regime to another. The model captures the behavior of a "state variable" that cannot be directly observed (s_t), such as a recession or depression in gross domestic product (GDP) growth. For the oil industry, the state variables that cannot be observed are a state of excess supply (an oversupplied market), excess demand (an undersupplied market), or balanced world oil markets.

$$p(MS_t|Inv_t; D_t; s_t) = \begin{cases} p(MS_t|Inv_t; D_t; \theta_1) \; if \; s_t = 1 \\ p(MS_t|Inv_t; D_t; \theta_2) \; if \; s_t = 2 \\ p(MS_t|Inv_t; D_t; \theta_3) \; if \; s_t = 3 \end{cases} \qquad (2)$$

where:
$\theta_m = \alpha_{om}, \beta_{1m}, \gamma_{i_m} \equiv$ Estimated parameters associated with regime m, with three distinct regimes (1, 2 and 3). The state variable evolves according to a Markov chain process. That is, the probability of being in any particular regime, or state of the oil market, in period t depends only on the state of the oil market in time (t-1) and not any other time (t-2) or (t-3).

The Markov chain process for the oil market has the following transition probabilities:

$$\begin{aligned} P(\lfloor s_t = 1\rfloor | s_{t-1} = 1) &= p_{11} \\ P(\lfloor s_t = 1\rfloor | s_{t-1} = 2) &= p_{12} \\ P(\lfloor s_t = 1\rfloor | s_{t-1} = 3) &= p_{13} \\ P(\lfloor s_t = 2\rfloor | s_{t-1} = 1) &= p_{21} \\ P(\lfloor s_t = 2\rfloor | s_{t-1} = 2) &= p_{22} \\ P(\lfloor s_t = 2\rfloor | s_{t-1} = 3) &= p_{23} \\ P(\lfloor s_t = 3\rfloor | s_{t-1} = 1) &= p_{31} \\ P(\lfloor s_t = 3\rfloor | s_{t-1} = 2) &= p_{32} \\ P(\lfloor s_t = 3\rfloor | s_{t-1} = 3) &= p_{33} \end{aligned} \quad (3)$$

where p_{ii} is the probability of remaining in state i, given that the world oil market was in state i in the last period, and p_{ij} is the transition probability of the markets changing to state i, given that the world oil market was in state j in the last period.

While some representations assume that the transition probabilities are fixed, this would appear to be an overly restrictive assumption for the energy markets. We permit the transition probabilities to vary through time (Bazzi *et al.*, 2017; Diebold and Inoue, 1999; Filardo, 1994; Fattouh, 2009).

In this formulation, the probability of switching from one regime to another is a function of the level of contango in world oil markets. The level of contango (c_{t-1}) for Brent crude oil prices is a conditioning vector that contains vital economic information affecting the transition probabilities.

$$P(\lfloor s_t = i\rfloor | s_{t-1} = j) = p_{ij(c_{t-1})} \text{ for i = 1,2,3, and j = 1,2,3.} \quad (4)$$

The estimated parameters for the MRS structure in equation (4) are estimated jointly using a Markov switching regression, a nonlinear optimization technique that uses the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm and Marquardt steps to provide a solution that estimates all the parameters of the complex nonlinear system simultaneously. The BFGS method belongs to quasi-Newton methods, a class of hill-climbing optimization techniques that seek a stationary point of a (preferably twice continuously differentiable) function (Bergmeir *et al.*, 2012; Bekiros and Paccagnini, 2015).

Results and Discussion

Three Market Regimes

The results of the MRS analysis using equation (1) are provided in Tables 1 through 3 on the following pages. The model finds clear evidence of three distinct regimes, regime 1—contango, regime 2—backwardation, and regime 3—extreme backwardation.

1. In **regime 1, contango**, the average value of contango is \$2.98, and there is a 90% probability of the values ranging between \$0.43 and \$5.66. The standard deviation of the time series for the contango regime is \$1.69.

2. In **regime 2, backwardation**, the modal value of backwardation is -$2.43, and the standard deviation estimated for regime 2 is $0.41. This regime is the most stable in terms of volatility.
3. In **regime 3, extreme backwardation**, the modal value of backwardation is -$2.67, and there is a 40% probability that the level of backwardation will be lower than -$2.50 $/b. The standard deviation is $8.70, by far the highest of any of the three regimes.

The basis exhibits the greatest volatility when the market is in regime 3, extreme backwardation. This is because backwardation is generally associated with just-in-time inventories, or low and falling stock levels, and can be quite sensitive to shocks, or new developments in the marketplace.

Table 1
Markov Regime Switching Results

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Regime 1				
ΔInv_t	-0.5444	0.2194	-2.4812	0.0131
Regime 2				
ΔInv_t	-2.0745	0.4857	-4.2715	0.0000
Regime 3				
ΔInv_t	1.9793	0.3849	5.1426	0.0000

Source: KAPSARC calculations.

<u>Transition Probabilities</u>

In the MRS analysis, transition probabilities measure the probability of moving from one regime to the next, for example, the probability of moving from contango to backwardation. The mean value of the transition probabilities is given in Table 2 on the next page. These results are similar to those obtained by Fattouh (1999) and show that it is more likely for the basis to remain in contango or to move from extreme backwardation to contango than from contango to extreme backwardation. Unsurprisingly, the market regime was most often in a state of contango during the period under investigation. The expected time duration of backwardation and extreme backwardation is only five and three days, respectively, throughout the observation period.

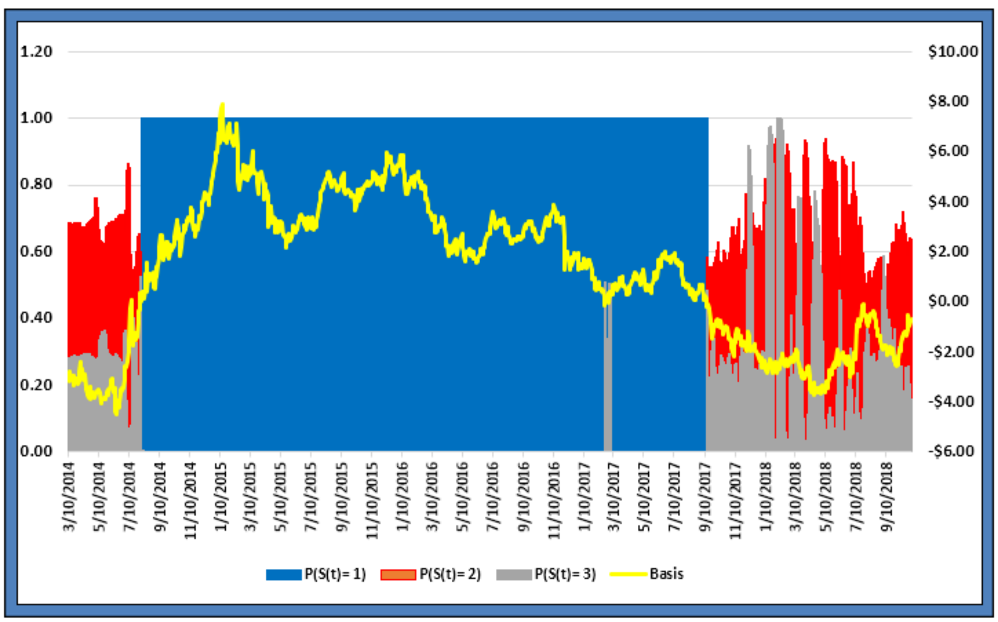
Table 2
Time-Varying Markov Transition Probabilities and Expected Durations

Time-varying transition probabilities:				
P(i, k) = P(s(t) = k | s(t-1) = i)				
(row = i / column = j)				
		1	2	3
Mean	1	0.6681	0.0872	0.2447
	2	0.0479	0.2859	0.6662
	3	0.6681	0.0636	0.2683

Source: KAPSARC calculations.

Figure 3 illustrates the filtered probability of being in regimes 1, 2, and 3, and the level of contango or backwardation in Brent crude oil futures prices. The probability of being in a particular regime ranges from 0 to 1 and is represented on the left vertical axis. The level of contango or backwardation ranges from -$4.5 to $7.9 and is represented on the right vertical axis. The probability of the markets being in regime 1 (contango) is represented in blue, and the probabilities of the markets being in regimes 2 (backwardation) and 3 (extreme backwardation) are given in red and grey, respectively. The level of the basis is given by the yellow line.

Figure 3
Filtered Regime Probabilities



Notes: P(S(t)) is the filtered probability of being in regime t, for t=1,2, and 3.
The filtrations are used to model the information that is available at a given point in time.

Source: KAPSARC calculations

As expected, the MRS estimates of the market structure in the three regimes—as measured by the spread option value—is captured by the actual level of the basis in the marketplace. The probability of the market being in regime 1 almost exactly matches the actual value of the basis. The model captures long periods of contango in the marketplace, and the shifts between backwardation (low volatility) and extreme periods of backwardation (high volatility). The shift back to contango at the end of the sample period, in October 2018, is clearly represented.

The Role of Inventories and Contango

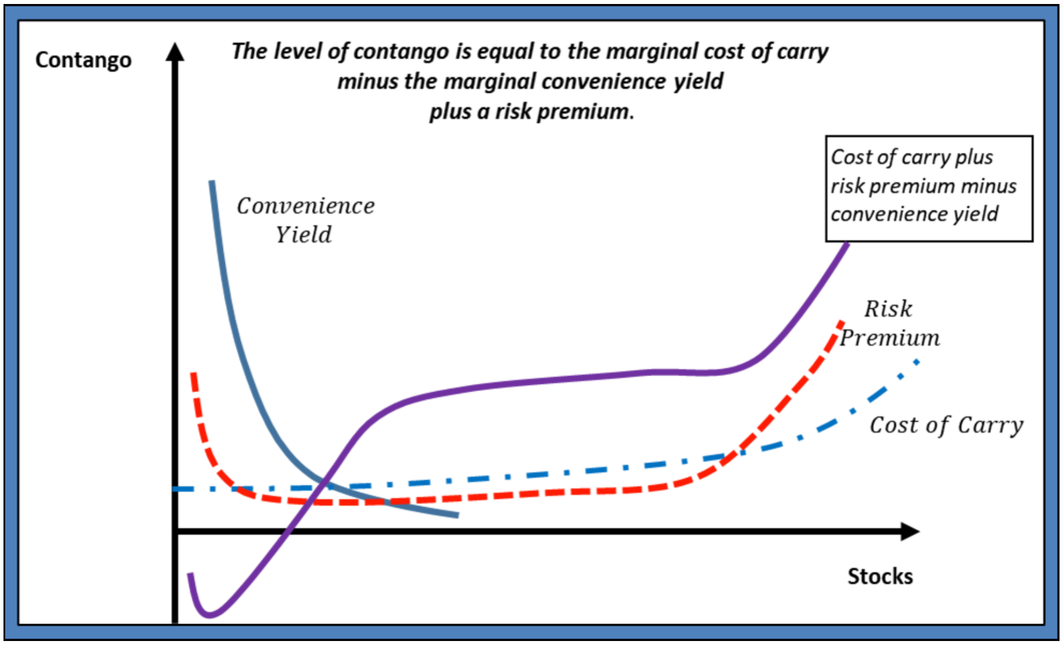
As predicted, the level of inventories varies significantly across the three states. The mean, or average, level of inventories is approximately 61.36 million barrels (MMb) in regime 1, 58.10 MMb in regime 2, and 60.10 MMb in regime 3.

The estimated coefficients of the Markov switching model are all statistically significant at the 1% confidence level. Unsurprisingly, the sensitivity of the market structure—as measured by the changes in the options value—to changes in inventories varies significantly across regimes. The estimated coefficients for the three regimes are as follows: (i) -0.54 for contango; (ii) -2.07 for backwardation, and (iii) 1.98 for extreme backwardation, as was shown in Table 1 above.

Changes in crude oil inventories have a greater impact on the market structure when prices are in backwardation. This is in line with conventional storage theory, which predicts that if stocks are in scarce supply, a reduction in inventories will increase the convenience yield, resulting in a reduction in the futures prices and large movements in the basis.

In extreme periods of backwardation with high volatility, the Markov switching model suggests a positive relationship between the market structure and changes in the level of inventories, and generally heralds a change in the direction of the movement of the basis, from falling to increasing. This can be explained by a slight variation to the risk premium theory of storage, which suggests that the risk premium in times of low storage levels and extremely high levels of volatility will be sufficiently high to induce an increase in the level of the basis when inventories rise (see Figure 4 on the next page).

Figure 4
The General Theory of Storage



Note: Contango = Risk Premium + Cost of Carry – Convenience Yield

Sources: Brennan (1958) and KAPSARC.

Inventories are higher in the contango regime, and there is little incentive to hold more stocks. As such, the convenience yield is lower (or zero), as is the volatility of crude oil prices, which suggests a lower risk premium. In this case, the cost of holding inventories reflects only storage costs and the costs of carry, which are less sensitive to changes in inventories than the convenience yield.

The results suggest that the level of the basis does not have a significant impact on the transition probabilities for most regimes. The sole exception to this general rule is the switch from regime 2 (backwardation) to regime 3 (extreme backwardation). In this case, a change in the direction of the price movement of the basis tends to increase the probability of moving from backwardation to extreme backwardation and high volatility. The estimated coefficient of 0.72 is significant at the 1% level. (See Table 3 on the next page.) This result is consistent with the theory of storage, in that an increase in the volatility of the basis will increase both the risk premium and the option value of storage.

Table 3
Markov Regime Transition Matrix Parameters

Transition Matrix Parameters				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
P11-CONTANGO__BRENT	447.5613	133510.3	0.003352	0.9973
P12-CONTANGO__BRENT	0.490343	0.909485	0.539143	0.5898
P21-CONTANGO__BRENT	-23.42116	57.10263	-0.410159	0.6817
P22-CONTANGO__BRENT	-24.38101	57.10312	-0.426965	0.6694
P31-CONTANGO__BRENT	388.7821	41003.48	0.009482	0.9924
P32-CONTANGO__BRENT	0.720326	0.20128	3.578721	0.0003

Source: KAPSARC calculations.

Finally, we test the proposition that the level of inventories affects the probability of being in each of the individual regimes. To accomplish this, we model the probabilities of remaining in each regime as a logistics function of the level of inventories. The estimated coefficients for the inventory variable in each regime are statistically significant at the 1% level. As expected, an increase in the level of inventories increases the probability of remaining in regime 1, contango. Similarly, a reduction in the level of inventories increases the probability of remaining in backwardation. These results are in line with *a priori* expectations and agree with the general theory of storage. See Table 4.

Table 4
Probability of Being in a Regime versus the Level of Stocks

Regime 1: Contango				
Time Varying Probability of Remining in Regime 1				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	-4.0412	1.0890	-3.7108	0.0002
Inventories	0.0520	0.0190	2.7410	0.0062
Regime 2: Backwardation				
Time Varying Probability of Remining in Regime 2				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	4.1415	5.2469	0.7893	0.4301
Inventories	-0.2956	0.0904	-3.2706	0.0011
Regime 3: Extreme Backwardation				
Time Varying Probability of Remining in Regime 3				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	3.0464	5.0248	0.6063	0.5445
Inventories	-0.2796	0.0867	-3.2240	0.0013

Source: KAPSARC calculations.

Concluding Remarks

Our results show that there are three well-defined and distinct market regimes that govern potential changes in the level of crude oil inventories: contango, backwardation, and extreme backwardation.

Their main characteristics within the time period under investigation are as follows:

1. Contango:
    - Positive basis: The average value of contango is $2.98, the mode is $3.20.
    - There is a 90% probability of the values ranging between $0.43 and $5.66.
    - There is a slight positive skew, but it is fairly evenly distributed. The skewness is 0.2786, so the distribution is fairly symmetrical.
    - Average volatility: The standard deviation of the time series for the contango regime is $1.69.

2. Backwardation:
    - Negative basis: The modal value of backwardation is -$2.43.
    - There is a slight negative skew, but it is fairly evenly distributed. The skewness is -0.2824, so the data has a slight negative skew, but it is fairly symmetrical.
    - Low volatility: The standard deviation estimated for regime 2 is $0.41. This regime is the most stable in terms of volatility.

3. Extreme backwardation:
    - Negative basis: The modal value of backwardation is -$2.67.
    - There is a 40% probability that the level of backwardation will be lower than -$2.50 $/b.
    - Positive skew: The skewness is 0.8853, so the data has a distinct positive skew.
    - High volatility: The standard deviation is $8.70, by far the highest of any of the regimes.

The answer to the question of whether there is a stable path between states is slightly more complex, but it can be derived through a detailed inspection of the transition probabilities. We find that the level of contango does not have a significant impact on the transition probabilities for most regimes. However, when the market is in backwardation, a reversal in the price movement of the basis tends to increase the probability of moving from backwardation to extreme backwardation and high volatility. This, combined with extreme volatility in oil prices and the short duration spent in extreme backwardation, suggests that the transition to the extreme backwardation regime is highly volatile.

The final question of how high or low must inventories be before the markets can be said to be stable, or in a state of contango, can be answered by observing the average level of inventories in each regime. As noted above, the mean, or average, level of inventories is approximately 61.36 MMb in regime 1, 58.10 MMb in regime 2, and 60.10 MMb in regime 3. Using storage data from 2016 to 2018, there is a 69.7% probability of being in the stable contango regime if inventories are above 60 MMb.

The level of inventories does not appear to be as effective as the level of contango in explaining the stability of world oil markets. In regime 1, there is a 40% probability of inventories being below 60 MMb, but only a 5% chance of the level of contango being below $0.43, and a 15.5% chance of the volatility (of inventories) being higher than 1.4 MMb, which is the average level of volatility expected in the unstable, extreme backwardation regime.

Our analysis confirms that there is generally a negative relationship between the spread option value of storage and inventories. In addition, the empirical results suggest that the actual levels of inventories have significant implications for the sensitivity of the market structure to changes in the levels of inventories. Specifically, changes in crude oil inventories have a greater impact on the market structure when prices are in backwardation. When inventories are at sufficiently low levels, and prices are volatile, the risk premium can be higher than the convenience yield, resulting in a positive relationship between inventories and the spread option value (the market structure).

Any policy prescription resulting from this analysis warrants a further investigation of the determination of the risk premium, and the complex relationship between the level of inventories and market structure. Future research could focus on identifying the regimes, the major drivers and their sensitivities for a number of major global crude oil storage and consumption nodes (besides Rotterdam) and alternative crudes (besides Brent). This would help to identify regional differences and create a more comprehensive picture of the global oil market.

The approach developed in this study provides market participants and policymakers with a tool that could be used to track developments in the global oil market and assess a variety of potential future scenarios. Specifically, large producers, exporters and traders can estimate the amount of crude that would have to be stored (delivered) to a particular location to trigger a regime switch in the oil market. For exporters, this can provide an excellent estimate of the additional shipments they can deliver to any location without causing significant pressure on prices. For those interested in balancing the oil market (*e.g.*, the Organization of the Petroleum Exporting Countries), this approach also provides a more precise measure of the additional supply required to bring the markets to a stable, or equilibrium, position.

Endnote

For further coverage of the crude oil markets, one can also read past *GCARD* articles, which include a past paper from a KAPSARC-affiliated author that covered, "The $200 Billion Annual Value of OPEC's Spare Capacity to the Global Economy."

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