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Trading Algorithm Navigation Using a Mixture Distribution Risk Model

An Application of the CME Market Sentiment Meter from 1QBit Finance Products

White Paper

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An Application of the CME Market Sentiment Meter from 1QBit Finance Products

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Abstract

The CME Market Sentiment Meter (MSM) provides a daily risk–return estimate based on end-of-day settlement data from previous days. We show how MSM can be used to "navigate" a reversion-to-mean (RTM) algorithm across changing market states, and, in doing so, increase its profitability (from 60% to 135% annualized ROI in our example). We then describe a procedure by which other trading algorithms can be similarly improved.

Keywords: Market Sentiment Meter, Computational Finance, Reversion to Mean, Algorithmic Trading, Automated Trading

1 Introduction

The CME Market Sentiment Meter (MSM) provides a daily risk–return estimate for eight products traded on CME Group exchanges: corn (C), crude oil (CL), euro/USD FX (EC), S&P 500® index e-minis (ES), gold (GC), natural gas (NG), soybeans (S), and 10-year treasury notes (TYF).[1] The Market Sentiment Meter is computed by 1QBit using end-of-day settlement data published by CME Group. It is available as a subscription product through CME DataMine.

The MSM risk–return estimate can be used to "navigate" a trading algorithm. We do this by finding a "navigation parameter", typically an algorithm setting that works successfully at a constant value, but where the best value is sensitive to changes in market volatility. We then define a "predictor", where an MSM time series is used to estimate the best value of the navigation parameter for succeeding days.

In simulations using prices from the NYMEX physically-settled natural gas futures contract (NG), we found that a correlation of 0.26 between the predictor and the best value was sufficient to increase the annualized return of our reference algorithm from 60% to 135%.

The MSM risk–return estimate is provided as a "mixture distribution": a multi-modal probability distribution that reflects the presence of multiple schools of thought within the trading community. Most of the time, these schools of thought are broadly similar, and the MSM risk–return distribution looks like the normal distribution used in conventional pricing models [1, 2, 3]. We refer to such a market as being in the Balanced state.

However, during times in which trader sentiments may not differ significantly, the mixture distribution can become

[1] These are the product codes used by CME DataMine, from which MSM receives its data.

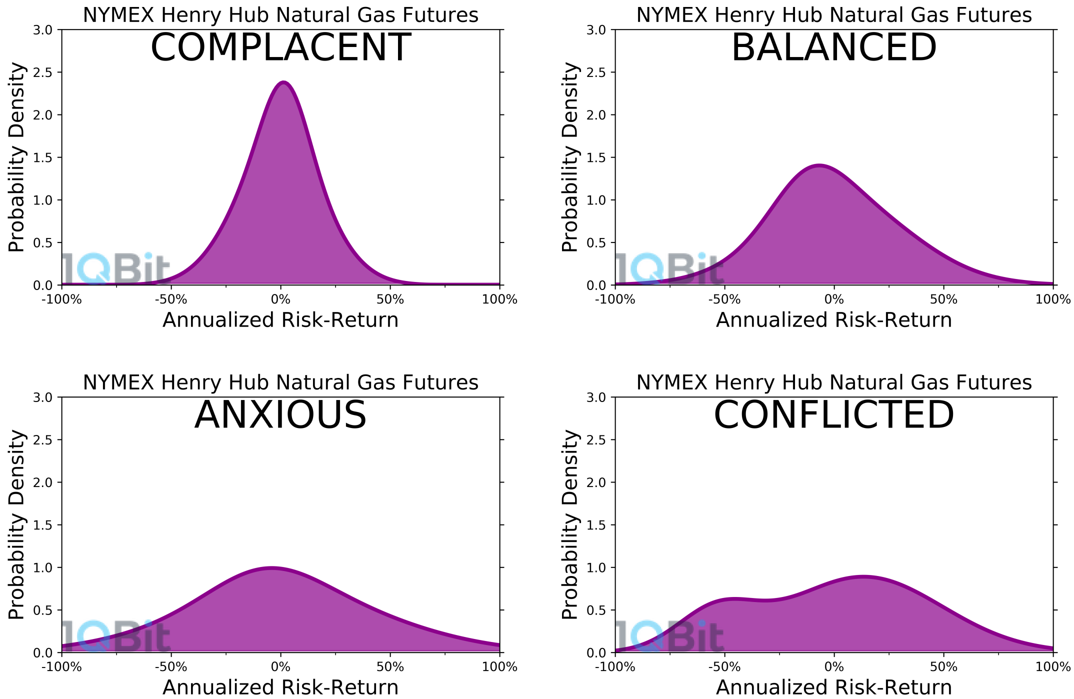

Figure 1: **MSM Market States.** Graphical representations of the risk–return curves for the four market states within the MSM: Complacent; Balanced; Anxious; and Conflicted states.

extremely narrow—a state that we refer to as Complacent.

At other times, the distribution can become extremely broad, a state that we refer to as Anxious. If more than one mode appears, we refer to the state as Conflicted.

Figure 1 gives examples of all four types.

The MSM mixture distribution is the output of a model. The model is based on the premise that multiple schools of thought are present in the market. The parameters of the mixture distribution are computed such that its shape indicates the convergence and divergence of their outlooks. Information on market sentiment is conveyed by the broad shape of the distribution, not by the areas that might be present under certain parts of it.

The model works best for events where the timing is known but the outcome is uncertain [4, 5]. Examples of this include elections in the United States and its major trade partners, scheduled economic announcements (e.g., from OPEC or the US Fed), and weather events at times when growing crops are known to be vulnerable.[2]

Subscriptions to the CME Market Sentiment Meter are available from CME DataMine, along with a complete description of the data product itself. It is also described on the 1QBit website, on the CME Group website, and in several published papers [6, 7, 8].

To illustrate the concept of algorithm navigation using the MSM, we will introduce a simple algorithm that we will refer to as "Single-Action-Mean-Reversion-Using-Lookback" (SAMRUL). The "single-action" property limits the algorithm to a single trade per day, which we execute at the settlement price.[3] We will also restrict the algorithm to 1-lot orders and positions that may be one-lot long or one-lot short.

We will illustrate the behaviour of SAMRUL in the NYMEX natural gas market, where the MSM risk–return distribution is

[2] Most of the CME Group futures products tracked by the MSM are based either on physically-delivered US commodities (Corn, Soybeans, etc.) or U.S. financial instruments (S&P 500® index futures, treasury notes, etc.)

[3] We can accomplish this in practice by entering a trade-at-settlement (TAS) order at the beginning of the day.

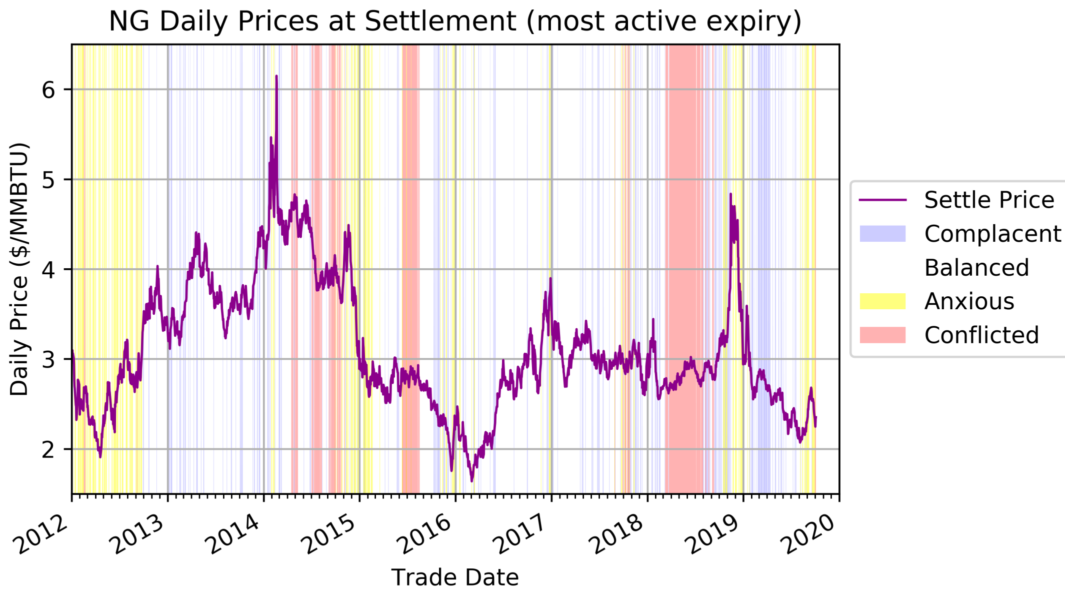

Figure 2: **2012-2020 Daily Settlement Price for NG** (most active expiry) (purple line). The shading indicates the market state. Regions where the MSM is Complacent (blue), Balanced (white), Anxious (yellow), and Conflicted (red) are highlighted. Figures for other instruments available at https://1qbit.com/market-sentiment-meter-msm/.

based on the NG physical future and the LO European option. For reference, Fig. 2 shows the daily settlement price for the most active contract in NG, with the MSM market state overlaid.

Our navigated algorithm contains a simple reversion-to-mean (RTM) algorithm that operates using constant parameters for a fixed trading interval of N days. For each upcoming interval, it chooses the parameters that gave the best results over the previous M intervals. More specifically, it re-runs the RTM algorithm over the previous M intervals with different sets of constant parameters, and then chooses the set that gives the greatest average gain. Intuitively, we might expect a calm market to favour longer lookbacks, and a choppy market to favour shorter lookbacks. A market state indicator that tells us something about upcoming calmness or choppiness can help us in choosing a "good" value of M.

Our premise is this:

> **If we can show how the MSM can be used to improve the performance of a simple algorithm, then the reader can potentially apply the same techniques to improve a more sophisticated algorithm of their own.**

2 Methods

2.1 Single-Action-Mean-Reversion-Using-Lookback (SAMRUL): Core Algorithm

The Single-Action-Mean-Reversion-Using-Lookback (SAMRUL) algorithm is based on the well-established reversion-to-mean (RTM) concept.

The end-of-day settlement price for a tradable instrument changes from day to day, and over a period of time, a mean price can be defined. Sometimes the daily price will be above the mean. Sometimes it will be below. A mean price, by its very nature, must lie somewhere between the extremes. At some point, the daily price must move from one side of the mean to the other. However, given that the mean price must inevitably lag the current price, markets with sustained directional price trends can experience long times between reversions. The definition of the mean is therefore of some interest to the algorithmic trader, as is the presence of sustained directional trends.[4]

[4] In our work with natural gas futures, a simple 60-day moving price average gave consistently usable results.

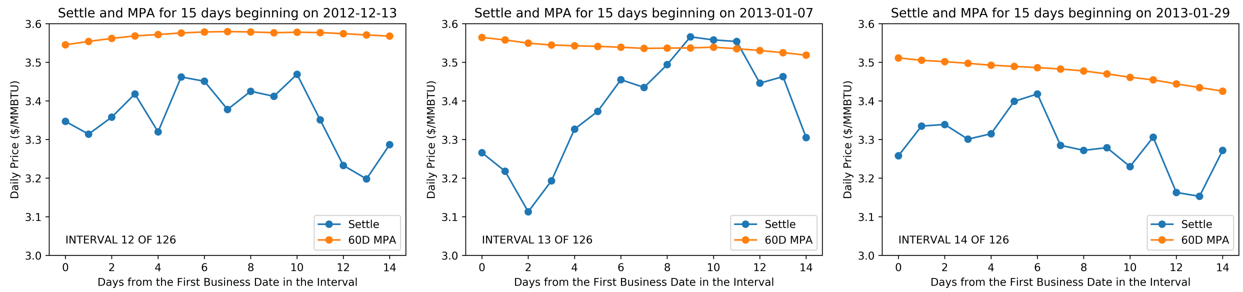

Figure 3: **Moving Price Averages and Settlement Prices.** A simple reversion to mean relies on the moving price average. In the panels above, we see the relationship between the 60-day moving price average and the daily settlement price, shown for three successive 15-day intervals. The settlement prices (in blue) are the same as those in Fig. 2, but taken from the last 15-day interval in 2012 and the first two 15-day intervals in 2013.

The RTM algorithm is based on the simple idea that if the settlement price on a given day is well above the mean, then subsequent daily settlement prices will be lower. If we can decide when a price is “well above the mean”, we can sell at that price and buy back when the price has dropped sufficiently. Similar logic applies to prices below the mean.

The RTM algorithm inside SAMRUL operates using constant parameters for a fixed trading interval of N days. Its decision-making rules inside the interval are represented by the following four parameters:

- k_{GoLong}, the percent below the W-day moving price average that the day’s price has to be in order for the RTM algorithm to enter a long position, if a position has not already been entered.
- k_{GoShort}, the percent above the W-day moving price average that the day’s price has to be in order for the RTM algorithm to enter a short position, if a position has not already been entered.
- k_{Exit}, the percent change to drive an exit from the position. This is taken in a profitable direction to trigger the profit taking.
- $k_{\text{CircuitBreak}}$, the percent change to drive a circuit breaker exit from the position. The percent change in an unprofitable direction to trigger the stop loss exit.

There are also three parameters that remain constant from interval to interval:

- W, which specifies the mean as the W-day moving price average up to and including the previous day, i.e., the mean evolves during the interval, but the number of days used to calculate it does not.
- N, the number of trading days in the trading interval, i.e., days when the NG market was open.
- M, the number of previous intervals to include in the lookback calculation.

At the beginning of each trading interval, SAMRUL determines the parameter set $\vec{k}$ to be used for the next N days, where we denote[5]

$$\vec{k} = (k_{\text{GoLong}}, k_{\text{GoShort}}, k_{\text{Exit}}, k_{\text{CircuitBreak}}). \tag{1}$$

Our goal in this paper is to illustrate the navigation concept as broadly as possible, so we apply the algorithm to the full 2012–2020 period.[6] With $W = 60$, $N = 15$, and $M = 5$, we have 121 navigable intervals.[7]

[5] At this point, we hasten to assure the reader that this is not a mathematical paper. However, our approach does have a mathematical foundation, and sometimes this will show through.

[6] Our data series actually ends on October 4, 2019. This is when the present study began, and to ensure consistency in the ranking of algorithm performance, the same time period was used for multiple experiments. Data beyond October 4, 2019 was reserved for later testing.

[7] Some time is needed to establish the 60-day moving point average and acquire some intervals for lookback. However, the starting point for the 15-day “grid” can be varied arbitrarily, which helps in testing some of our conjectures numerically.

Our study is based on the NYMEX physically-settled Natural Gas contract (NG). This contract is priced in USD/MMBTU, and has a size of 10,000 MMBTU. It ticks in increments of $0.001. Each tick corresponds to a change of $10.00.

- On January 3, 2012, the first day in our available data, NGG12 (February) was the most active expiry. It settled at $2.993. The mark-to-market value of a one-lot position at the end of that day would be $29,930.[8]

- On October 4, 2019, the last day of our available data, NGX19 (November) was the most active expiry. It settled at $2.352, a drop of 21% from its value almost eight years in the past. Natural gas is volatile, but there is no secular trend that implicitly favours "buy and hold" passivity over action.

We can make money by trading NG. However, before we begin this in earnest, we take a moment to examine the upper bounds on the performance of our algorithms. For example, to better understand the limits of a single-action algorithm, suppose we had a crystal ball that told us how the price would move each day from the open to the close. We could make money by buying (or selling) at the opening, and exiting our position with a TAS order at the close.

Figure 4 shows how this would work if we bought or sold a single lot of NG at a time. We will frequently use this "crystal ball" concept to identify the maximum possible gains that an algorithm can make.[9]

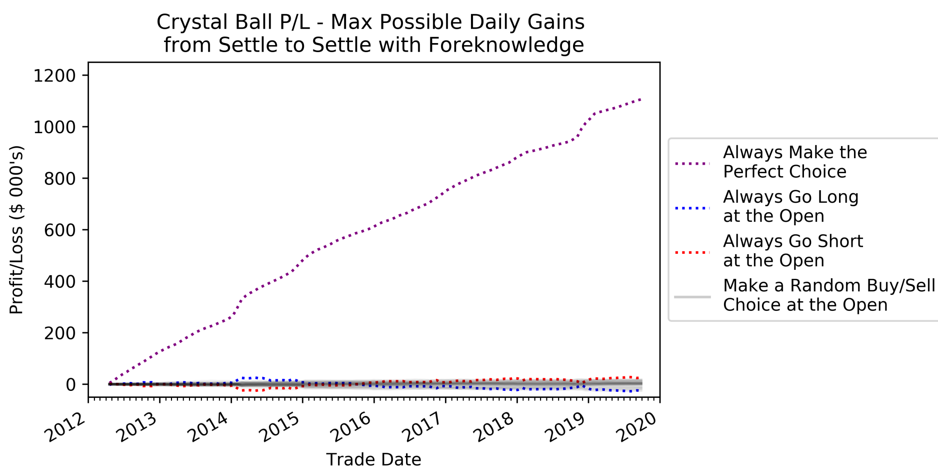

Figure 4: **Crystal Ball Trading.** The resulting gains from perfect "crystal ball" trading with complete freedom of action (purple dots), random choice (grey trace), only long positions (blue dots), and only short positions (red dots). For natural gas, the always-long and always-short strategies are comparable to random choice.

Our analysis of single-action algorithm performance will draw on the idea that there are two extremes:

- Perfect "crystal ball" information with complete freedom of action, leading to the "Always Make the Perfect Choice" plot shown in Fig. 4 . The same trace appears in Fig. 5 as the "best settle-to-settle gains".

- No information, when we decide at random whether to buy or sell.

In Fig. 4 we also include the gains we could have made by consistently buying at the beginning of the day and selling at the end ("always long"), and by its counterpart, "always short". For natural gas, these curves are very close to the curves obtained by buying and selling randomly. As can be seen in Fig. 2, natural gas does not have a consistent directional price trend, at least in the 2012–2020 period studied here.

Looking back for a moment to Fig. 3, we can also see one of the inherent limitations faced by simple reversion-to-mean. When the current price is below the mean, it is only possible to profit from upward moves. Above the mean, it is only possible to profit from downward moves. If we assume that upward moves and downward moves are equally likely, and can occur on either side of a longer-term moving price average, it follows that an RTM algorithm can only act on half of the price moves available to the full crystal ball.

[8] All figures in this study are in U.S. dollars (USD).

[9] Note that this example is closer to "double-action" than single-action, but the goal here is to work our way down from one upper bound to the next. When we constrain our actions, we reduce the usefulness of our crystal ball.

There are also some challenges in making the decisions to buy and sell. For example, in Fig. 3, the middle graph in the sequence (interval 13) shows what most people expect in thinking about RTM algorithms. The mean lies "naturally" between the extremes.

However, the first interval and the third interval are somewhat problematic. There is no way for the RTM logic to enter a short position at a price below the moving price average. To make money in the first and third intervals, the RTM decision parameters must make the algorithm go long at the beginning of the interval (to capture the small upward movement), but avoid going long before the downward movement at the end. This "fine tuning" of the parameters changes from interval to interval, and is one of the motivations for "looking back" to see what would have worked in the immediate past.

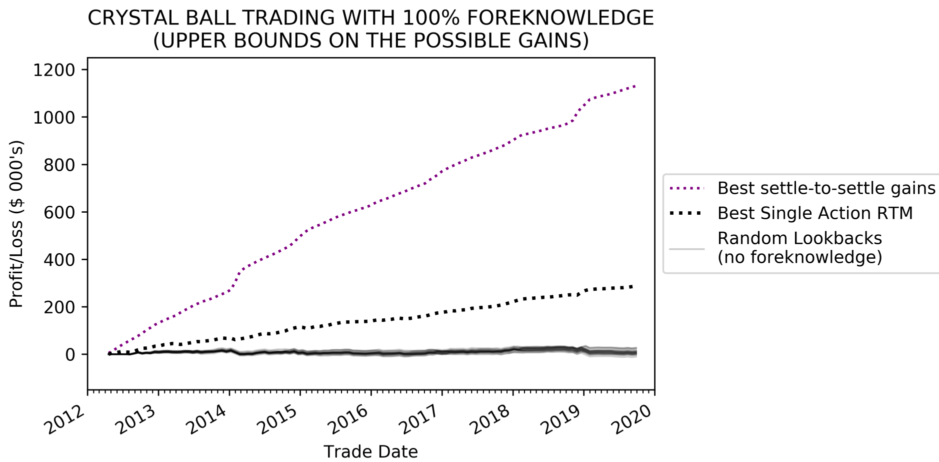

Figure 5: **Upper Bound for Profit.** There is an upper bound to the profit achievable. Plotted here is the upper bound on gains using the "crystal ball" knowledge (purple dashed line), the best Single Action RTM (black dashed line), and with 30 randomly chosen lookbacks (grey traces).

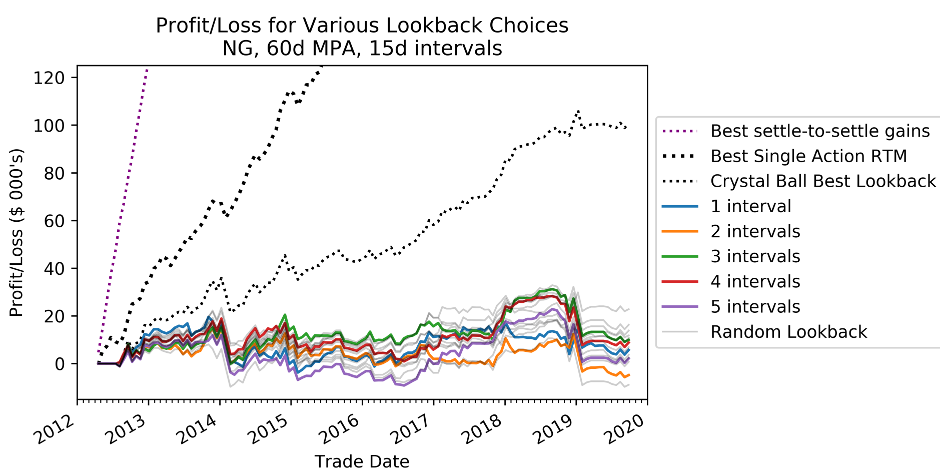

Figure 6: **Lookback Comparisons.** Three crystal balls, five genuine algorithms, and thirty guesses (random choice of lookback). The vertical P/L scale has shrunk from $1.2M to $120,000. The "Best settle-to-settle" trace and the "Best Single Action RTM" trace have been left on the chart for comparison.

In our study, we examined the performance of SAMRUL with different constant lookback periods. With a 15-day trading interval, a one-interval lookback means that we set the internal RTM parameters to what would have been the best parameters in the preceding 15-day interval. A two-interval lookback does the same thing for 30 days, three intervals for 45 days, and so on.

SAMRUL with fixed lookback periods is profitable, but only barely. However, if we can select the best lookback period according to the state of the market, the algorithm does much better. If we had a crystal ball, and could always select the best number of intervals for our lookback, we would have the cumulative cash position shown in Fig. 6 by the black dotted line.

To put this in context, Fig. 6 shows the cumulative cash traces for the fixed lookbacks, plotted alongside a set of traces generated by choosing the lookback period at random. On the surface, the traces for fixed lookback intervals do not look all that different from the traces created by randomly chosen intervals. Yet, by using a simple MSM-based selection rule, we can lift our cumulative cash trace out of the random band.

Viewed from the top down rather than the bottom up, the "best choice of lookbacks" does not look like much in comparison to the other crystal balls ("Best settle-to-settle" and "Best Single Action RTM"). However, when the return is calculated (P/L divided by initial outlay), the growth in value along this line is equivalent to a compound annual growth rate (CAGR) of 70%.

Before taking up the challenge of how to select the best lookback period using MSM, three things should be noted:

- **No circuit breakers.** The version of SAMRUL described in this report was operated without circuit breakers. This allows the algorithm to generate significant losses, which we can then study to improve its performance.[10] As will be seen in a later section, even a simple circuit breaker can have a large effect.

- **Active in every interval.** There were times when even the best SAMRUL gain was negative, as can be seen in the occasional downward movement of the dotted line in Fig. 5. In late 2015, for example, there was a price spike followed by a large downward movement. As we saw earlier, the RTM logic cannot take advantage of upward price movements above the mean, or downward movements below the mean. Later versions of SAMRUL were programmed to sit out intervals where the lookbacks showed that simple RTM could not be operated profitably. Here, however, we include these intervals, to illustrate that although simple RTM does not work everywhere, it works in more places than one might first expect.

- **Fixed execution mechanism.** The potential gain of an algorithm is limited not just by its underlying theory of operation, but also by its execution mechanics. With SAMRUL, we trade only with TAS orders that are executed at the end of the business day[11] The decision to buy or sell is not influenced by the intraday price. If the market moves against us, we must absorb the loss. We also gain on occasion, and in theory the gains and losses should cancel out. In practice, however, we are limited in the times that we can buy or sell, and this inevitably causes us to miss some opportunities for profit.

2.2 Accounting for the Roll

Accounting for the roll is often a challenge in futures trading. See, for example, *Deconstructing Futures Returns: The Role of Roll Yield*, available online from the CME Institute [9].

Trading in NG terminates on the third-last business day of the month prior to the contract month. Most of the time, the most active NG contract is in the front month, i.e., the closest expiry. As the expiry date gets nearer, however, trading activity moves from the front month to the next month. In NG, this shift in activity typically occurs just a few days before the last trade date[12] It is common for traders to "roll" their positions from the soon-to-expire contract to the the soon-to-be front month contract.

In our experiments with NG, the decision-making rules inside our algorithms were based on the price of the most active NG contract, as contained in the Curated Data Files provided by the CME Market Sentiment Meter. This is a convenient way to deal with windows and intervals that extend over many days.[13] However, when the most active contract changes

[10] It is often useful to adjust circuit breakers according to the state of the market. In lookback selection, however, we do not want to tune the circuit breaker for each interval, since it gives the algorithm another way to exit from a position, and can result in overfitting. This is especially true of time-based circuit breakers, where liquidating on "exactly the right day" can make a decision rule seem better than it really is.

[11] We also assume that our TAS order will trade. In practice, TAS orders can be entered at prices that are ticks away from the settlement price. As with other types of orders, a higher bid entered later will take precedence.

[12] The most common roll day in the 2012–2020 period was the 24th of the month.

[13] There are at most five trading days in a week, and a trading year is often taken as 252 trading days. Without going into the intricate details of month lengths and leap years, it is clear that a 60-day moving price average will always contain two rolls. Similarly, a trading interval of 15 days is more likely to contain a roll than not.

from one day to the next, this raises the question of how to account for the change. The prices for the fills used to calculate the profit and loss (P/L) are required to be the prices of actual instruments.

A single-action algorithm is limited to a single buy or sell in any given day. Although in theory we could roll from one expiry to another in this way, it is more practical to buy or sell a spread contract, and to do this "virtually", so that the position in the soon-to-expire contract is replaced by a position in the soon-to-be front month contract.

The mechanism we use in our analysis works as follows:

- If the algorithm has a position (long or short) on the day before the volume in the second month exceeds the volume in the front month, execute a spread trade at the settlement prices. The number of lots in the position remains unchanged, but the entry price is updated, and the algorithm's cash balance is adjusted to account for any difference in price.
- The algorithm can then exit its position on the next day (or any subsequent day) using the same logic as before. The change to its P/L is based on the change in price of the new most active contract.
- The spread trade contributes two executions to the algorithm execution count.

In Fig. 7 below, we repeat the panels of Fig. 3, with the second month settlement price and an indication of where the change in instrument occurs. In most of the intervals studied, the price of the second month stayed close to the price of the front month. The main exception occurred in February of 2014. Cold winter weather in the United States led to high natural gas consumption and large withdrawals from storage. However, the more distant expiries fell in months with warmer weather, and were less affected.

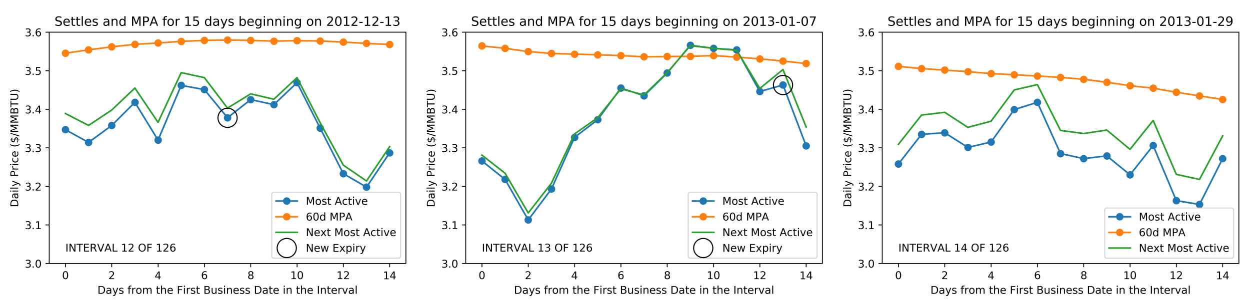

Figure 7: **Moving Price Averages and Settlement Prices with Additional Detail.** In the panels above, we see the relationship between the front month settlement price, the second month settlement price, and the 60-day moving price average—shown for three successive 15-day intervals. The black circle marks the day when the second month becomes the most actively traded (nor present in every interval).

2.3 Navigating SAMRUL with the CME MSM

Algorithm navigation is based on the concept that information from the market being traded can be supplemented with information from related markets, and that this is especially useful when the related market is strongly influenced by the anticipation of future events.

The major futures markets at CME Group are accompanied by multiple options markets. The interplay of the futures markets and their options markets is a rich source of data.

The CME Market Sentiment Meter distills this data into a model risk–return mixture distribution for the most active futures contract, e.g., the front month in NG. Note that MSM itself does not predict future price moves. Its role is to aggregate the predictions made by professional options traders, who are themselves studying the market and putting actual money at risk.

The core algorithm for SAMRUL is the simple reversion-to-mean algorithm described in the previous section, whose behaviour is specified by the $\vec{k}$ vector of decision parameters.

In our example, $\vec{k}$ is determined by a two-step procedure:

- Predicting the best value of M, i.e., the number of intervals to be used for the lookback period. M will be a function of the MSM data during the lookback period.
- Running the core RTM algorithm over the most recent M intervals with multiple values of $\vec{k}$, and selecting the value that gives the best average gain.

We refer to M as the "navigation parameter". The function that predicts M from the immediately preceding MSM mixture distributions is referred to as the "predictor". The complete procedure of predicting M and computing $\vec{k}$ is referred to as navigation. We will show later in this section that it is possible to relate the width of the mixture distribution to the length of the best lookback interval, and that simple predictors are not difficult to construct.

In general, we design our simulations so that the core algorithm does not need to "know" that it is being navigated. This opens the possibility of studying MSM-based navigation for algorithms where we are given the results, but not the internal details of the algorithm itself.

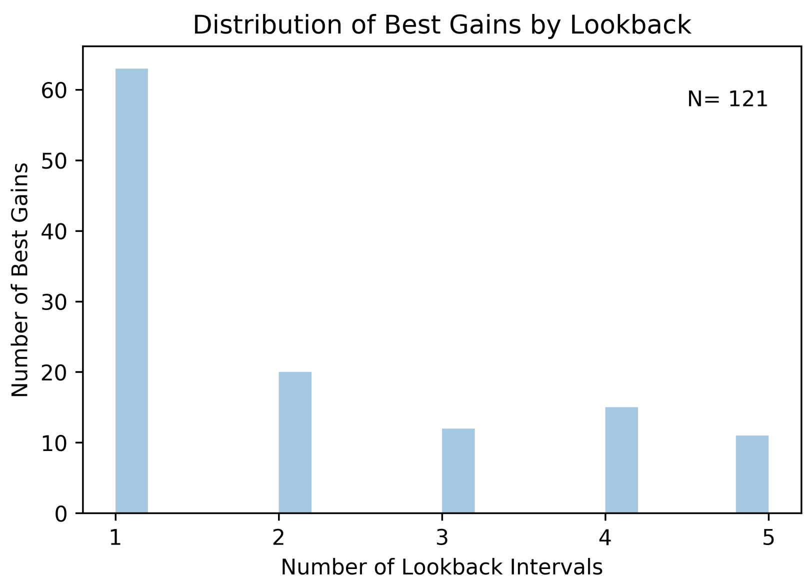

Figure 8: **Distribution of Best Gains.** Here is the distribution of the best gains by lookback period. A single interval lookback gives the best results more than half the time.

The key to using the MSM successfully is to find a navigation parameter and a predictor that are adequately correlated. This is where the intuitive properties of the MSM can be used to advantage. The width of the mixture distribution is like a volatility. If we can find a place in our algorithm where increasing or decreasing volatility is likely to have an effect, even just intuitively, we can search for correlations. From the correlations we can look for a prediction function.

The search for a navigation parameter and the construction of a predictor is inevitably time-consuming. Moreover, a concept that works in a full interval analysis must still be tested rigorously before it can be used for actual trading. The description that follows is necessarily just a sketch of how this search can be performed.

Our first step was to look at how many times each value of our navigation parameter period led to the best possible gain in the upcoming interval. For our natural gas example, we see in Fig. 8 that the best gain is most frequently associated with a single lookback.

When we look at the detailed profit and loss behaviour for the single interval lookback (Fig. 10), we find that although it generally makes a profit, it sometimes makes bad choices.

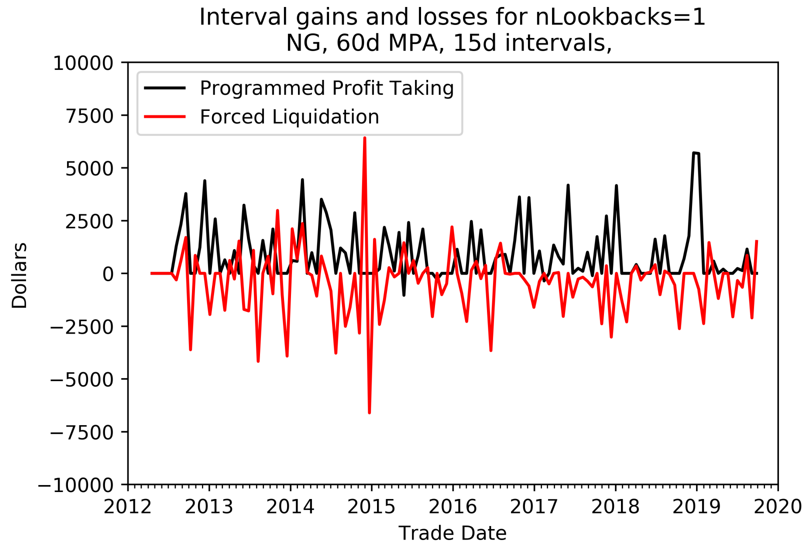

Figure 9: **Profit and Loss by Interval.** In each of the 15-day intervals, there are two possible ways to exit a position. The first is a programmatic "Take Profit" (also referred to as a TP event). The other is a forced liquidation at the end of the interval. This typically occurs when the value of k_{Exit} selected by the lookback procedure is too large to generate a TP event.

The losses occur when the RTM algorithm has not encountered a price in the current interval that meets the criterion for a "take profit" action on the next event. As a result, it is forced to exit its position at the end of a trading interval.

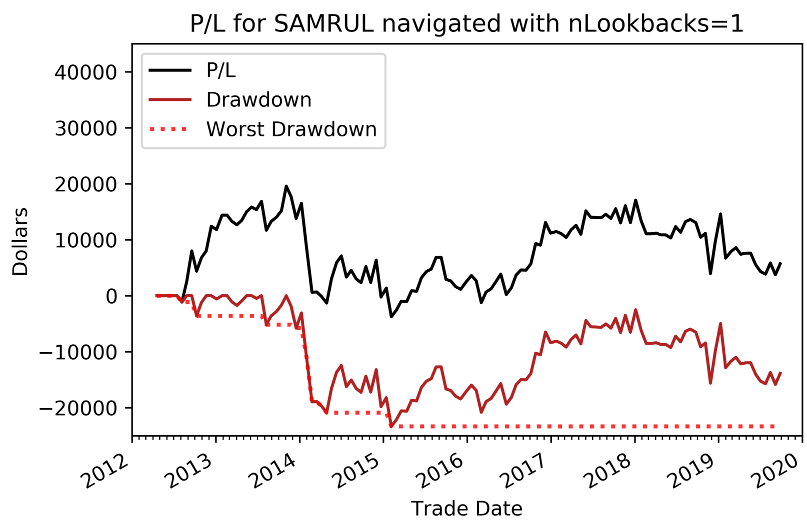

Figure 10: **Drawdown.** Defined as the drop from the previously established highest value to the lowest value before a new highest value is established. The worst drawdown is the largest drawdown encountered in the analyzed trading period.

We could limit many of the losses in Fig. 10 by using a price-driven circuit breaker, but it would be better to navigate the algorithm to a lookback period where it actually made a profit.

Our next step is to look at the general market behaviour during times when a single lookback gives poor results. Figure 11 shows the daily NG settlement price, the MSM market state, and the number of lookbacks that gave the best result in each trading interval.

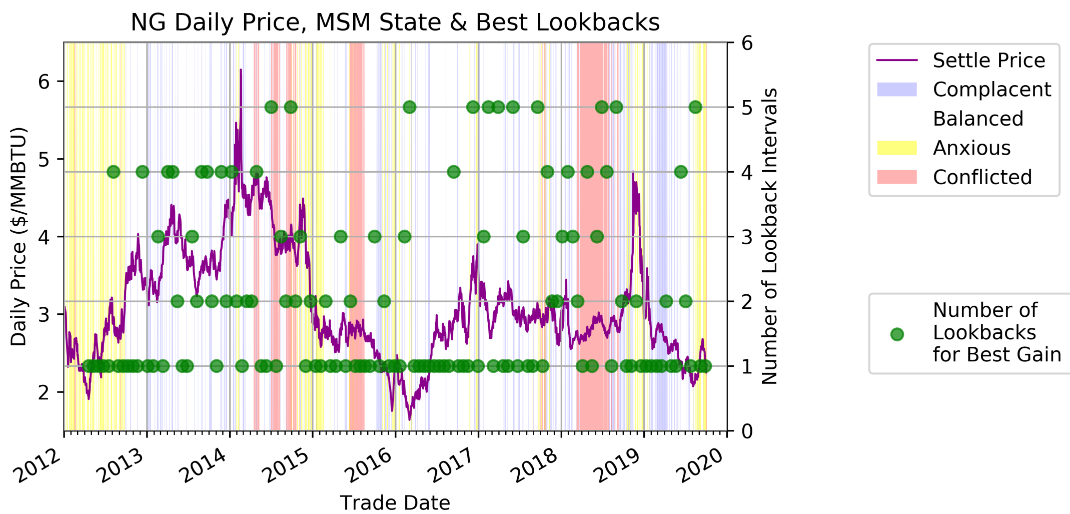

Figure 11: **MSM States and Best Lookbacks.** Plotted here are the settlement price for NG (most active expiry) (purple line), the Complacent (blue), Balanced (white), Anxious (yellow), and Conflicted (red) market states, and best number of lookback intervals (green circles).

In Fig. 11 there are several periods of time where a single lookback does not give the best interval gains. For example:

- From March 2013 to March 2014, the best lookback markers (the green dots) are mostly on the 2-lookback line and the 4-lookback line.
- From September 2014 to October 2014, the markers are mostly on the 2, 3, and 5-lookback lines.
- From November 2017 to March 2018, the markers are mostly on the 2, 3, and 4-lookback lines.

In the first period and the third period, the MSM market state is moving back and forth between Balanced and Complacent (alternating white and blue-shaded regions). In the second period there are more Conflicted states, but still some oscillation. This tells us that the width of the risk–return distribution is growing and shrinking (as illustrated in Fig. 1). Intuitively, we hypothesize that an increase in anxiety will be followed by changes in market behaviour, and that long lookbacks would put too much emphasis on the past.

This leads us to create the **Declining Anxiety Predictor:**

- If the preceding two intervals show declining anxiety, i.e., the width of the mixture distribution is getting narrower, then use three lookback intervals to select the parameters for the upcoming interval (set $M = 3$).
- Otherwise, use a single lookback interval (set $M = 1$).

The Declining Anxiety Predictor is limited in what it can do. There are five values of M to be predicted, and the predictor can only return two of them. However, we hypothesize that simply getting away from the bad choices made by the constant single lookback will give us some improvement.[14]

Figure 12 shows how the Declining Anxiety Predictor compares with the actual best choice. The coefficient of correlation between the predictor time series and the best time series[15] is only 0.26, but this is enough to lift the performance of the algorithm, as we will see in the Results section.

[14] The first goal of navigation is to avoid the rocks and shoals. Charting the optimal course is a topic for future work.
[15] A simple inner product between the two time series normalized

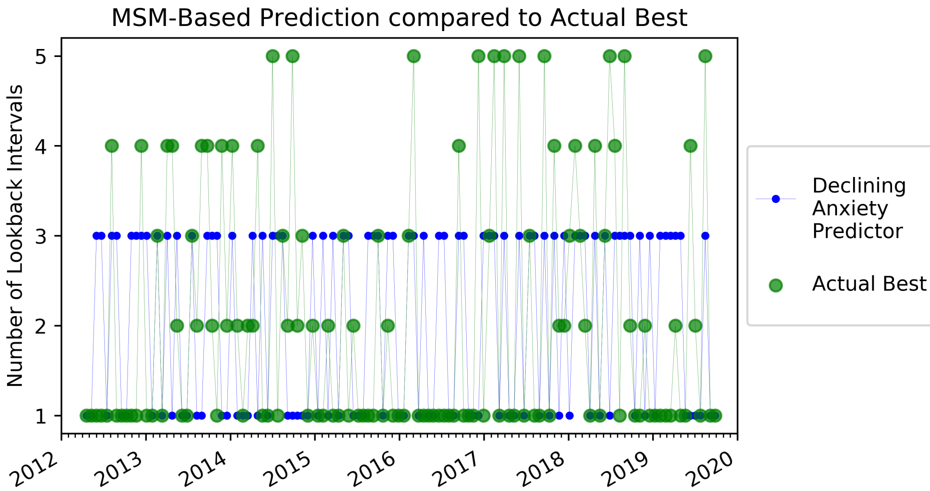

Figure 12: **MSM-Predicted Best vs. Actual-Best.** A comparison of the MSM-predicted best using the Declining Anxiety predictor (blue) to the actual best given by the "crystal ball" (green). The lines denote the temporal relation between each point. There is a quantifiable overlap in these points, demonstrated by the correlation coefficient of 0.26.

2.4 Algorithm Performance Metrics

The **analyzed trading period** of 1815 trading days (121 intervals of 15 days) was the same for all of the algorithms.[16]

The **initial outlay** of $2300 was the same for all of the algorithms. This is the amount of performance bond required to open up a one-lot position in the most active NG expiry on the first day of the analyzed trading period.[17]

The NYMEX physically settled Natural Gas contract (NG) used in this analysis is priced in USD/MMBTU and has a contract size of 10,000 MMBTU. On Tuesday July 17, 2012, the first day of trading in our analysis, NG settled at $2.796. The mark-to-market value of a one-lot position at the end of that day would be $27,960.

For comparison with other published algorithms, the following metrics are reported at the end of the Results section.

- **Total P/L:** The total profit or loss (P/L) over the entire analyzed trading period, in dollars.
- **Total Return:** The Total P/L divided by the initial outlay (the performance bond is returned on liquidation).
- **Annual ROI:** The total return divided by the number of years in the period.
- **Worst Drawdown:** Drawdown is the drop from a previously established highest value to the lowest value before a new highest value is established. The worst drawdown is the largest drawdown encountered in the analyzed trading period. Reported in dollars.
- **Execution Count:** The number of buys and sells by the algorithm in the analyzed trading period, as a proxy for transaction fees.[18]

[16] Our data starts on January 3, 2012, but we have to allow time to establish a 60-day moving price average, and to have five 15-day periods available for lookbacks. Our trading period runs from Tuesday July 17, 2012 to Friday, September 27, 2019, equivalent to 7.2 calendar years (used to compute annualized values).

[17] The average NG front month performance bond for all of 2012 was $2265.

[18] Multiplying this number by the exchange fee per side will give the transaction costs. Exchange fees have changed over the years, but a nominal value of $1.00/side can be used to asses the transaction costs in relation to the Total P/L.

3 Results

The Declining Anxiety Predictor was able to navigate the Single-Action-Mean-Reversion-Using-Lookback (SAMRUL) algorithm to a significantly better P/L, as shown in Fig. 13.

Table 1 shows the performance metrics for all of the algorithms included in the study.

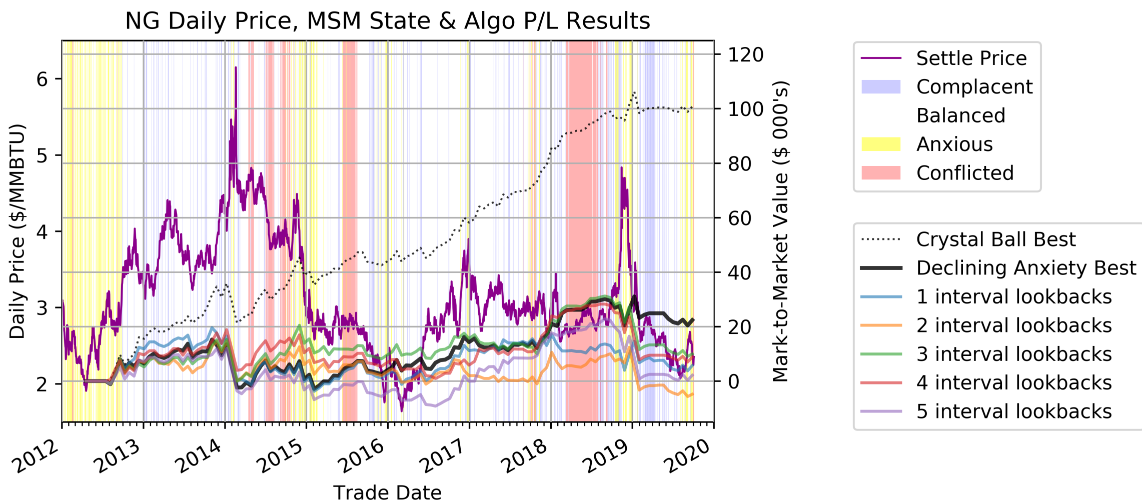

Figure 13: **Results of SAMRUL navigated with a Declining Anxiety Predictor.** The navigated algorithm delivers the best P/L overall. However, there are areas where a better predictor might have given better results, e.g., in late 2014, where Anxious and Conflicted states were common. The "Crystal Ball Best" represents the upper bound on what SAMRUL could achieve with a "perfect" predictor.

Comparison of SAMRUL Algorithm Performance

Variant	Total P/L	Annual ROI	Worst Drawdown	Exec Count
Declining Anxiety Predictor	$ 22,380	135%	($ 18,100)	496
1-interval lookback	$ 5,710	35%	($ 23,330)	522
2-interval lookback	($ 4,280)	-29%	($ 20,310)	478
3-interval lookback	$ 9,950	60%	($ 22,130)	468
4-interval lookback	$ 8,820	53%	($ 21,290)	434
5-interval lookback	$ 2,140	13%	($ 22,570)	430

Table 1: **Performance Metrics Comparison.** Tabulated here are the P/L, annual ROI, worst drawdown, and execution count for each algorithm explored in this study. The inclusion of the MSM Market Sentiment States through the Declining Anxiety Predictor results in the largest P/L, the largest annual ROI, and the smallest worst drawdown.

4 Summary and Future Work

- The CME Market Sentiment Meter (MSM) provides a daily risk–return estimate based on end-of-day settlement data from previous days. The MSM subscriber uses an API to download a Curated Data File from CME DataMine. The file contains over 60 time series, along with a numerical representation of its model risk–return distribution.

- The MSM risk–return estimate can be used to "navigate" a trading algorithm. Specifically, this involves setting an algorithm parameter that will govern the behaviour of the algorithm for a specified number of succeeding days.

- For the “Single-Action-Mean-Reversion-Using-Lookback” (SAMRUL) algorithm used in this study, it was possible to use the number of lookback periods as a “navigation parameter”.

- Intuitively, we hypothesized that a calm market would favour longer lookbacks, and that a choppy market would favour shorter lookbacks. We created a “Declining Anxiety Predictor” that would lengthen the lookback period when the market sentiment was going from Anxious to Balanced and from Balanced to Complacent.

- In simulations using prices from the NYMEX physically settled natural gas contract (NG), we found that a relatively small correlation of 0.26 between the predictor and the best value of the navigation parameter was enough to increase the annualized return of our reference algorithm:
  - Best constant-lookback ($M = 3$), annualized ROI of 60%.
  - Navigated with the Declining Anxiety Predictor, **annualized ROI of 135%.**

- The technique described in this paper can in principle be applied to any algorithm in any market where a navigation parameter can be found.

The use of the CME Market Sentiment Meter for algorithm navigation has been presented here as a concept. The results are from simulations only. For a clear-headed view of validation and back-testing, we refer the reader to *Advances in Financial Machine Learning* by López de Prado [10] .

The Finance Products Team at 1QBit continues to work on model trading algorithms and the definition of navigation parameters, in collaboration with MSM subscribers and other interested parties.

The MSM is available for corn (C), crude oil (CL), euro/USD FX (EC), S&P 500 index e-minis (ES), gold (GC), natural gas (NG), soybeans (S), and 10-year treasury notes (TYF). Additional details can be found on 1QBit’s MSM page.

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References

[1] "The capital asset pricing model: Some empirical tests." (1972) M.C. Jensen, F. Black, M.S. Scholes. *Studies in the Theory of Capital Markets*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=908569

[2] "A value at risk approach to risk-return analysis." (1999) K. Dowd. *The Journal of Portfolio Management*, 25, no. 4 (1999): 60-67. doi:10.4236/tel.2018.83025

[3] "Reference-dependent preferences and the risk–return trade-off." (2017) H. Wang, J. Yan, J. Yu. Journal of Financial Economics 123, no. 2: 395-414. doi:10.1016/j.jfineco.2016.09.010

[4] "Commodity Risks: Describing the Unobservable." (2019) B. Putnam. *CME Group*. https://www.cmegroup.com/education/articles-and-reports/commodity-risks-describing-the-unobservable.html.

[5] "Managing Risk in the Era of Dissonance." (2019) B. Putnam. *CME Group*. https://www.cmegroup.com/education/articles-and-reports/managing-risk-in-the-era-of-dissonance.html.

[6] "Market Reactions to COVID-19." (2020) A. Verma, A. Milne. *1QB Information Technologies*. https://1qbit.com/whitepaper/market-reactions-covid-19/.

[7] "CME Market Sentiment Meter Historical Market Analyses – Gold – 2019 Federal Funds Rate Cuts". (2020) A. Verma, A. Milne. *1QB Information Technologies*. https://1qbit.com/whitepaper/cme-market-sentiment-meter-historical-market-analyses-gold/.

[8] "CME Market Sentiment Meter Historical Market Analyses – September 14, 2019 Abqaiq-Khurais Attack." (2020) A. Verma, A. Milne. *1QB Information Technologies*. https://1qbit.com/whitepaper/cme-market-sentiment-meter-historical-market-analyses/.

[9] "Deconstructing Futures Returns: The Role of Roll Yield." (2014) Campbell White Paper Series. *Campbell & Company*. https://www.cmegroup.com/education/files/deconstructing-futures-returns-the-role-of-roll-yield.pdf

[10] "Advances in Financial Machine Learning." (2018) M.López De Prado. *John Wiley & Sons.*