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Timing strategy performance in the crude oil futures market

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ABSTRACT

The rewards to speculative trading in the crude oil futures market are assessed. For investors who adopt timing strategies that maximise their (iso-elastic) utility during each trading session, the rewards can be economically significant providing that transaction costs are small. Moreover, we are able to show via a decomposition of performance that the bulk of this benefit is due to their ability to predict realised volatility (that is, the second realised moment). The benefits derived from predicting other realised moments either require unrealistic levels of skill (all odd moments) or an infeasible degree of risk aversion (the fourth moment and higher even moments).

1. Introduction

There is sustained interest in speculative trading strategies that take temporal positions in assets (henceforth *timing strategies*). While practitioners tend to focus on promoting (only) strategies that beat the market, the academic community takes a more skeptical stance. The traditional approach of the latter has been to critically evaluate the performance of *market timing* strategies based on forecasts of future returns (that is, first realised moment forecasts); see Kandel and Stambaugh (1996) and Welch and Goyal (2008) for seminal examinations of equity return predictability amongst a huge literature, and Wang and Yang (2010), Kristoufek and Vosvrda (2014), Liu et al. (2015b) Lubnau and Todorova (2015), Wang et al. (2016a) and Liu et al. (2017a,b) for recent applications in the context of energy futures trading.[1] We build on this literature by considering the performance of investors who seek to maximise their (iso-elastic) utility during each trading session by taking temporal positions in crude oil futures contracts traded on the Chicago Mercentile Exchange (CME).

The previously documented mixed performance of market timing strategies has led to growing interest in the predictability (or otherwise) of higher order return moments. For instance, a number of studies reveal that the performance of *volatility timing* strategies is generally economically significant; see, e.g., West et al. (1993), Fleming et al. (2001, 2003), Marquering and Verbeek (2004), Chiriac and Voev (2011) and Taylor (2014a) for applications to equity data, and Wang et al. (2016b) and Kang et al. (2017) for recent applications in the context of energy futures trading.[2] We unify the market and volatility timing literatures by considering a framework in which the performance of more general timing strategies is decomposed into the forecasting ability of all realised moments; Jondeau and Rockinger (2012) refer to similar strategies based on non-realised moments as *distribution timing* strategies. However, given our use of realised moments we refer to ours as *realised distribution timing* (henceforth ReDiT) strategies. The proposed framework is able to

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[1] Most market timing strategies are binary in nature in the sense that they involve constructing forecasts of broad asset classes in order to take a position in the market or not. Merton (1981) refers to investors who employ these strategies as *macro-forecasters*. This is in contrast to *micro-forecasters* who seek mispriced individual stocks.

[2] A volatility timing strategy typically involves taking a position in a security based on its predicted volatility.

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identify the drivers of ReDiT strategy performance within the context of crude oil futures trading. This is the primary contribution of the paper.

There are good reasons why higher moments are important within the context of trading strategies. Consider an investor who seeks to maximise her utility during a trading session. Providing that the utility function depends on the strategy returns and is infinitely differentiable (at a real or complex number), then it follows that a Taylor series expansion can be applied to give a function that is linear in terms of all return moments. A seminal example of this approach is Levy and Markowitz (1979) who consider the performance of an approximation to expected utility via the first two return moments; see Garlappi and Skoulakis (2011) for details of the properties of this approximation and those based on inclusion of higher moments. Consequently, the performance of a timing strategy that seeks to maximise such a function is determined by the ability to forecast each of the return moments. This is the underlying approach in the current paper.

Under a set of realistic assumptions (including transaction costs), we are able to provide an explicit expression for the performance of optimal ReDiT strategies as a function of a simple measure of ability to forecast individual realised (return) moments. Using this expression we consider the benefits of trading futures contracts in a leading energy futures market, viz., crude oil. For utility maximising investors, the specific conditions under which there are benefits to ReDiT strategies are identified. The results indicate that the benefits to employing these strategies rest solely on investors' ability to forecast the second realised moment (that is, realised volatility). This is because either investors have little ability to forecast the other realised moments (the odd realised moments) or require a huge degree of risk aversion (the fourth realised moment). Transaction costs are also an important consideration. Only when transactions are small are benefits available. The results reenforce the efficient nature of energy futures markets.

The rest of the paper is organised as follows. The next section provides the investment framework that includes an explicit expression for the expected performance of ReDiT strategies. This section also includes a description of the models used to generate forecasts of the realised moments. Section 3 contains the application to crude oil futures data, and the final section concludes.

2. Methodologies

This section contains the framework within which investors are assumed to operate, and a description of the models used by these investors to generate forecasts of the realised (return) moments.

2.1. The investment framework

Investors accord to the following set of assumptions.

Assumption 1. Trading takes place during the tth trading session. There are S intra-session periods in each session such that $s = 1, \ldots, S$. Intra-session returns to the ReDiT strategy are denoted $R_{k,s,t}$, where the subscripts represent the kth ReDiT strategy associated with the sth intra-session period of the tth session.

Assumption 2. Investor utility within each session (henceforth *intra-session utility*) belongs to the iso-elastic (power) utility function given by

$$f\,[R_{k,s,t}] = \frac{(1 + R_{k,s,t})^{1-\gamma} - 1}{1-\gamma}, \qquad (1)$$

where $\gamma \geq 0$ and $R_{k,s,t} > -1$. Note that minus unity is included in the numerator so that all investors (irrespective of their risk preferences, that is, their γ value) have zero utility when the return to the strategy is zero.

Remark 1. This utility function can be approximated as an Nth order polynomial series. To minimise the approximation error associated with this series we take a log transformation of returns such that $r_{k,s,t} = ln[1 + R_{k,s,t}]$. Taking this expansion about κ we obtain

$$\tilde{f}\,[R_{k,s,t}] = \sum_{n=0}^{N} \beta_n \delta_{k,s,t}^{n}, \qquad (2)$$

where

$$\beta_n = \begin{cases} (1-\gamma)^{-1}\left(e^{(1-\gamma)\kappa} - 1\right), & \text{if } n = 0, \\ (1-\gamma)^{n-1} e^{(1-\gamma)\kappa}/n!, & \text{otherwise.} \end{cases} \qquad (3)$$

Here $\delta_{k,s,t} = r_{k,s,t} - \kappa$ is the stochastic deviation.

Assumption 3. Over each session, ReDiT strategies involve either investing all wealth in a single risky asset or all wealth in a safe asset earning zero interest. This decision is determined in the previous session and is based on an information set denoted $\mathcal{F}_{k,t-1}$.

Remark 2. The binary nature of the ReDiT strategies is consistent with the market timing strategies proposed and analysed previously; see Merton (1981).

Assumption 4. No inventory is held in the period between trading sessions. That is, all (open) positions are closed out at the end of each session.

Remark 3. This assumption is the hallmark of modern investment strategies such the low-latency trading strategies employed by high-frequency traders; see Jones (2013) for an overview of this literature.

Assumption 5. Each ReDiT strategy is subject to a transaction cost, incurred whenever a trade in the risky asset occurs.

Remark 4. Assumptions 4 and 5 together imply that returns to each ReDiT strategy are given by

$$1 + R_{k,s,t} = (1 + x_{k,t-1}R_{s,t})(1 - c_{k,t-1}), \qquad (4)$$

where $R_{s,t}$ is the return to the risky asset, $x_{k,t-1}$ is the trade indicator such that it equals unity (trade) or zero (no trade), $c_{k,t-1} = \tau x_{k,t-1}$ is the total cost of trading, and τ is the transaction cost associated with trading the asset.

Remark 5. Taking logs of Eq. (4) and subtracting κ we obtain an expression in terms of the stochastic deviation, that is,

$$\delta_{k,s,t} = \ln[1 + x_{k,t-1}R_{s,t}] + \ln[1 - c_{k,t-1}] - \kappa, \qquad (5)$$

where previous notation is maintained.