



# Spread trading strategies in the crude oil futures market

Thorben Lubnau

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European University Viadrina Frankfurt (Oder)  
Department of Business Administration and Economics  
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• **Thorben Manfred Lubnau**

Chair of Business Administration, in particular Finance and Capital Market Theory

European University Viadrina, Frankfurt (Oder), Germany

E-mail: [lubnau@europa-uni.de](mailto:lubnau@europa-uni.de)

Postal address: European University Viadrina

Chair of Business Administration, in particular Finance and Capital Market Theory

P.O.Box 1786

D-15207 Frankfurt (Oder)

Germany

# Spread trading strategies in the crude oil futures market

This article explores whether common technical trading strategies used in equity markets can be employed profitably in the markets for WTI and Brent crude oil. The strategies tested are Bollinger Bands, based on a mean-reverting hedge portfolio of WTI and Brent. The trading systems are tested with historical data from 1992 to 2013, representing 22 years of data and for various specifications. The hedge ratio for the crude oil portfolio is derived by using the Johansen procedure and a dynamic linear model with Kalman filtering. The significance of the results is evaluated with a bootstrap test in which randomly generated orders are employed. Results show that some setups of the system are able to be profitable over every five-year period tested. Furthermore they generate profits and Sharpe ratios that are significantly higher than those of randomly generated orders of approximately the same holding time. The best results with some Sharpe ratios in excess of three, are obtained when a dynamic linear model with Kalman filtering and maximum likelihood estimates of the unknown variance of the state equation is employed to constantly update the hedge ratio of the portfolio. The results indicate that the crude oil market may not be weak-form efficient.

*Keywords:* Oil Prices; Commodities; Technical trading; Market efficiency; Future returns; Kalman Filtering

## 1 Introduction

In the new Millenium, investors' interest in commodities, especially crude oil, has risen dramatically. On the one hand commodities are by and large seen as an additional asset class that widens the opportunity set for portfolio optimization and allows for less volatile portfolios due to rather low historical correlation between equity and commodity markets. On the other hand, markets with a high liquidity like crude oil attract short-term investors who intend to go long or short the asset for only a few days or even on an intraday basis. What Yergin (2012) calls paper barrels, meaning investing in the oil market via derivative financial instruments without any interest in receiving or selling the physical commodity itself, seem to have changed the market dramatically ever since the New York Mercantile Exchange (NYMEX) introduced futures on light sweet crude linked to West Texas Intermediate (WTI) in March 1983. An albeit extreme example given by Yergin (2012) is CalPERS, the largest retirement fund in the US. Having discovered commodities as a new asset class the fund announced a sixteenfold increase of its investments in commodities in

2008. Bern (2011) points out that institutional investors today are active even beyond the futures market by holding physical inventories as well.<sup>1</sup> Even oil-producing countries are participants in the market, for example Mexico used OTC derivatives to hedge against falling oil prices in 2008, cashing in \$8 billion with this trade (Yergin 2012).

However, not only financial speculation but more fundamental factors like the ones brought forward among others by Alquist and Gervais (2013) give rise to the strong trends that can be observed in the crude oil market. The forces of demand and supply are still moving the prices of crude brands and, of course, oil is an extremely political commodity for the importing nations as well as for those exporting petroleum. The increasing demand from the emerging economies of Asia has a considerable impact on the market. According to BP (2013), China alone has doubled its consumption of crude oil over the ten years from 2002 to 2012 to reach a level of more than ten million barrels per day.

On the supply side, political tensions in the Middle East and North Africa like the embargo on Iranian oil and the civil unrest in Libya, and a peaking or slowly decreasing traditional production in many oil producing countries may be reasons for higher price levels than those in the 1990s or 1980s. While this causes the price to trend upwards, downward pressure on the price may result from the increasing production of non-traditional oil fields, so-called tight oil, mainly in the states of Montana, Colorado, North Dakota and Texas. Especially in the US hydraulic fracturing, or fracking, is used on a large scale and has already led to a considerable increase in production so that the US is now recording the highest crude production levels since 1988. According to the BP Statistical Review of World Energy June 2013, US production in 2012 rose by more than 13% on a year to year basis (BP 2013). It should also be noted that the Energy Policy and Conservation Act, dating back to 1975, bans exports of crude oil from the US with only small exceptions. In light of the growing production of crude oil there may be initiatives in Congress to lift the export ban, but the outcome is far from certain. Besides fracking technological advances like directional drilling allow to increase production up to ten times the level of conventional drilling as one well can reach multiple reservoirs (see

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<sup>1</sup>A way to hold large quantities of physical oil is for example to lease storage capacity in Cushing, OK, one of the most important pipeline hubs in the United States and point of delivery of the WTI Futures contracts.

Bern 2011 for details). Deepwater production is becoming more and more important as well, with large basins being explored in the Golden Triangle off Brazil, West Africa and the Gulf of Mexico. Whereas, based on an estimation given in Yergin (2012), only about 35% to 40% of the crude from an oil field can be extracted using traditional methods, oil companies are working on new technologies to raise this rate considerably.<sup>2</sup> Therefore, the danger of reaching a peak in oil production and then moving into decline must be placed in perspective to technological advances and the ongoing discoveries of new fields. Given these developments, the crude oil market nowadays does not seem to be under extreme pressure from the supply side, although there are no longer lavish spare capacities like the East Texas field up to the 1970s or Saudi-Arabia up to the 1990s and disruptions in the production or export of crude like in Libya after the ousting of the Gaddafi regime may lead to spikes in the price of oil.

Inspecting the settlement prices of the nearest-month WTI (West Texas Intermediate) and Brent futures in Fig. 1 reveals that the arguments given may result in the growing spread between WTI and Brent over the last three years. Another reason cited for WTI being traded at a discount to Brent is the bottleneck of pipeline capacity at Cushing, Oklahoma, the main storage for WTI in the US, although the completion of the southern leg of TransCanada Corp.'s Keystone XL pipeline that connects Cushing with Port Arthur, Texas, will ease this problem. On a press conference in January 2014 TransCanada stated that the pipeline offers a 700,000 barrel capacity to float oil from Cushing to the Gulf Coast, highlighting the importance of transportation for crude pricing.<sup>3</sup> Nevertheless, as pointed out by Carollo (2012), it is nowadays very hard to distinguish movements due to shifts in demand and supply from those initiated by financial speculation. Financial institutions closely monitor the oil market and react accordingly to news reaching the market, for example the weekly reports on US stocks by the Energy Information Administration (EIA) are closely monitored. This amplifies price movements and leads to more volatile prices than in the 1980s or 1990s.

Technical trading systems are discussed in a number of research studies like Brock *et al.* (1992), Levich and Thomas (1993), Bessembinder and Chan (1998) or Kwon and Kish

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<sup>2</sup>For an in depth discussion see the chapter on exploration and production in Downey (2009).

<sup>3</sup>Numbers taken from Bloomberg's news on February 4.

(2002). The comprehensive survey by Park and Irwin (2007) shows that the main focus of attention of academic research is on equity and foreign exchange markets. Lukac *et al.* (1988) is one of the studies that test various commodities, but do not address the crude oil market. More recent studies, like Dunis *et al.* (2006) and Dunis *et al.* (2008), target the crude oil market and use spread trading strategies in their studies. Dunis *et al.* (2006) for example examine the profitability of trading the WTI-Brent spread but use a slightly different set-up for their trading rules. However, they find their rules to be profitable for a data sample from 1995 to 2004. Despite the fact that Bollinger Bands form an important part in lots of trading setups used by practitioners, the academic literature investigating their performance is rather limited. Moreover, these studies cast substantial doubts on their profitability. Using data of equity indices and the forex market, Lento *et al.* (2007) establish that the Bollinger Bands are consistently unable to earn profits in excess of a buy-and-hold strategy. Leung and Chong (2003) compare the profitability of Moving Average Envelopes and Bollinger Bands for a broad sample of equity market indices and find that Bollinger Bands to underperform the Moving Average Envelopes.

Price forecasts for WTI are discussed in Alquist *et al.* (2011) and Merino and Albacete (2010), albeit not in connection with trading systems, but on a rather macroeconomic scale as a means to allow producers and consumers of oil to assess economic risks associated with sudden price changes. Soucek and Todorova (2013) use oil prices as an indicator for a trading system in emerging markets equities. The efficiency of the oil market is also a much discussed topic, examples include Alvarez-Ramirez *et al.* (2008), who find markets inefficient in the short term and becoming more efficient in the long term for their sample 1987 to 2007, Wang and Liu (2010) who extend this line of research and conclude that the WTI market gets more efficient over time by studying the dynamics of local Hurst exponents with the method of rolling windows based on multiscale detrended fluctuation analysis. Alvarez-Ramirez *et al.* (2010) test WTI spot prices from 1986 to 2009 to find deviations from efficiency. Tabak and Cajueiro (2007) test especially for weak-form efficiency and conclude that Brent and WTI markets were more inefficient in the 1980s than in the 1990s. Lean *et al.* (2010) study WTI crude oil spot and futures prices using mean-variance and stochastic dominance approaches and find that there are

no arbitrage opportunities between spot and futures prices.

There is a large gap between academic perception and use by practitioners of technical analysis and trading systems based upon it. The Efficient Market Hypothesis (EMH) brought forth by Nobel laureate Eugene Fama (Fama 1970), the foundation of modern finance, rules out the existence of profitable trading systems based on historical data whenever markets are weakly efficient. In the wake of Fama (1970) academia looked upon chart analysis as a kind of esotericism and defended the EMH vigorously, good examples being Jensen (1978) and Malkiel (2003). On the other hand studies like Taylor and Allen (1992) or Menkhoff and Taylor (2007), show again and again the widespread use of technical analysis by institutional and private investors. The large number of websites and books devoted to technical analysis, like Appel (2007) or Stridsman (2001), give further proof to its importance in practical trading. The use of computer generated orders contributes to the influence of technical indicators as well, as these algorithms often place orders around certain moving averages or resistance and support levels, as is indicated by the common reference of these levels in information sources like Bloomberg.

This paper extends the existing literature on technical trading systems and market efficiency by implementing a set of rather simple trading rules based on Bollinger Bands for a hedge portfolio consisting of WTI and Brent. Various techniques to calculate the hedge ratio are used, including a dynamic linear model with Kalman filtering. Furthermore, data spanning 22 years is used to assess the performance of the technical trading systems, starting in 1992 and going up to the end of 2013. Thus, this study contains periods with very distinct characteristics, like the 1990s with rather low oil prices, the first years of the new millennium with prices spiking up to almost \$150 and then dropping to barely over \$30, and the years since 2010 marked by a steadily growing production of unconventional oil production.

The remainder of the paper is organized as follows. Section 2 gives an overview of the data used in the testing of the trading strategies. The methodology of the various trading strategies and significance tests is presented in Section 3. Section 4 follows up with the results of the backtests, Section 5 concludes.

## 2 Data

Settlement prices of the nearest month futures for WTI and Brent were obtained from Datastream. WTI and Brent are benchmark crudes for the US and North Sea oil. According to ICE, Brent is used for pricing approximately 60% of the world's traded oil and the crude light futures of the NYMEX are the most actively traded commodity futures worldwide (Wang and Yang 2010). Pricing of futures for these crudes is available on the NYMEX and ICE exchanges and trading takes place almost all day long. Therefore, an investor can use these financial instruments in a liquid market to set up a trading strategy.

Summary statistics for WTI and Brent daily prices and returns from January 1992 to December 2013 are reported in Table 1. Fig. 1 shows that WTI and Brent prices reached their peaks in 2008 with both brands being traded at prices of \$145, far above the prices in the 1990s where Brent recorded prices even below \$10 per barrel in the wake of the Asian financial crises and increasing production by OPEC. The financial crises starting in 2008 led to a sharp decline of oil prices so that both WTI and Brent traded in the \$40 range only a few months after they reached their all-time highs. Bern (2011) states that "the industry has never before witnessed the top of the commodity cycle and the bottom within two quarters". Over the next four years the market witnessed a rebound with Brent trading in a stable range of \$100 to \$120 and WTI in a range of \$85 to \$110. This spread is remarkable as the chemical characteristics of WTI like gravity and sulfur content make it superior compared to Brent and in general no other light crude exhibits such a discount to Brent. As already discussed, a negative WTI-Brent spread cannot simply be arbitrated away as cheap WTI is banned from exports and thus cannot be brought to European refineries. On the other hand, as soon as Brent trades at a discount to WTI that makes Atlantic arbitrage profitable, more oil will be moved westwards preventing the spread from becoming too wide.



## 3 Methodology

### Mean-Reversion Trading Rules

The trading rules considered are based on mean-reversion characteristics of price time series. A short term investor would be rather happy to find a time series that exhibits this kind of behavior as it translates to a simple set of trading rules, namely go long (short) whenever the price is considerably below (above) the mean and exit the position when the price is back at the mean. Unfortunately it is hard to find assets that mean-revert in the real world. WTI and Brent are no exception, as the standard Augmented Dickey-Fuller tests for the whole sample period and two sub periods in Table 2 show that the hypothesis that the price series are non-stationary cannot be rejected at the 5% significance level. Therefore, a mean-reverting strategy is not appropriate for trading either WTI or Brent individually. However, an investor is not confined to single price series but can set up a portfolio of assets which may lead to a stationary market value of the portfolio. In other words, if the price series of WTI and Brent are cointegrated, then there exists a linear combination of both series that is stationary. The Johansen-procedure shows that a combination of WTI and Brent is cointegrated. However, due to the changing spread between the two brands of crude oil, the test statistic is getting weaker over time. The test statistics for the periods 1992-2013, 1992-2002 and 2003-2013 are reported in Table 3. As can be seen, for the second sub period the test statistic is no longer significant even at the 10% level.

A setup for the mean-reverting trading strategy is provided by the so-called Bollinger Bands, as described for example in Chan (2013). The indicator  $z$  is made up of the value of the WTI/Brent-portfolio  $p$ , a simple moving average of  $p$ , practitioners usually using one of length 20, and the rolling standard deviation of  $p$  as specified in Eq. 1. Although the classical Bollinger Band uses the moving average length of 20, we test moving averages and rolling standard deviations of length 50, 100 and 200 as well.

$$z_t = \frac{p_t - \text{MA}_t}{\sigma_t} \quad (1)$$

Entry signals for long and short positions in the portfolio are generated whenever the

indicator reaches certain extreme values, for example -2 and 2 on the lower and upper side. This rule translates to a deviation of the current portfolio value of more than two standard deviation away from the moving average. The simple moving average is used to allow for changes in the portfolio value level over time.

An exit value has to be provided as well, values of  $z = 0, 0.2$  are used. The indicator  $z = 0$  means that the long or short position is closed whenever the portfolio value reaches the moving average again. The second combination using  $z = 0.2$  is implemented because often price movements will not stop at the moving average but tend to overshoot this mark. To profit from this overshooting an investor should close the long or short position when the price has crossed the moving average and moved a little bit further.<sup>4</sup> In case the mean-reversion trading system is in the market at the end of the sample period, the position is closed using the last available closing price. For backtesting we assume that an investor starts with \$100 of equity. Whenever the system signals an entry he goes either long or short one unit of the portfolio, that means he is either long WTI and short Brent or the other way round.

The trading rules described tend to stay only a fraction of the available time in the market. We assume that an investor does not earn any interest during times he is not invested. In other words, the money market rate is  $r_f = 0$ .

## Static Hedging Ratio for Mean-Reverting Strategies

What remains is to specify the crude oil hedge ratio of WTI and Brent. Taking  $p_H$  to be the value of the hedge portfolio leads to

$$p_H = Q_W \cdot p_W - Q_B \cdot p_B \quad (2)$$

with  $p_W$  and  $p_B$  being the prices of WTI and Brent and  $Q_W$  and  $Q_B$  the quantities of WTI and Brent in the portfolio. The change of the portfolio value is therefore

$$\Delta p_H = Q_W \cdot \Delta p_W - Q_B \cdot \Delta p_B. \quad (3)$$

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<sup>4</sup>To be precise: The exit  $z$ -score for the long position is 0.2, the one for the short position  $-0.2$ .

As the intention of building a hedge portfolio is to achieve  $\Delta p_H = 0$ , the hedge ratio  $h$  is given by

$$h = \frac{Q_B}{Q_W} = \frac{\Delta p_W}{\Delta p_B}. \quad (4)$$

As the Johansen-procedure gives eigenvectors of the linear combinations of the inputs we can use this information in building the portfolio. The hedge ratio is estimated by using the WTI and Brent prices of the last year before the test period starts and is not changed over the course of the test period, although it would be possible to adjust the weights on a more frequent basis. The portfolio values  $p_t$  needed for the indicator function in Eq. 1 are calculated by combining the daily closing prices of WTI and Brent with the hedge ratio.

$$p_t = p_{W,t} - hp_{B,t}. \quad (5)$$

## Dynamic Hedging Ratio for Mean-Reverting Strategies

As argued in Hatemi-J and Roca (2006) while the hedge ratio can be represented as the coefficient in a regression, having time varying instead of static coefficients is appropriate if the value of the hedged portfolio should be kept relatively stable. The introduction of a time varying hedge ratio can be justified because of changes in certain non-observable factors. In the oil market, investor sentiment and expectations tend to change rather frequently. Especially the Brent market tends to be influenced by political tensions in the Middle East, like the economic sanctions and oil embargo against Iran because of its nuclear arms program or the ongoing turmoil in Lybia that disrupts production and shipment of oil for the European market. WTI's price reactions depend to a large extend on US specific factors like crude production and inventories of crude and distillates.

To account for changes in the hedge ratio of WTI and Brent, a dynamic linear model in state space form is used with a Kalman Filter to update the estimated ratio according to the arrival of new data over time. The Kalman Filter has its roots in engineering applications but is widely used in the field of finance nowadays and is no stranger to

hedging applications (see for example Schwartz 1997 or Lautier and Galli 2004). However, most studies do not address hedges of two different futures but rather hedging a spot instrument with its futures.

When using a linear regression setting or the Johansen eigenvectors, the lookback period is specified and the data sampled in this lookback period is used to get the best estimate of the hedge ratio over the whole sample period. This approach gives rise to a number of problems. First of all the lookback period is set arbitrarily to, in this study, one year. Another critical point is that as the lookback period shifts forward certain observations are dropped from the calculation while new observations are added. This can lead to abrupt changes in the hedge ratio. One way to cope with this problem is to use exponential weighting to preserve the impact of older observations. Another is to set up a state space model and use the Kalman Filter which, in its simplest form, is a linear algorithm that updates the forecast of an unobservable variable, the hedge ratio, with every new information coming in. Although the trading system uses daily closing prices and therefore rather low frequent data an investor is interested in updating the input parameters as fast as possible. The Kalman Filter is a very fast means to achieve this goal as pointed out by Lautier and Galli (2004) and allows to update the forecast of the hedge ratio very quickly. The state space model used in this study is a dynamic linear model (DLM), that is, as the name already tells, linear and Gaussian.

To avoid the pitfall of hindsight bias in parameter estimation, the Kalman Filter is not set up once for the whole sample period, as this would include observations an investor does not know yet. However, making use of the fast algorithm helps to circumvent this problem. The filter is recalculated every trading day when new prices for WTI and Brent become available.<sup>5</sup>

The dynamic linear model presented here is similar to the linear regression but allows for time-varying coefficients. The specification of the model is as follows.

$$p_{W,t} = \beta_{1,t} + \beta_{2,t}p_{B,t} + \epsilon_t \quad \epsilon_t \sim N(0, \sigma^2) \quad (6)$$

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<sup>5</sup>Given the data processing capabilities even a private investor usually has at hand, it does not take more than a few seconds to update the hedge ratio. Software for implementing the Kalman Filter is freely available, like the `dlm`-package in the R statistical software suite, see Petris *et al.* (2009).

The daily forecast of the hedge ratio,  $\beta_{2,t}$ , is used to calculate the market value of the crude oil hedge portfolio. The dynamic linear model (DLM) used for the trading strategy in general can be described in two equations, namely the observation equation and the state equation.

$$p_{W,t} = x'_t \theta_t + v_t \quad v_t \sim N(0, \sigma_t^2) \quad (7)$$

$$\theta_t = G_t \theta_{t-1} + w_t \quad w_t \sim N(0, W_t) \quad (8)$$

where  $x'_t = [1, p_{t,B}]$  is the vector of explanatory variables with a constant term and the price of Brent.  $G_t$  is called the evolution matrix and, following the default setting of Petris *et al.* (2009), is an identity matrix here.<sup>6</sup> The unobservable variables  $\theta_t = [\beta_{1,t}, \beta_{2,t}]$  are the intercept and the hedge ratio. Matrix  $W$  models the variances in the state equation and is usually diagonal which translates to independent random walks for the regression coefficients. The Kalman Filter is the method of choice to recursively update the parameter estimates whenever new information arrives. A prior view on the distribution of the parameters,  $\theta_0 \sim N(m_0, C_0)$  is specified, although we assume a low level of confidence in this view. Therefore, the filtering process is started with  $m_0 = 1.0$  and  $C_0 = 1e^7$ , the default value of the `dml`-package in the R software suite.

Following the description given in Petris *et al.* (2009), the Kalman Filtering for the dynamic linear model specified in Eq. 7 and Eq. 8 proceeds as follows. Using the data available up to time  $t - 1$ , the parameter estimate at  $t - 1$  is

$$\theta_{t-1} | p_{W,1:t-1} \sim N(m_{t-1}, C_{t-1}), \quad (9)$$

and we move ahead to predict the Gaussian distributions of  $\theta_t$  and  $p_{W,t}$  with parameters

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<sup>6</sup> $G$  could be changed to reflect seasonal effects, for example.

$$a_t = E(\theta_t | p_{W,1:t-1}) = G_t m_{t-1} \quad (10)$$

$$R_t = Var(\theta_t | p_{W,1:t-1}) = G_t C_{t-1} G_t' + W_t \quad (11)$$

$$f_t = E(p_{W,t} | p_{W,1:t-1}) = x_t a_t \quad (12)$$

$$Q_t = Var(p_{W,t} | p_{W,1:t-1}) = x_t R_t x_t' + V_t. \quad (13)$$

The updates for the filtering distribution after the arrival of new price information and with a forecast error of  $e_t = p_{W,t} - f_t$  are

$$m_t = E(\theta_t | p_{W,1:t}) = a_t + R_t x_t' Q_t^{-1} e_t \quad (14)$$

$$C_t = Var(\theta_t | p_{W,1:t}) = R_t - R_t x_t' Q_t^{-1} x_t R_t. \quad (15)$$

To maintain numerical stability, the variance  $V_t$  is set to a value of 0.0025 to prevent singular matrices in the optimization procedure. A special and indeed the most simple case is to set the variance terms in  $W_t$  to zero, as it translates to a static regression model with frequent parameter updates on the arrival of new data or in the words of Petris *et al.* (2009) "  $m_t$  is the Bayesian estimate under a quadratic loss function of the regression coefficients".

Another approach tested is to derive estimates of the unknown variance terms in  $W_t$  by using a Maximum-Likelihood Estimation (MLE). With a vector of unknown parameters  $\Phi$  representing the variances in the state equation, the loglikelihood  $\mathcal{L}$  is

$$\mathcal{L}(\Phi) = -\frac{1}{2} \sum_{t=1}^n \log |Q_t| - \frac{1}{2} \sum_{t=1}^n (p_{W,t} - f_t)' Q_t^{-1} (p_{W,t} - f_t) \quad (16)$$

and is numerically optimized to get the Maximum Likelihood Estimation (MLE). The parameters from the MLE are then plugged into Eq. 8 and the Kalman Filtering process is run to calculate the dynamic hedge ratio.

Inspection of Figure 2 on page 23 reveals that the hedge ratio for the zero variance model was quite stable in the second half of the 1990s but is subject to frequent changes since 2000/2001, taking values greater than 1 in 2005 and experiencing a sharp decline

since 2010 to values of about 0.9. The decrease in the hedge ratio over the last four years reflects the widening spread between WTI and Brent in that period.

The MLE variance version of the Dynamic Linear Model, represented by the dotted line, moves more erratically as the estimate is more influenced by new data. Nevertheless the general trends are also present in the MLE variance DLM. Since 2010 the ratio is significantly below 1, there is only an up spike in the summer of 2013 when the spread narrowed and almost was closed for a short period of time.

## Testing the Significance

Based on the the approaches discussed in Lo *et al.* (2000), to assess the significance of the results of the trading simulations sets of simulated trades are generated. The simulated trades are constrained in so far as the number of long and short trades has to be equal to the number of long and short trades in the original back test and they should have the same mean holding time, that means the average period of time until the position is closed, as the original trades. For each test period, the number of long and short entries and the average holding period is recorded. Then random entries on the long and short side are generated and the positions are closed after the passing of the average holding period. The profit and loss and the daily returns and their standard deviations are recorded and compared to those of the strategies tested. This procedure is repeated 1,000 times. The number of simulated runs that perform better than the tested strategy is used to calculate an achieved significance level or simulated p-value. This procedure follows the idea of the computer-based bootstrap methodology outlined in Efron and Tibshirani (1986) and Efron and Tibshirani (1993). Assume, for example, that out of 1,000 bootstrap runs 15 show a profit in excess of the original back test. This yields an achieved significance level or simulated p-value of 0.015 or 1.5 %.

In the words of Shleifer (2000) "[s]howing that a particular strategy based on exploiting stale information on average earns a positive cash flow over some period of time is not, therefore, by itself evidence of market inefficiency. To earn this profit, an investor may have to bear risk and his profit may just be a fair market compensation for risk-bearing." Whenever the performance of technical trading systems is assessed, it is of utmost impor-

tance to consider the investor's risk exposure. We calculate the Sharpe ratio by adjusting the mean daily returns of the strategy with the standard deviation as we assume a risk-free rate of 0.0 and annualize this number. This statistic is calculated for each bootstrap sample, too.

Although speculative investors in the crude oil market will act rather short-term, this only means that they are frequently entering and existing positions. However, trading systems like the ones described here should be evaluated given their long-run performance. Therefore, rolling five year periods are used to test the profitability of the technical rules. This is in line with investment practice as an investor should not abandon a strategy just because it produced some losing trades. The strategy should rather be able to produce more profits than losses and profits should rather come constantly from trades than just depending on one lucky punch.

## **The Choice of Financial Instruments**

We assume that an investor uses WTI and Brent futures that are traded on the New York Mercantile Exchange (NYMEX) and the Intercontinental Exchange (ICE) in London. More specifically, we are using the nearest-month futures as they are usually the most liquid. Professional commodity trading companies are active in the physical market as well (see Carollo 2012), but adding physical oil to a strategy based on financial instruments introduces various new aspects that have to be considered, like terms of delivery, storage costs, transportation, insurance etc. Although trading physical oil allows for an abundance of strategies, it is a field not open to the retail investor and is therefore not considered here. On the other hand, even if an investor chooses not to use the instruments offered by NYMEX and ICE, certificates for difference (CFD) or mini futures offered by banks to retail customers are in general priced according to these futures prices. Thus it makes sense to set up a trading strategy based on these instruments. The nearest-month contract is, with the exception of maybe one or two days before expiry, by far the most liquid futures contract traded, therefore it is the natural choice for an investor.



## Transaction Costs

To account for costs of entering and exiting futures positions, transaction fees of 0.1% of the respective futures price are assumed for each trade. As an investor is trading the spread of WTI and Brent, one round-turn transaction consists of four trades, for example entering long Brent and short WTI and then closing both positions. The transaction costs used are higher than the numbers given for example by Dunis *et al.* (2008) and Dunis *et al.* (2006), however the strategy may make it necessary to roll over to the next futures contract at expiry or to make adjustments due to changes in the hedge ratio. Therefore, working with a kind of additional safety margin in the costs reflects these problems.

## 4 Results

The average results of the backtests of the strategies for the five year testing periods are reported in Tables 4 and 5. All in all, there are 18 five year periods in the sample, the first starting in January 1992 and the last in January 2009. The first two columns indicate the strategy used by giving the length of the moving average and the exit  $z$  score. The profit (or loss) is reported in the third column, followed by the total number of trades and the winning trades. The sixth and seventh columns contain information about the mean holding time of one trade and the strategy's time in the market. To evaluate the performance of a strategy we report the mean daily return and standard deviation as well as the Sharpe Ratio in the last three columns. No matter whether the static or the dynamic hedging versions are used, the shortest moving average rules (20 days) are by far the most profitable in terms of absolute profit as well as Sharpe ratio. This is quite interesting in so far as the 20 days moving average is the standard length of the Bollinger Band system. To assess the performance of these rules in depth, the results for each five year period from 1992 up to 2009 are reported as well, Tables 6, 7 and 8 contain detailed information. Here, the starting year of the tested five year period is given in the first column, for example the starting year 1992 is the five year period spanning 1992 to 1996. The last period under consideration is therefore 2009 to 2013.

Inspecting the average results, we find the 20 days moving average rules to produce the

largest number of trades, with the averages over the five year testing periods ranging from 53.2 for the zero variance dynamic hedging strategy with an exit score of 0.2 to 66.1 for the MLE DLM strategy with an exit score of 0.0. As the short moving averages tend to react the fastest to movements of the hedge portfolio, the mean holding time per trade is significantly shorter than for the longer moving averages. This is clearly exemplified by comparing the average 7.8 days per trade for the zero variance DLM 20/0.0 strategy with the 45.2 days for the 200/0.0 strategy. Although the 20 days moving average produces the most trades, because of the short holding period its time in the market is the lowest of all strategies for example only 32.4% compared to 39.6% for the 100 days moving average in the zero variance DLM setting with a  $z$  score of 0.0. The very concept of trying to capture the overshooting movement above or below the moving average with the 0.2 exit score leads to longer average holding periods compared to the 0.0 exit score as the closing of the respective positions will occur later. This is evident for all setups.

Even though the 20 days moving average rules spend the least time in the market and produce the most trades and therefore the highest transaction costs, they generate the highest profits and Sharpe ratios in the static as well as the dynamic setups. A possible explanation is that on the entry side they react the fastest to extreme deviations in the value of the hedge portfolio and are also the fastest to exit the market when the move back to the mean has occurred. Another benefit of the short time in market is that the standard deviation of the daily returns is smallest for the 20 days moving average rules in all three setups, with the MLE DLM having by far the smallest standard deviation. However, the trading strategies seem to exhibit higher standard deviations than the randomly placed orders, as the simulated p-values indicate. Nevertheless for the most part an investor is more than compensated for the higher risk by the higher returns he earns, as the highly significant Sharpe ratios show. For the MLE DLM, all Sharpe ratios have p-values of 0.0. The zero variance DLM's Sharpe ratios are significant at the 5% level except for the 50 days moving average rules. The static version performs worst with only the 20 days moving average rules' Sharpe ratios being significant at the 5% level. Comparing the Sharpe ratios of the static and dynamic setups, we find the MLE DLM to strongly outperform the other two approaches. The smallest Sharpe ratio for the MLE DLM is

recorded for the 200 days moving average with an exit score of 0.2, but it is still higher than all Sharpe ratios for the static system and the zero variance DLM.

The detailed results for the 20 days rules reveal that the performance deteriorates for all setups over the last five year period starting in 2009, with the static hedge ratio's profit turning negative. The MLE DLM, even though recording lower profits than in the years before, still keeps up its good performance, with only one losing trade and Sharpe ratios well above three in the last five year period. The dynamic setups are able to generate (positive) profits over each and every five year period under consideration. With the exception of the last five year period for the zero variance DLM, the trading systems' performances are much better than using random entries and deliver significantly higher Sharpe ratios. As expected, the highest profits were generated from 2000 on, due to more volatile prices and larger involvement of financial investors. The mean-reverting strategies, no matter whether the static or dynamic versions are used, record the highest Sharpe ratios in the periods starting in 2000, 2001, 2002 and 2003. The highest absolute profits occur in the periods starting 2004 and 2005, but obviously these profits came at a higher risk.

The main disadvantage of the static version is that it produces a rather high number of losing trades compared to the dynamic versions. Over the last five years, out of 44 signals only 30 are profitable (MLE DLM 76 and 72 out of 77 and 73). The static setup has the highest percentage of time in market and the longest average holding periods per trade. We already saw that this usually leads to higher risk. The standard deviation is indeed higher than for the dynamic versions leading to lower Sharpe ratios.

The zero variance DLM mean-reverting trading system shows highly significant profits. Except for the very last five year period, the strategy performs obviously a lot better than just placing random orders, with simulated p-values of 0.0. The number of winning trades compared to the total number of trades is remarkably high except for the last two five year periods. This fact supports that the devised system works quite well and does not depend on just a few lucky and profitable trades to balance the losers. Although the strategy tends to be riskier than the random orders, as is indicated by the low simulated p-values for the standard deviation, the higher returns compared to the random strategy

lead to significantly higher Sharpe ratios in almost all five year periods tested.

The MLE DLM system is by far the best performing of the three setups. The system is able to identify profitable trades with almost 100% certainty, as can be seen by the high number of winning trades in comparison to the total number of trades. Profits, daily mean returns and Sharpe ratios are significantly higher than those of random entries with p-values of 0.000. The system is the one with the lowest time in market, the 20 days moving average has just between 15% and 27% time in market as Table 8 shows. For this setup, trades last only about three to four days on average. This leads to smaller risk exposure compared to the other setups, although the standard deviation of the daily returns tends to be higher than for random orders. The high Sharpe ratios, often in excess of three further highlight this favorable risk-reward characteristics. One other fact places this setup way ahead of the other two. Over the last five year period from 2009 to 2013, the system still performs remarkably well, with much higher profits and Sharpe ratios than the other strategies. As the standard deviation of the strategy's daily returns is lower than for the preceding periods, the Sharpe ratios of 3.6 and 3.3 for the exit  $z$  scores of 0.0 and 0.2 are amongst the highest recorded. Except for the last three five year periods, the exit  $z$  score of 0.2 gives slightly better profits and Sharpe ratios, however, differences tend to be small.

## 5 Conclusion

The markets for WTI and Brent have evolved dramatically since futures trading started in the 1980s. The number of participants in these markets has risen considerably over the years, from just a few professional investors to hedge funds, pension funds and all kinds of institutional and retail investors. Over the last decade investors have moved significant funds into various forms of alternative investments, among them energy commodities and especially crude oil. This coincided with growing global demand for oil, mainly driven by the fast booming economies in Asia. The growing amount of money invested in commodities naturally gives rise to questions as to how trading strategies originating from the equity markets perform in the crude oil market. This study showed that trading

the WTI-Brent spread is profitable, especially since 2000.

That a rather simple mean-reverting strategy based on the widely used Bollinger Bands and applied to a hedge portfolio of the two crudes proved to be very successful, although it is only based on an analysis of historical data, may be a hint that the Efficient Market Hypothesis in its weak form does not hold. In fact, the strategies tested only incorporate historical price series, macroeconomic data usually used to forecast oil prices, like oil inventories or spare capacity as in Merino and Albacete (2010), is not employed.

To establish whether our findings are significant, we compare the results of the trading rules with those of randomly generated orders. Over each testing period, the same number of random orders as in the original series is generated and they share the same mean holding time. Given that the Bollinger Band did not possess any kind of predictive power, one would expect randomly placed orders to perform on average as well as the rules tested. If, on the other hand, the Bollinger Band performs better we may be inclined to question whether the WTI-Brent market is weakly efficient. Although rather high transaction costs are incorporated into the backtests, the total profits, mean daily returns and Sharpe ratios especially of the short moving average strategies are significantly higher than those of random entry strategies.

It may come as a surprise that a trading system whose basic setup is known for decades is significantly profitable in the crude oil market. To use a strategy that aims at keeping the time in the market and therefore the exposure to risk as low as possible is a reasonable approach in a market that is characterized by frequent periods of high volatility and dramatic price changes. Furthermore, the inherent hedge given a portfolio of similar assets like WTI and Brent makes it clear that the focus is not on picking trends but rather to exploit extreme deviations from an average spread level. It must be stressed that the general idea of setting up a hedge portfolio is to achieve a certain degree of immunization from adverse market movements. A comparison of the Bollinger Band results with those of buy and hold strategies of either WTI or Brent would therefore be misleading.

An investor implementing the Bollinger Band system described here would in fact be hedged against influences affecting the oil market as a whole, like the global recession in the wake of the financial crisis of 2007/2008. But when extreme deviations in the ratio

of oil prices appear, the system indicates favorable trading opportunities with a high probability. Nevertheless, structural changes in the WTI-Brent spread may occur. The situation since 2010 makes it obvious that although WTI and Brent are both benchmark crude brands, their prices are sometimes driven by different forces as WTI is basically an American benchmark that must not be exported whereas Brent as benchmark for about 60% of the traded oil worldwide is much more prone to global influences.<sup>7</sup> Today it seems that the price of WTI is mainly driven by factors unique to the US market, like the rising production of unconventional oil and inventory levels. Brent on the other hand is strongly influenced on the supply side by production rates in countries like Libya and Nigeria. Political decisions like lifting the economic sanctions against Iran or the tensions in Eastern Europe are directly reflected in the price of Brent. The trading rules are able to account for these factors because they work with moving averages and standard deviations and, in case of the DLMS, with constant updates of the hedge ratio.

A finding of this study is that the profitability of the Bollinger Band strategy, after peaking in the first years of the new millennium, seems to become lower over time, in line with the widening of the spread between WTI and Brent over the last few years and with the results of other studies like Alvarez-Ramirez et al. (2008) and Tabak and Cajueiro (2007). Although the systems still records profits in this wide spread environment, in the case of the MLE DLM still with quite high returns and Sharpe ratios, it can be assumed that a reduction in or closing of the spread would boost profitability again to levels recorded up to the years 2008 or 2009. This may be the case when political tensions in Europe and the Middle East are solved or the American export ban on crude is lifted by Congress.

However, it may be premature to assign to the oil markets the tribute of weak efficiency. The results reported in this study indicate a strong deviation from market efficiency, given the fact that especially the short moving average combinations record highly significant profits, daily returns and Sharpe ratios most of the time and only two versions lose their significance in the last five year period. Although the basic idea behind the tested systems is straightforward and rather simple, the results show that what can be considered

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<sup>7</sup>To circumvent this problem an investor may consider to use calendar spreads instead of inter-market spreads.

to be the most sophisticated approach, namely the MLE DLM that utilizes maximum likelihood estimators of the unknown variances in the state equation, offers the most rewarding characteristics like low time in market and high Sharpe ratios and keeps up its good performance even over the last few years. The MLE DLM may perform the most advanced calculations, but it still depends solely on the input of historical price information. Therefore, this leads to the conclusion that a system of technical rules can show a remarkably steady performance and that the oil market considered here is not efficient as defined in the EMH.

## Appendix A: Figures

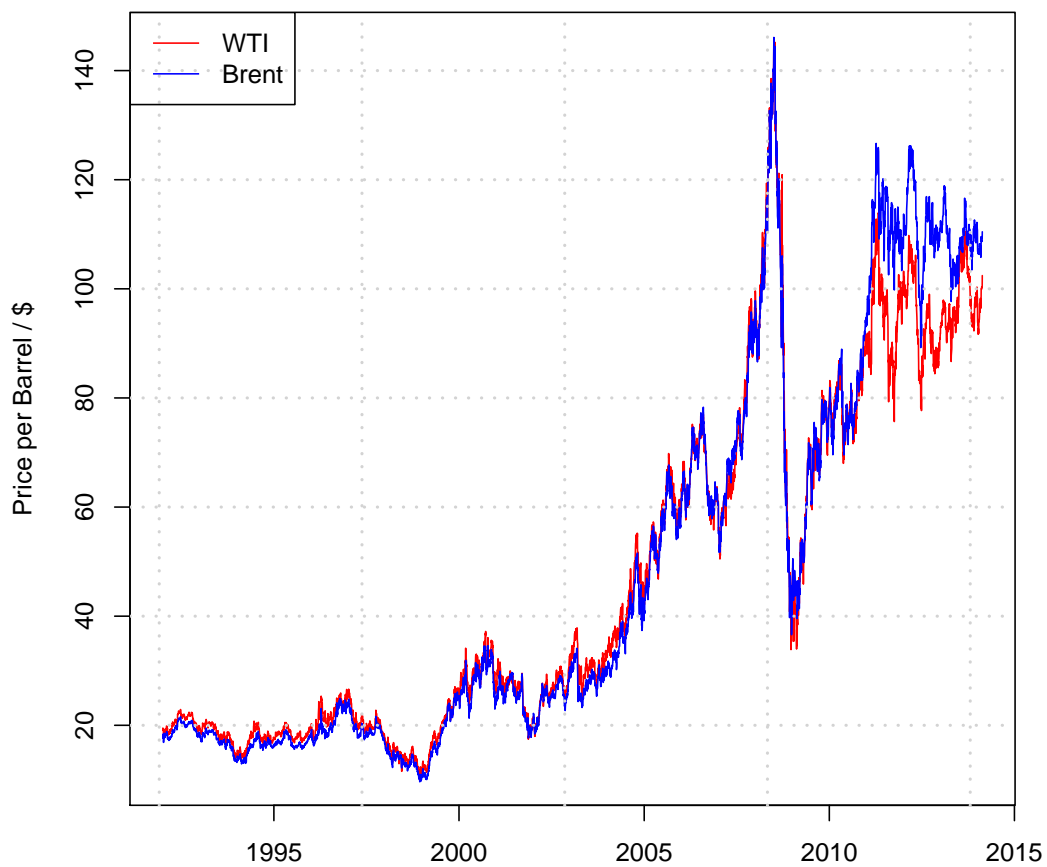


Figure 1: Nearest-month Futures Prices of WTI and Brent 1992-2013



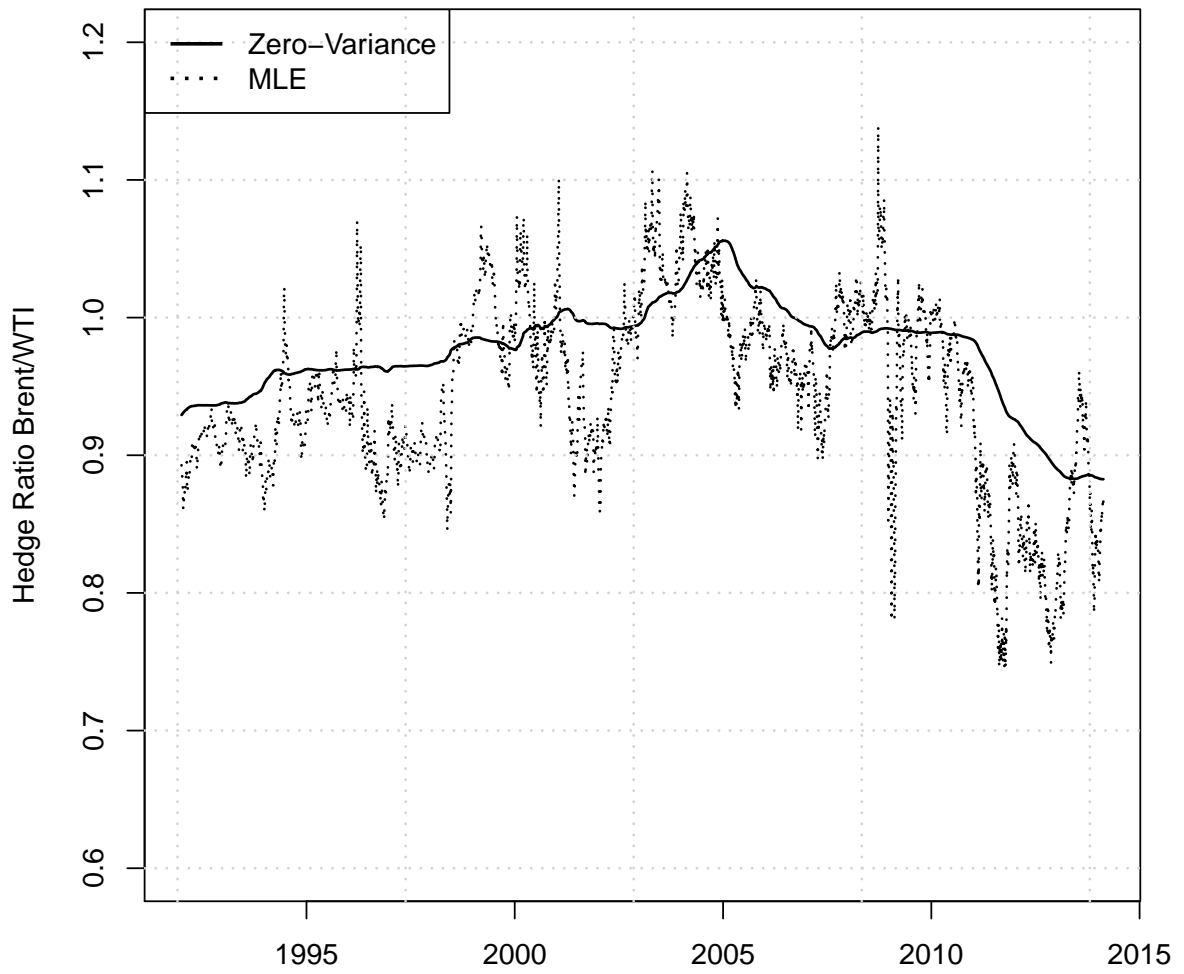


Figure 2: Dynamic Hedge Ratios of WTI and Brent using Kalman Filtering with zero variance (solid line) and MLE variance (dotted line) in the state equation 1992-2013

## Appendix B: Tables

	WTI		Brent	
	Prices	Returns	Prices	Returns
Observations	5775	5774	5775	5774
Arithmetic Mean	47.09	0.000	48.16	0.0005
Geometric Mean	37.74	0.0003	36.98	0.0003
Minimum	10.72	-0.1525	9.64	-0.1344
Quartile 1	20.14	-0.0108	18.79	-0.0098
Median	31.04	0.0000	29.06	0.0004
Quartile 3	73.52	0.0120	73.61	0.0110
Maximum	145.29	0.1783	146.08	0.1377
SE Mean	0.41	0.0003	0.47	0.0003
Variance	993.12	0.0005	1255.13	0.0004
St. Deviation	31.51	0.0223	35.43	0.0205
Skewness	0.74	0.1209	0.82	-0.0328
Kurtosis	-0.77	5.1237	-0.74	3.5673
Jarque-Bera	673.827	6329.801	787.254	3062.579

Table 1: Summary Statistics for WTI and Brent Futures daily settlement prices and returns 1992-2013

	Statistic p-value		Statistic p-value		Statistic p-value	
	1992-2013		1992-2002		2003-2013	
WTI	-3.2119	0.08579	-2.8454	0.2204	-2.7168	0.2749
Brent	-2.7633	0.2551	-2.7039	0.2803	-2.5062	0.364

Table 2: Standard augmented Dickey-Fuller tests for WTI and Brent futures prices

	Test Statistic	10pct	5pct	1pct
1992-2013				
$r \leq 1$	1.69	7.52	9.24	12.97
$r = 0$	23.37	13.75	15.67	20.20
1992-2002				
$r \leq 1$	3.95	7.52	9.24	12.97
$r = 0$	113.30	13.75	15.67	20.20
2003-2013				
$r \leq 1$	3.04	7.52	9.24	12.97
$r = 0$	13.00	13.75	15.67	20.20

Table 3: Johansen-procedure for WTI and Brent futures prices

MA	Exit	PNL	Trades	Win	MeanHold	TiM	MeanR	SD	Sharpe
20	0.0	36.618153 (0.026474)	55.894737	49.894737	8.272943	0.348756	0.000241 (0.024526)	0.003350 (0.158526)	1.352872 (0.027053)
50	0.0	20.264616 (0.056789)	29.526316	25.631579	19.065520	0.418032	0.000148 (0.048947)	0.003867 (0.096158)	0.810976 (0.057421)
100	0.0	17.941426 (0.057421)	18.368421	16.842105	33.494072	0.437360	0.000134 (0.049368)	0.003830 (0.096053)	0.719242 (0.059368)
200	0.0	18.446959 (0.050895)	11.947368	11.473684	46.649549	0.370708	0.000135 (0.044526)	0.003657 (0.109474)	0.722865 (0.052632)
20	0.2	36.777660 (0.027632)	54.052632	48.157895	9.510986	0.388859	0.000243 (0.022474)	0.003492 (0.157211)	1.337735 (0.029158)
50	0.2	15.679794 (0.103105)	27.157895	23.157895	23.241921	0.467457	0.000119 (0.092737)	0.004102 (0.084947)	0.702258 (0.097737)
100	0.2	18.538331 (0.058895)	17.315789	15.947368	38.956081	0.482105	0.000137 (0.051368)	0.003872 (0.104842)	0.699306 (0.056368)
200	0.2	18.869097 (0.047579)	11.052632	10.368421	53.754912	0.403512	0.000139 (0.040421)	0.003721 (0.110000)	0.723512 (0.051211)

Table 4: Mean results of the mean-reversion trading system with static hedging

MA	Exit	PNL	Trades	Win	MeanHold	TiM	MeanR	SD	Sharpe
Zero Variance State Space Model									
20	0.0	51.197471 (0.011333)	55.222222	50.722222	7.756220	0.324177	0.000315 (0.008889)	0.003133 (0.173000)	1.716639 (0.011167)
50	0.0	25.470785 (0.047222)	28.555556	25.333333	18.521474	0.390315	0.000179 (0.039444)	0.003742 (0.100889)	0.955174 (0.053389)
100	0.0	27.186994 (0.011722)	19.611111	18.166667	27.884817	0.395768	0.000190 (0.006556)	0.003643 (0.100444)	0.925780 (0.018333)
200	0.0	21.934872 (0.027278)	11.444444	11.166667	45.226577	0.366254	0.000156 (0.020222)	0.003601 (0.127389)	0.751150 (0.038278)
20	0.2	50.874731 (0.014667)	53.222222	49.111111	9.055247	0.364593	0.000314 (0.011611)	0.003195 (0.202889)	1.686722 (0.015500)
50	0.2	23.111274 (0.068556)	27.055556	24.111111	22.307103	0.446361	0.000165 (0.056833)	0.003872 (0.110111)	0.889298 (0.070944)
100	0.2	27.320127 (0.015833)	18.111111	17.222222	34.496384	0.457647	0.000191 (0.006611)	0.003696 (0.122278)	0.898589 (0.017889)
200	0.2	21.521411 (0.029389)	10.555556	10.055556	53.790659	0.396748	0.000154 (0.022667)	0.003683 (0.134556)	0.729671 (0.035389)
MLE State Space Model									
20	0.0	52.873644 (0.000000)	66.055556	65.722222	4.163076	0.210892	0.000323 (0.000000)	0.001765 (0.169556)	2.898995 (0.000000)
50	0.0	47.937422 (0.000000)	52.277778	51.944444	6.157263	0.244707	0.000298 (0.000000)	0.001786 (0.186722)	2.626845 (0.000000)
100	0.0	42.652698 (0.000000)	40.833333	40.777778	9.449586	0.281845	0.000270 (0.000000)	0.001857 (0.178722)	2.279819 (0.000000)
200	0.0	35.724065 (0.000000)	31.944444	31.388889	17.024717	0.357091	0.000231 (0.000000)	0.001938 (0.245556)	1.893131 (0.000000)
20	0.2	54.070684 (0.000000)	65.333333	65.000000	4.764267	0.239510	0.000329 (0.000000)	0.001787 (0.200833)	2.925147 (0.000000)
50	0.2	49.258031 (0.000000)	50.500000	50.444444	8.046707	0.304415	0.000303 (0.000000)	0.001877 (0.206000)	2.523928 (0.000000)
100	0.2	42.791387 (0.000000)	39.277778	39.222222	11.509171	0.328478	0.000271 (0.000000)	0.001916 (0.204222)	2.230340 (0.000000)
200	0.2	35.236115 (0.000000)	29.888889	29.333333	21.535045	0.429192	0.000228 (0.000000)	0.002040 (0.263944)	1.754336 (0.000000)

Table 5: Mean results of the mean-reversion trading system with dynamic hedging

Year	MA	Exit	PNL	Trades	Win	MeanHold	TiM	$\bar{r}$	$\sigma$	Sharpe
1992	20	0.0	23.1438 (0.000)	55	53	6.56	0.2766	0.0002 (0.000)	0.0018 (0.002)	1.4198 (0.000)
	20	-0.2	22.6002 (0.000)	52	49	8.21	0.3272	0.0002 (0.000)	0.0018 (0.010)	1.3709 (0.000)
1993	20	0.0	26.9704 (0.000)	61	58	6.31	0.2952	0.0002 (0.000)	0.0018 (0.012)	1.5992 (0.000)
	20	-0.2	27.4326 (0.000)	58	55	7.71	0.3428	0.0002 (0.000)	0.0018 (0.015)	1.6104 (0.000)
1994	20	0.0	26.4237 (0.000)	58	55	6.22	0.2768	0.0002 (0.000)	0.0020 (0.002)	1.4648 (0.000)
	20	-0.2	27.7755 (0.000)	57	54	7.19	0.3144	0.0002 (0.000)	0.0020 (0.009)	1.5312 (0.000)
1995	20	0.0	31.8558 (0.000)	61	57	6.84	0.3195	0.0002 (0.000)	0.0020 (0.005)	1.6731 (0.000)
	20	-0.2	32.5835 (0.000)	59	55	7.95	0.3594	0.0002 (0.000)	0.0020 (0.013)	1.6955 (0.000)
1996	20	0.0	29.6931 (0.000)	54	50	7.61	0.3149	0.0002 (0.000)	0.0023 (0.015)	1.3862 (0.000)
	20	-0.2	31.2244 (0.000)	53	50	8.43	0.3425	0.0002 (0.000)	0.0023 (0.030)	1.4465 (0.000)
1997	20	0.0	27.6936 (0.000)	57	51	8.07	0.3528	0.0002 (0.000)	0.0021 (0.098)	1.4100 (0.000)
	20	-0.2	28.8440 (0.000)	56	50	9.02	0.3873	0.0002 (0.000)	0.0021 (0.019)	1.4474 (0.000)
1998	20	0.0	30.5008 (0.000)	56	50	7.98	0.3428	0.0002 (0.000)	0.0024 (0.070)	1.3888 (0.000)
	20	-0.2	32.0793 (0.000)	54	48	9.07	0.3758	0.0002 (0.000)	0.0024 (0.147)	1.4264 (0.000)
1999	20	0.0	40.0285 (0.000)	60	54	7.65	0.3520	0.0003 (0.000)	0.0025 (0.007)	1.6323 (0.000)
	20	-0.2	42.2990 (0.000)	59	54	8.53	0.3857	0.0003 (0.000)	0.0026 (0.025)	1.6951 (0.000)
2000	20	0.0	52.5632 (0.000)	66	60	7.73	0.3908	0.0003 (0.000)	0.0027 (0.146)	1.9074 (0.000)
	20	-0.2	53.6027 (0.000)	63	57	9.46	0.4567	0.0003 (0.000)	0.0028 (0.216)	1.8763 (0.000)
2001	20	0.0	47.5737 (0.000)	61	55	8.33	0.3893	0.0003 (0.000)	0.0024 (0.501)	1.9565 (0.000)
	20	-0.2	51.4345 (0.000)	60	55	9.72	0.4467	0.0003 (0.000)	0.0025 (0.467)	2.0194 (0.000)
2002	20	0.0	52.7495 (0.000)	56	54	6.89	0.2960	0.0003 (0.000)	0.0026 (0.077)	1.9644 (0.000)
	20	-0.2	51.1910 (0.000)	55	53	7.95	0.3351	0.0003 (0.000)	0.0027 (0.086)	1.8500 (0.000)
2003	20	0.0	41.5510 (0.000)	57	48	9.32	0.4072	0.0003 (0.000)	0.0033 (0.347)	1.3025 (0.000)
	20	-0.2	42.3931 (0.000)	56	49	10.61	0.4555	0.0003 (0.000)	0.0034 (0.377)	1.2918 (0.000)
2004	20	0.0	61.3811 (0.000)	56	52	7.11	0.3050	0.0004 (0.000)	0.0042 (0.391)	1.4016 (0.000)
	20	-0.2	63.9477 (0.000)	55	50	8.18	0.3448	0.0004 (0.000)	0.0043 (0.390)	1.4319 (0.000)
2005	20	0.0	60.9795 (0.000)	52	46	8.27	0.3298	0.0004 (0.000)	0.0047 (0.373)	1.2715 (0.000)
	20	-0.2	63.5539 (0.000)	51	45	9.18	0.3589	0.0004 (0.000)	0.0047 (0.371)	1.3070 (0.000)
2006	20	0.0	49.1995 (0.000)	54	44	9.28	0.3839	0.0003 (0.000)	0.0050 (0.343)	1.0147 (0.000)
	20	-0.2	38.7941 (0.001)	51	42	10.75	0.4199	0.0003 (0.000)	0.0062 (0.094)	0.6917 (0.012)
2007	20	0.0	50.0798 (0.001)	52	44	9.90	0.3946	0.0003 (0.001)	0.0058 (0.363)	0.8953 (0.005)
	20	-0.2	52.3621 (0.000)	51	43	10.92	0.4268	0.0003 (0.000)	0.0057 (0.408)	0.9338 (0.003)
2008	20	0.0	29.2618 (0.035)	47	34	12.57	0.4529	0.0002 (0.010)	0.0080 (0.075)	0.4498 (0.053)
	20	-0.2	21.1507 (0.109)	44	30	14.64	0.4935	0.0002 (0.039)	0.0089 (0.026)	0.3329 (0.132)
2009	20	0.0	-3.3665 (0.467)	44	30	14.25	0.4808	-0.0001 (0.455)	0.0067 (0.063)	neg. (0.454)
	20	-0.2	-0.4692 (0.415)	44	30	14.82	0.5000	0.0000 (0.388)	0.0067 (0.043)	0.0482 (0.407)

Table 6: Results of the mean-reversion trading system with static hedging and 20 days moving average for all five year periods 1992-2009

Year	MA	Exit	PNL	Trades	Win	MeanHold	TiM	MeanR	SD	Sharpe
1992	20	0.0	25.8913 (0.000)	54	52	6.50	0.2690	0.0002 (0.000)	0.0018 (0.002)	1.5869 (0.000)
	20	-0.2	24.9034 (0.000)	50	46	8.40	0.3218	0.0002 (0.000)	0.0018 (0.007)	1.5055 (0.000)
1993	20	0.0	28.5387 (0.000)	55	54	6.65	0.2807	0.0002 (0.000)	0.0018 (0.006)	1.7363 (0.000)
	20	-0.2	28.0016 (0.000)	52	50	8.29	0.3305	0.0002 (0.000)	0.0018 (0.020)	1.6773 (0.000)
1994	20	0.0	27.0430 (0.000)	51	49	6.96	0.2722	0.0002 (0.000)	0.0019 (0.000)	1.5478 (0.000)
	20	-0.2	27.3525 (0.000)	50	47	8.28	0.3175	0.0002 (0.000)	0.0019 (0.04528)	1.5471 (0.000)
1995	20	0.0	30.3848 (0.000)	53	50	6.70	0.2720	0.0002 (0.000)	0.0019 (0.0030)	1.7374 (0.000)
	20	-0.2	31.4873 (0.000)	52	49	7.58	0.3019	0.0002 (0.000)	0.0019 (0.007)	1.7856 (0.000)
1996	20	0.0	36.6878 (0.000)	55	52	7.35	0.3096	0.0002 (0.000)	0.0023 (0.0120)	1.6523 (0.000)
	20	-0.2	39.2283 (0.000)	54	51	8.54	0.3533	0.0003 (0.000)	0.0023 (0.016)	1.7370 (0.000)
1997	20	0.0	31.0364 (0.000)	53	48	7.72	0.3137	0.0002 (0.000)	0.0022 (0.0040)	1.5150 (0.000)
	20	-0.2	34.3814 (0.000)	52	48	8.98	0.3581	0.0002 (0.000)	0.0022 (0.020)	1.6457 (0.000)
1998	20	0.0	36.7305 (0.000)	56	52	6.80	0.2922	0.0002 (0.000)	0.0023 (0.0120)	1.6703 (0.000)
	20	-0.2	38.7952 (0.000)	54	51	8.19	0.3390	0.0003 (0.000)	0.0023 (0.023)	1.7285 (0.000)
1999	20	0.0	48.8197 (0.000)	62	58	6.95	0.3305	0.0003 (0.000)	0.0024 (0.0120)	1.9938 (0.000)
	20	-0.2	48.8214 (0.000)	59	56	8.49	0.3842	0.0003 (0.000)	0.0025 (0.035)	1.9505 (0.000)
2000	20	0.0	65.8692 (0.000)	64	61	6.73	0.3303	0.0004 (0.000)	0.0027 (0.059)	2.2650 (0.000)
	20	-0.2	65.6017 (0.000)	62	60	8.15	0.3870	0.0004 (0.000)	0.0028 (0.154)	2.2106 (0.000)
2001	20	0.0	63.0342 (0.000)	61	58	6.92	0.3234	0.0004 (0.000)	0.0024 (0.220)	2.4876 (0.000)
	20	-0.2	61.7258 (0.000)	59	57	8.17	0.3693	0.0004 (0.000)	0.0025 (0.359)	2.3645 (0.000)
2002	20	0.0	66.8635 (0.000)	61	58	6.66	0.3113	0.0004 (0.000)	0.0025 (0.251)	2.5201 (0.000)
	20	-0.2	62.7566 (0.000)	58	55	7.98	0.3551	0.0004 (0.000)	0.0026 (0.187)	2.2699 (0.000)
2003	20	0.0	66.8688 (0.000)	59	55	7.34	0.3321	0.0004 (0.000)	0.0027 (0.402)	2.2851 (0.000)
	20	-0.2	66.3222 (0.000)	58	54	8.12	0.3612	0.0004 (0.000)	0.0028 (0.450)	2.2203 (0.000)
2004	20	0.0	82.1748 (0.000)	57	55	6.81	0.2973	0.0005 (0.000)	0.0039 (0.393)	1.9102 (0.000)
	20	-0.2	84.5011 (0.000)	56	54	7.54	0.3234	0.0005 (0.000)	0.0039 (0.424)	1.9299 (0.000)
2005	20	0.0	78.3628 (0.000)	53	48	8.08	0.3282	0.0005 (0.000)	0.0043 (0.380)	1.6537 (0.000)
	20	-0.2	80.9102 (0.000)	52	47	8.79	0.3505	0.0005 (0.000)	0.0044 (0.396)	1.6862 (0.000)
2006	20	0.0	76.4599 (0.000)	53	47	8.70	0.3533	0.0004 (0.000)	0.0046 (0.351)	1.5321 (0.000)
	20	-0.2	73.0615 (0.000)	50	44	10.02	0.3839	0.0004 (0.000)	0.0047 (0.428)	1.4643 (0.000)
2007	20	0.0	72.4443 (0.000)	52	46	9.62	0.3831	0.0004 (0.000)	0.0053 (0.428)	1.2794 (0.000)
	20	-0.2	69.3082 (0.000)	50	44	10.90	0.4176	0.0004 (0.000)	0.0053 (0.493)	1.2347 (0.001)
2008	20	0.0	66.8309 (0.000)	50	40	9.96	0.3816	0.0004 (0.000)	0.0057 (0.399)	1.1379 (0.000)
	20	-0.2	65.7510 (0.000)	48	40	11.35	0.4176	0.0004 (0.000)	0.0057 (0.496)	1.1142 (0.000)
2009	20	0.0	17.5140 (0.204)	45	30	13.18	0.4548	0.0001 (0.160)	0.0057 (0.182)	0.3886 (0.201)
	20	-0.2	12.8358 (0.264)	42	31	15.24	0.4908	0.0001 (0.209)	0.0061 (0.136)	0.2890 (0.278)

Table 7: Results of the mean-reversion trading system with zero variance dynamic hedging and 20 days moving average for all five year periods 1992-2009

Year	MA	Exit	PNL	Trades	Win	MeanHold	TiM	$\bar{r}$	$\sigma$	Sharpe
1992	20	0.0	30.7261 (0.000)	58	58	4.34	0.1931	0.0002 (0.000)	0.0013 (0.018)	2.5091 (0.000)
	20	-0.2	31.4253 (0.000)	58	58	4.69	0.2084	0.0002 (0.000)	0.0013 (0.015)	2.5669 (0.000)
1993	20	0.0	31.3472 (0.000)	58	58	4.43	0.1971	0.0002 (0.000)	0.0013 (0.012)	2.5211 (0.000)
	20	-0.2	32.2676 (0.000)	58	58	4.74	0.2109	0.0002 (0.000)	0.0013 (0.013)	2.5912 (0.000)
1994	20	0.0	32.1673 (0.000)	57	57	4.21	0.1840	0.0002 (0.000)	0.0014 (0.002)	2.3900 (0.000)
	20	-0.2	33.1249 (0.000)	57	57	4.61	0.2017	0.0002 (0.000)	0.0014 (0.008)	2.4530 (0.000)
1995	20	0.0	31.9983 (0.000)	56	56	3.71	0.1594	0.0002 (0.000)	0.0014 (0.000)	2.3457 (0.000)
	20	-0.2	33.3695 (0.000)	56	56	4.20	0.1801	0.0002 (0.000)	0.0014 (0.001)	2.4289 (0.000)
1996	20	0.0	37.9789 (0.000)	56	56	4.18	0.1793	0.0002 (0.000)	0.0017 (0.005)	2.3248 (0.000)
	20	-0.2	40.0175 (0.000)	56	56	4.71	0.2023	0.0003 (0.000)	0.0017 (0.002)	2.4099 (0.000)
1997	20	0.0	35.3690 (0.000)	56	56	4.12	0.1771	0.0002 (0.000)	0.0014 (0.075)	2.5702 (0.000)
	20	-0.2	38.0340 (0.000)	56	56	4.68	0.2009	0.0002 (0.000)	0.0015 (0.007)	2.6953 (0.000)
1998	20	0.0	40.2418 (0.000)	59	59	4.05	0.1833	0.0003 (0.000)	0.0015 (0.075)	2.7389 (0.000)
	20	-0.2	42.9344 (0.000)	59	59	4.66	0.2109	0.0003 (0.000)	0.0015 (0.048)	2.8503 (0.000)
1999	20	0.0	48.5860 (0.000)	61	61	4.46	0.2086	0.0003 (0.000)	0.0015 (0.124)	3.1422 (0.000)
	20	-0.2	51.8637 (0.000)	61	61	4.90	0.2293	0.0003 (0.000)	0.0016 (0.095)	3.2654 (0.000)
2000	20	0.0	59.7663 (0.000)	64	64	4.31	0.2115	0.0004 (0.000)	0.0018 (0.126)	3.1850 (0.000)
	20	-0.2	61.7018 (0.000)	64	64	4.62	0.2268	0.0004 (0.000)	0.0018 (0.010)	3.2615 (0.000)
2001	20	0.0	60.8460 (0.000)	70	70	3.86	0.2069	0.0004 (0.000)	0.0016 (0.109)	3.6697 (0.000)
	20	-0.2	62.9369 (0.000)	70	70	4.29	0.2299	0.0004 (0.000)	0.0016 (0.318)	3.7712 (0.000)
2002	20	0.0	63.9020 (0.000)	72	72	3.62	0.2002	0.0004 (0.000)	0.0016 (0.047)	3.6776 (0.000)
	20	-0.2	65.8376 (0.000)	72	72	4.03	0.2224	0.0004 (0.000)	0.0016 (0.152)	3.7360 (0.000)
2003	20	0.0	63.9354 (0.000)	70	70	3.87	0.2078	0.0004 (0.000)	0.0017 (0.037)	3.6140 (0.000)
	20	-0.2	65.9485 (0.000)	70	70	4.43	0.2377	0.0004 (0.000)	0.0017 (0.167)	3.6585 (0.000)
2004	20	0.0	68.1747 (0.000)	72	71	4.35	0.2398	0.0004 (0.000)	0.0022 (0.337)	2.8282 (0.000)
	20	-0.2	68.9086 (0.000)	71	70	5.04	0.2743	0.0004 (0.000)	0.0023 (0.396)	2.8358 (0.000)
2005	20	0.0	72.1207 (0.000)	75	74	4.27	0.2454	0.0004 (0.000)	0.0022 (0.358)	2.9556 (0.000)
	20	-0.2	73.6814 (0.000)	74	73	5.05	0.2868	0.0004 (0.000)	0.0023 (0.447)	2.9815 (0.000)
2006	20	0.0	71.2737 (0.000)	75	74	4.17	0.2398	0.0004 (0.000)	0.0023 (0.286)	2.8088 (0.000)
	20	-0.2	72.7847 (0.000)	74	73	4.82	0.2736	0.0004 (0.000)	0.0024 (0.292)	2.8250 (0.000)
2007	20	0.0	72.7709 (0.000)	75	74	4.09	0.2352	0.0004 (0.000)	0.0025 (0.256)	2.6712 (0.000)
	20	-0.2	71.8219 (0.000)	72	71	5.25	0.2897	0.0004 (0.000)	0.0025 (0.312)	2.5940 (0.000)
2008	20	0.0	74.0692 (0.000)	78	77	4.65	0.2782	0.0004 (0.000)	0.0027 (0.255)	2.5458 (0.000)
	20	-0.2	72.5918 (0.000)	75	74	5.69	0.3272	0.0004 (0.000)	0.0027 (0.287)	2.4528 (0.000)
2009	20	0.0	56.4521 (0.000)	77	76	4.22	0.2492	0.0003 (0.000)	0.0015 (0.930)	3.6840 (0.000)
	20	-0.2	54.0220 (0.000)	73	72	5.33	0.2983	0.0003 (0.000)	0.0016 (0.876)	3.2753 (0.000)

Table 8: Results of the mean-reversion trading system with dynamic MLE hedging and 20 days moving average for all five year periods 1992-2009

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