Day trading returns across volatility states¹

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Abstract

This paper measures the returns of a popular day trading strategy, the Opening Range Breakout strategy (ORB), across volatility states. We calculate the average daily returns of the ORB strategy for each volatility state of the underlying asset when applied on long time series of crude oil and S&P 500 futures contracts. We find an average difference in returns between the highest and the lowest volatility state of around 200 basis points per day for crude oil, and of around 150 basis points per day for the S&P 500. This finding suggests that the success in day trading can depend to a large extent on the volatility of the underlying asset.

Key words: Contraction-Expansion principle, Futures trading, Opening Range Breakout strategies, Time-varying market inefficiency.

JEL classification: C21, G11, G14, G17.

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1. Introduction

Day traders are relatively few in number – approximately 1% of market participants – but account for a relatively large part of the traded volume in the marketplace, ranging from 20% to 50% depending on the marketplace and the time of measurement (e.g., Barber and Odean, 1999; Barber et al., 2011; Kuo and Lin, 2013). Studies of the empirical returns of day traders using transaction records of individual trading accounts for various stock and futures exchanges can be found in Harris and Schultz (1998), Jordan and Diltz (2003), Garvey and Murphy (2005), Linnainmaa (2005), Coval et al. (2005), Barber et al. (2006, 2011) and Kuo and Lin (2013). When measuring the returns of day traders using transaction records, average returns are calculated from trades initiated and executed on the same trading day. Most of these studies report empirical evidence that some day traders are able to achieve average returns significantly larger than zero after adjusting for transaction costs, but that profitable day traders are relatively few – only one in five or less (e.g., Harris and Schultz, 1998; Garvey and Murphy, 2005; Coval et al., 2005; Barber et al., 2006; Barber et al., 2011; Kuo and Lin, 2013). Linnainmaa (2005), on the other hand, finds no evidence of positive returns from day trading. We note that, if markets are efficient with respect to information, as suggested by the efficient market hypothesis (EMH) of Fama (1965; 1970), day traders should lose money on average after adjusting for trading costs. Therefore, empirical evidence of long-run profitable day traders is considered something of a mystery (Statman, 2002).

Why is it that some traders profit from day trading while most traders do not? We note that the difference between profitable traders and unprofitable traders can come from either trading different assets and/or trading differently, i.e., different trading strategies. The account studies of Harris and Schultz (1998), Jordan and Diltz (2003), Garvey and Murphy (2005), Linnainmaa (2005), Coval et al. (2005), Barber et al. (2006, 2011) and Kuo and Lin (2013) do not relate trading success to any specific assets or to any specific trading strategy. Harris and Schultz (1998) and Garvey and Murphy (2005) report that profitable day traders react quickly to market information, but they do not investigate the underlying strategy of the traders studied. Holmberg, Lönnbark and Lundström (2013), hereafter HLL (2013), link the positive returns of a popular day trading strategy, the Opening Range Breakout (ORB) strategy, to intraday momentum in asset prices. The ORB strategy is based on the premise that, if the price moves a certain percentage from the opening price level, the odds favor a continuation of that movement until the closing price of that day, i.e., intraday momentum. The trader should therefore establish a long (short) position at some predetermined threshold placed a
certain percentage above (below) the opening price and should exit the position at market close (Crabel, 1990). Because the ORB is used among profitable day traders (Williams, 1999; Fisher, 2002), assessing the ORB returns complements the account studies literature and could provide insights on the characteristics of day traders’ profitability, such as average daily returns, possible correlation to macroeconomic factors, robustness over time, etc. For a hypothetical day trader, HLL (2013) find empirical evidence of average daily returns significantly larger than the associated trading costs when applying the ORB strategy to a long time series of crude oil futures. When splitting the data series into smaller time periods, HLL (2013) find significantly positive returns only in the last time period, ranging from 2001-10-12 to 2011-01-26, which are thus not robust to time. Because this time period includes the sub-prime market crisis, it is possible that ORB returns are correlated with market volatility.

This paper assesses the returns of the ORB strategy across volatility states. We calculate the average daily returns of the ORB strategy for each volatility state of the underlying asset when applied on long time series of crude oil and S&P 500 futures contracts. This undertaking relates to the recent literature that tests whether market efficiency may vary over time in correlation with specific economic factors (see Lim and Brooks, 2011, for a survey of the literature on time-varying market inefficiency). In particular, Lo (2004) and Self and Mathur (2006) emphasize that, because trader rationality and institutions evolve over time, financial markets may experience a long period of inefficiency followed by a long period of efficiency and vice versa. The possible existence of time-varying market inefficiency is of interest for the fundamental understanding of financial markets but it also relates to how we view long-run profitable day traders. If profit is related to volatility, we expect profit in day trading to be the result of relatively infrequent trades that are of relatively large magnitude and are carried out during the infrequent periods of high volatility. If so, we could view positive returns from day trading as a tail event during time periods of high volatility in an otherwise efficient market. This paper contributes to the literature on day trading profitability by studying the returns of a day trading strategy for different volatility states. As a minor contribution, this paper improves the HLL (2013) approach of assessing the returns of the ORB strategy by allowing the ORB trader to trade both long and short positions and to use stop loss orders in line with the original ORB strategy in Crabel (1990).

Applying technical trading strategies on empirical asset prices to assess the returns of a hypothetical trader is nothing new (for an overview, see Park and Irwin, 2007). This paper refers to technical trading strategies as strategies that are based solely on past information. As
well as in HLL (2013), the returns of technical trading strategies applied intraday are discussed in Marshall et al. (2008b), Schulmeister (2009), and Yamamoto (2012). By assessing the returns of technical trading strategies, this paper achieves two advantages relative to studying individual trading accounts, as done in Harris and Schultz (1998), Jordan and Diltz (2003), Garvey and Murphy (2005), Linnainmaa (2005), Coval et al. (2005), Barber et al. (2006, 2011) and Kuo and Lin (2013). First, by assessing the returns of technical trading strategies, we may test longer time series than in account studies, thereby avoiding possible volatility bias in small samples. Second, we can study trading strategies that are specifically used for day trading, in contrast to the recorded returns of trading accounts. That is because trading accounts may also include trades initiated for reasons other than profit, such as consumption, liquidity, portfolio rebalancing, diversification, hedging or tax motives, etc., creating potentially noisy estimates (see the discussion in Kuo and Lin, 2013).

This paper recognizes two possible disadvantages when assessing the returns of a hypothetical trader using a technical trading strategy relative to studying individual trading accounts when the strategy is developed by researchers. First, if we want to assess the potential returns of actual traders, the strategy must be publicly known and used by traders at the time of their trading decisions (see the discussion in Coval et al., 2005). Assessing the past returns of a strategy developed today tells little or nothing of the potential returns of actual traders because the strategy is unknown to traders at the time of their trading decisions. This paper avoids this problem by simulating the ORB strategy returns using data from January 1, 1991 and onward, after the first publication in Crabel (1990). Second, even if the strategy has been used among traders, the researcher could still potentially over-fit the strategy parameters to the data and, in turn, over-estimate the actual returns of trading. This is related to the problem of data snooping (e.g., Sullivan et al. 1999; White, 2000). Because the ORB strategy is defined by only one parameter – the distance to the upper and lower threshold level – we avoid the problem of data snooping by assessing the ORB returns for a large number of parameter values.

By empirically testing long time series of crude oil and S&P 500 futures contracts, this paper finds that the average ORB return increases with the volatility of the underlying asset. Our results relate to the findings in Gencay (1998), in that technical trading strategies tend to result in higher profits when markets “trend” or in times of high volatility. This paper finds that the differences in average returns between the highest and lowest volatility state are around 200 basis points per day for crude oil, and around 150 basis points per day for S&P
This finding explains the significantly positive ORB returns in the period 2001-10-12 to 2011-01-26 found in HLL (2013). In addition, when reading the trading literature (e.g., Crabel, 1990; Williams, 1999; Fisher, 2002) and the account studies literature (e.g., Harris and Schultz, 1998; Garvey and Murphy, 2005; Coval et al., 2005; Barber et al., 2006; Barber et al., 2011; Kuo and Lin, 2013), one may get the impression that long-run profitability in day trading is the same as earning steady profit over time. Related to volatility, however, the implication is that a day trader, profitable in the long-run, could still experience time periods of zero, or even negative, average returns during periods of normal, or low, volatility. Thus, even if long-run profitability in day trading could be possible to achieve, it is achieved only by the trader committed to trade every day for a very long period of time or by the opportunistic trader able to restrict his trading to periods of high volatility. Further, this finding highlights the need for using a relatively long time series that contains a wide range of volatility states when evaluating the returns of day traders to avoid possible volatility bias.

We note that day traders may trade according to strategies other than the ORB strategy and that positive returns from day trading strategies may coincide with factors other than volatility, but the ORB strategy is the only strategy and volatility the only factor considered in this paper. To the best of our knowledge, the ORB strategy is the only documented trading strategy actually used among profitable day traders.

The remainder of the paper is organized as follows. Section 2 presents the ORB strategy, outlines the returns assessment approach, and presents the tests. Section 3 describes the data and gives the empirical results. Section 4 concludes.

2. The ORB strategy

2.1 The ORB strategy and intraday momentum

The ORB strategy is based on the premise that, if the price moves a certain percentage from the opening price level, the odds favor a continuation of that move until the market close of that day. The trader should therefore establish a long (short) position at some predetermined threshold a certain percentage above (below) the opening price and exit the position at market close (Crabel, 1990). Positive expected returns of the ORB strategy implies that the asset
prices follow intraday momentum, i.e., rising asset prices tend to rise further and falling asset prices to fall further, at the price threshold levels (e.g., HLL, 2013). We note that momentum in asset prices is nothing new (e.g., Jegadeesh and Titman, 1993; Erb and Harvey, 2006; Miffre and Rallis, 2007; Marshall et al., 2008a; Fuertes et al., 2010). Crabel (1990) proposed the Contraction-Expansion (C-E) principle to generally describe how asset prices are affected by intraday momentum. The C-E principle is based on the observation that daily price movements seem to alternate between regimes of contraction and expansion, i.e., periods of modest and large price movements, in a cyclical manner. On expansion days, prices are characterized by intraday momentum, i.e., trends, whereas prices move randomly on contraction days (Crabel, 1990). This paper highlights the resemblance between the C-E principle and volatility clustering in the underlying price returns series (e.g., Engle, 1982).

Crabel (1990) does not provide an explanation of why momentum may exist in markets. In the behavioral finance literature, we note that the appearance of momentum is typically attributed to cognitive biases from irrational investors, such as investor herding, investor over- and under-reaction, and confirmation bias (e.g., Barberis et al., 1998; Daniel et al., 1998). As discussed in Crombez (2001), however, momentum can also be observed with perfectly rational traders if we assume noise in the experts’ information. The reason why intraday momentum may appear is outside the scope of this paper. We now present the ORB strategy.

We follow the basic outline of HLL (2013) and we denote \( P_t^o, P_t^h, P_t^l \) and \( P_t^c \) as the opening, high, low, and closing log prices of day \( t \), respectively. Assuming that prices are traded continuously within a trading day, a point on day \( t \) is given by \( t + \delta \), \( 0 \leq \delta \leq 1 \), and we may write: \( P_t^o = P_t \), \( P_t^c = P_{t+1} \), \( P_t^h = \max_{0 \leq \delta \leq 1} P_{t+\delta} \), and \( P_t^l = \min_{0 \leq \delta \leq 1} P_{t+\delta} \). Further, we let \( \psi_t^u \) and \( \psi_t^l \) denote the threshold levels such that, if the price crosses it from below (above), the ORB trader initiates a long (short) position. These thresholds are placed at some predetermined distance from the opening price, \( 0 < \rho < 1 \), i.e. \( \psi_t^u = P_t^o + \rho \) and \( \psi_t^l = P_t^o - \rho \). This paper refers to \( \rho \) as the range; it is a log return expressed in percentages. As positive ORB returns are based on intraday momentum, i.e., trends, the range should be small enough to enter the market when the move still is small, but large enough to avoid market noise that does not result in trends (Crabel, 1990). This paper assumes that day traders have no \textit{ex ante} bias regarding future price trend direction and, in line with HLL (2013), uses symmetrically placed thresholds with the same \( \rho \) for long and short positions.
If markets are efficient with respect to the information set, $\Psi_{t+\delta}$, we know from the martingale pricing theory (MPT) model of Samuelson (1965) that no linear forecasting strategy for future price changes based solely on information set $\Psi_{t+\delta}$ should result in any systematic success. In particular, we may write the martingale property of log prices and log returns, respectively, as follows;

\begin{align}
    E_{t+\delta}[P_{t+1}|\Psi_{t+\delta}] &= P_{t+\delta} \quad (1) \\
    E_{t+\delta}[R_{t+1}|\Psi_{t+\delta}] &= E_{t+\delta}[P_{t+1}|\Psi_{t+\delta}] - P_{t+\delta} = 0 \quad (2)
\end{align}

where $E_{t+\delta}$ is the expected value operator evaluated at time $t + \delta$.

Relating ORB returns to intraday momentum, this paper tests whether prices follow momentum at the thresholds, $\psi_{t}^u$ and ($\psi_{t}^l$), such that:

\begin{align}
    E_{t+\gamma}[P_{t+1}|P_{t+\gamma} = \psi_{t}^u] > \psi_{t}^u \text{ or } E_{t+\gamma}[P_{t+1}|P_{t+\gamma} = \psi_{t}^l] < \psi_{t}^l \quad (3)
\end{align}

where $0 < \gamma < 1$ represents the point in time when a threshold is crossed for the first time during a trading day. We note that intraday momentum, as shown by Eq. (3), contradicts the MPT of Eq. (1).

2.2 Assessing the returns

This paper assesses the returns of the ORB strategy using time series of futures contracts with daily readings of the opening, high, low, and closing prices. The basic observation is that, if the daily high ($P_{t}^h$) is equal to or higher than $\psi_{t}^u$, or if the daily low ($P_{t}^l$) is equal to or lower than $\psi_{t}^l$, we know with certainty that a buy or sell signal was triggered during the trading day. From the returns assessment approach of HLL (2013), we can calculate the daily returns for long ORB trades by $R_{t}^l = P_{t}^c - \psi_{t}^u |P_{t}^h \geq \psi_{t}^u$, and for short ORB trades by $R_{t}^s = \psi_{t}^l - P_{t}^c |P_{t}^l \leq \psi_{t}^l$, assuming that traders can trade at continuous asset prices to a trading cost equal
to zero. Further, the trader is expected to trade only on days when thresholds are reached, so the ORB strategy returns are not defined for days when the price never reaches $\psi_t^u$ or $\psi_t^l$ (e.g., Crabel, 1990; HLL, 2013).

Figure 1 illustrates how a profitable ORB position may evolve during the course of a trading day.

![Figure 1](image)

**Figure 1.** An ORB strategy trader initiates a long position when the intraday price reaches $\psi_t^u$ and then closes the position at $P_t^c$, with the profit $P_t^c - \psi_t^u > 0$.

This paper recognizes two limitations when assessing the ORB strategy returns using $R_t^L$ and $R_t^S$ independently from each other. The first limitation is that $R_t^L$ obviously only captures the returns from long positions and $R_t^S$ only captures the returns from short positions. Because ORB strategy traders should be able to profit from long or short trades, whichever comes first, we expect that the HLL (2013) approach of assessing trades in only one direction at a time (either by using $R_t^L$ or $R_t^S$) may under-estimate the ORB strategy returns suggested in Crabel (1990) and in trading practice. The second limitation is that $R_t^L$ and $R_t^S$ are both exposed to large intraday risks, with possibly large losses on trading days when prices do not trend but move against the trader. Crabel (1990) suggests that the ORB trader should always limit intraday losses by using stop loss orders placed a distance below (above) a long (short) position.

This paper improves the approach used in HLL (2013) to assess the returns of ORB strategy traders by allowing the trader to initiate both long and short trades with limited intraday risk,
in line with Crabel (1990), still applicable to time series with daily readings of the opening, high, low, and closing prices. We denote it the “ORB Long Strangle” returns assessment approach because it is a futures trader’s equivalent to a Long Strangle option strategy (e.g., Saliba et al., 2009). The ORB Long Strangle is done in practice by placing two resting market orders: a long position at \( \psi_t^u \) and a short position at \( \psi_t^l \), both positions remaining active throughout the trading day. Assuming that traders can trade at continuous asset prices and to a trading cost equal to zero, the Long Strangle produces one of three possible outcomes: 1) only the upper threshold is crossed, yielding the return \( R_t^L \); 2) only the lower threshold is crossed, yielding the return \( R_t^S \); or 3) both thresholds are crossed during the same trading day, yielding a return equal to \( \psi_t^l - \psi_t^u < 0 \). We note that, if a trader experiences an intraday double crossing, the trader should not trade during the remainder of the trading day (e.g., Crabel, 1990). Because there are only two active orders in the Long Strangle, we can safely rule out more than two intraday crossings. As before, ORB strategy returns are not defined for days when the price reaches neither threshold.

This paper calculates the daily returns of the Long Strangle strategy, \( R_{t}^{L&S} \), as:

\[
R_{t}^{L&S} = \begin{cases} 
P_t^c - \psi_t^u & \geq 0, \text{if } \left( P_t^h \geq \psi_t^u \right) \cap \left( P_t^l > \psi_t^l \right) \\
\psi_t^l - P_t^c & \geq 0, \text{if } \left( P_t^h < \psi_t^u \right) \cap \left( P_t^l \leq \psi_t^l \right) \\
\psi_t^l - \psi_t^u & < 0, \text{if } \left( P_t^h \geq \psi_t^u \right) \cap \left( P_t^l \leq \psi_t^l \right)
\end{cases}
\]

(4)

The ORB Long Strangle approach in Eq. (4) allows us to assess the returns of traders initiating long or short positions, whichever comes first, using the opposite threshold as a stop loss order\(^1\), effectively limiting maximum intraday losses to \( \psi_t^l - \psi_t^u = -2\rho < 0 \) (for symmetrically placed thresholds). Therefore, the returns \( R_{t}^{L&S} \) provide a closer approximation of the ORB returns in Crabel (1990) relative to studying \( R_t^L \) and \( R_t^S \) independently and separately from each other. Henceforth, we refer to the ORB Long Strangle strategy as the ORB strategy if not otherwise mentioned. This paper assumes an interest rate of money equal to zero so that profit can only come from actively trading the ORB strategy and not from

\(^1\) One could think of other possible placements of stop loss orders but this placement is the only one tested in this paper.
passive rent-seeking. In the empirical section, we also study ORB returns when trading costs are added, and we discuss the effects on ORB returns if asset prices are not continuous.

2.3 Measuring the average daily returns across volatility states

This paper measures the average daily returns for different volatility states by grouping the ORB returns into ten volatility states based on the deciles of the daily price returns volatility distribution. The volatility states are ranked from low to high, with the 1:st decile as the state with the lowest volatility and the 10:th decile as the state with the highest volatility. We then calculate the average daily return for each volatility state by the following dummy variable regression, given $\rho$:

$$R_{\rho,t}^{LS} = \sum_{\tau=1}^{10} a_{\rho,\tau} D_{\rho,\tau} + v_{\rho,t}$$

(5)

where $a_{\rho,\tau}$ is the average ORB return in the $\tau$: th volatility state, $D_{\rho,\tau}$ is a binary variable equal to one if the returns corresponds to the $\tau$: th decile of the volatility distribution, or zero otherwise, and $v_{\rho,t}$ is the error term. From the expected (positive) correlation between ORB returns and volatility, the ORB returns will experience heteroscedasticity and possibly serial correlation. To assess the statistical significance of Regression (5), we therefore apply Ordinary Least Squares (OLS) estimation using Newey-West Heteroscedasticity and Autocorrelated Consistent (HAC) standard errors.

The $D_{\rho,\tau}$ in Regression (5) requires that we estimate the volatility. Unfortunately, volatility, $\sigma_{t+\delta}$, is not directly observable (e.g., Andersen and Bollerslev, 1998). Another challenge for this study is to estimate intraday volatility over the time interval $0 \leq \delta \leq 1$, when limited to time series with daily readings of the opening, high, low, and closing prices.

Making good use of the data at hand, this paper uses the simplest available approach to estimate daily volatility $\sigma_{t+1}$ by tracking the daily absolute return (log-difference of prices) of day $t$:
\[
\sigma_t^c = +\sqrt{(P_t^c - P_t^o)^2} = |P_t^c - P_t^o|
\]  

Using absolute returns as a proxy for volatility is the basis of much of the modeling effort presented in the volatility literature (e.g., Taylor, 1987; Andersen and Bollerslev, 1998; Granger and Sin, 2000; Martens et al., 2009), and has shown itself to be a better measurement of volatility than squared returns (Forsberg and Ghysels, 2007). Although \( \sigma_t^c \) is unbiased, i.e., \( E_t\sigma_t^c = \sigma_{t+1} \), it is a noisy estimator (e.g., Andersen and Bollerslev, 1998). One extreme example would be a very volatile day, with widely fluctuating prices, but where the closing price is the same as the opening price. The daily open-to-close absolute return would then be equal to zero, whereas the actual volatility has been non-zero. Because positive ORB returns imply a closing price at a relatively large (absolute) distance from the opening price, we expect reduction in noise for the higher levels of positive ORB returns.

Because the ORB strategy trader is profiting from intraday price trends, it stands to reason that he should increase his return on days when volatility is relatively high. When using \( \sigma_t^c \) to estimate volatility, the relationship between intraday momentum (by Eq. (3)) and volatility is straightforward. For a profitable long trade, we have the relationship \( R_t^{L&S} = P_t^c - \psi_t^u = P_t^c - P_t^o - \rho = \sigma_t^c - \rho \) because \( R_t^{L&S} = P_t^c - \psi_t^u > 0 \) and \( P_t^c - P_t^o = \sigma_t^c > 0 \). For a profitable short trade, we have the relationship \( R_t^{L&S} = -\big(P_t^c - \psi_t^l\big) = -(P_t^c - P_t^o + \rho) = -(\sigma_t^c + \rho) = \sigma_t^c - \rho \) because \( R_t^{L&S} = -\big(P_t^c - \psi_t^l\big) > 0 \) and \( P_t^c - P_t^o = -\sigma_t^c < 0 \). Thus, a positive ORB return equals the volatility minus the range for both long and short trades.

From this exercise, we learn that the ORB strategy trader should increase his expected return during days of relatively high volatility and decrease his expected return during days of relatively low volatility, suggesting different expected returns in different volatility states. In addition, we learn that positive ORB returns imply high volatility, but not the other way around, since the ORB strategy trader still can experience losses when volatility is high, associated with intraday double crossing: \( R_t^{L&S} = \psi_t^l - \psi_t^u = -2\rho < 0 \).

When a price series is given in a daily open, high, low, and close format, Taylor (1987) proposes that the (log) price range in day \( t \) \( (\zeta_t = P_t^h - P_t^l > 0) \) could also serve as a suitable measure of the daily volatility. To strengthen the empirical results, this paper also estimates
daily volatility $\sigma_{t+1}$ by the price range of day $t$, i.e., $\zeta_t$. Finding qualitatively identical results whether we use $\zeta_t$ or $\sigma_t$, we report only the empirical results when using $\sigma_t$.

3. Empirical results

3.1 Data

We apply the ORB strategy to long time series of crude oil futures and of S&P 500 futures. Futures contracts are used in this paper because long time series are readily available, and because futures are the preferred investment vehicle when trading the ORB strategy in practice (e.g., Crabel, 1990; Williams, 1999; Fisher, 2002). There are many reasons why futures are the preferable investment vehicle relative to, for example, stocks. Futures are as easily sold short as bought long, are not subject to short-selling restrictions, and can be bought on a margin, providing attractive leverage possibilities for day traders who wish to increase profit. In addition, costs associated with trading, such as commissions and bid-ask spreads, are typically smaller in futures contracts than in stocks due to the relatively high liquidity.

The data includes daily readings of the opening, high, low, and closing prices, during the US market opening hours. We note that ORB traders should trade only during the US market opening hours, when the liquidity is high, even if futures contracts may trade for 24 hours (Crabel, 1990). Thus, the US market opening period is the only time interval of interest for the study of this paper.

The crude oil price series covers the period January 2, 1991 to January 26, 2011 and the S&P 500 price series covers the period January 2, 1991 to November 29, 2010. Both series are obtained from Commodity Systems Inc. (CSI) and are adjusted for roll-over effects such as contango and backwardation by CSI. The future contract typically rolls out on the 20th of each month, one month prior to the expiration month; see Pelletier (1997) for technical details. We analyze the series separately and independent of each other.

Figures 2 and 3 illustrate the price series over time for crude oil and S&P 500 futures, respectively.
**Figure 2.** The daily closing prices for crude oil futures over time, adjusted for roll-over effects, from January 2, 1991 to January 26, 2011. Source: Commodity Systems Inc.

**Figure 3.** The daily closing prices for S&P 500 futures over time, adjusted for roll-over effects, from January 2, 1991 to November 29, 2010. Source: Commodity Systems Inc.
Notable in Figure 2 is the sharp price drop for the crude oil series during the 2008 sub-prime crisis. In Figure 3, there are two price drops for the S&P 500 series, during the 2000 dot-com crisis and the 2008 sub-prime crisis.

Table 1 presents some descriptive statistics for the daily price returns of both assets, and Figures 4 and 5 graphically illustrate the daily price returns volatility over time for crude oil and S&P 500, respectively.

<table>
<thead>
<tr>
<th></th>
<th>Obs.</th>
<th>Mean</th>
<th>Std.Dev.</th>
<th>Min</th>
<th>Max</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>crude oil</td>
<td>4845</td>
<td>0.0002</td>
<td>0.0077</td>
<td>-0.0606</td>
<td>0.0902</td>
<td>0.22</td>
<td>9.67</td>
</tr>
<tr>
<td>S&amp;P 500</td>
<td>5018</td>
<td>0.0001</td>
<td>0.0093</td>
<td>-0.0912</td>
<td>0.0808</td>
<td>-0.06</td>
<td>11.73</td>
</tr>
</tbody>
</table>

**Figure 4.** The daily price returns volatility (%) for crude oil futures over time, from January 2, 1991 to January 26, 2011.
Table 1 shows that daily price returns display the expected characteristics of empirical returns series, with close-to-zero means and positive kurtosis for both assets. As expected, we can confirm that the means for crude oil and S&P 500 are not significantly larger than zero, although this is not explicitly shown. Figures 4 and 5 reveal apparent volatility clustering over time for both assets. These results are expected for empirical returns (e.g., Cont 2001).

### 3.2 The average daily returns across volatility states

This paper assesses strategy returns for different levels of $\rho$, ranging from small to large, thereby spanning the profit opportunities of ORB strategies. For simplicity and without loss of information, we only present the results for thresholds $\rho \in \{0.5\%, 1.0\%, 1.5\%, 2.0\%\}$, for both assets. Figures 6-9 and Figures 10-13 present the average daily ORB returns across volatility states for crude oil futures and for S&P 500 futures, respectively. We illustrate the ORB returns in basis points ($\%\%$, $(a \cdot 10000)$, where $a$ is the average ORB return for a given volatility state (see the definition of $a$ in the previous section). We use 95% point-wise confidence intervals based on the HAC standard errors.
Figure 6. Average returns (bp:s) across volatility states (τ) when trading crude oil futures using ρ = 0.5%. We use 95% confidence intervals based on the HAC standard errors.

Figure 7. Average returns (bp:s) across volatility states (τ) when trading crude oil futures using ρ = 1.0%. We use 95% confidence intervals based on the HAC standard errors.

Figure 8. Average returns (bp:s) across volatility states (τ) when trading crude oil futures using ρ = 1.5%. We use 95% confidence intervals based on the HAC standard errors.

Figure 9. Average returns (bp:s) across volatility states (τ) when trading crude oil futures using ρ = 2.0%. We use 95% confidence intervals based on the HAC standard errors.
Figures 6-13 show significantly negative returns for lower volatility states, $\tau \leq 3$, and significantly positive returns for higher volatility states, $\tau \geq 7$, for both assets. That is, the average daily returns from day trading using ORB strategies are correlated with volatility. The difference in average daily returns between state 1 and 10 are remarkably high – around 200 basis points per day for crude oil and around 150 basis points per day for S&P 500, given $\rho = 0.5\%$. For larger $\rho:s$, the differences grow even larger.

Because the returns are calculated daily, relatively small differences in the average daily returns have substantial effects on wealth when annualized. The annualized return from a 200
point daily difference between state 1 and state 10 amounts to \((1 + 0.02)^{240} - 1 = 115\%\), and a 150 point daily difference amounts to \((1 + 0.015)^{240} - 1 = 35\%\), given 240 trading days in a year. Thus, the annualized returns differ substantially for a day trader consistently trading in the lowest volatility state compared to one trading in the highest volatility state. This is merely an example to illustrate the effect that daily returns have on annualized returns; however, it should not be taken as the result of actual trading. This is because the results so far are based on the assumption that the trader \textit{a priori} knows the volatility state; in this respect, these are in-sample results. In actual trading, traders do not \textit{a priori} know the volatility state and are not able to trade assets in high volatility states every day.

To shed more light on profitability when using the ORB strategy in actual trading, this paper also assesses the ORB strategy returns without \textit{a priori} knowledge of the volatility state among traders, i.e., the results of trading out-of-sample. We assess both daily and annual returns because both are relevant for traders – a strategy yielding a high daily return on average is of limited use to a trader who trades only once a year.

### 3.3 Returns when trading the ORB strategy out-of-sample

When trading the ORB strategy, the idea is to restrict trading only to expansion days (high volatility) and avoid trading during contraction days (normal or low volatility). When trading out-of-sample, however, the trader does not \textit{a priori} know the volatility state, so some form of volatility prediction is necessary. The trader either can try to predict volatility states using econometric approaches (e.g., Engle, 1982; Andersen and Bollerslev, 1998) or can use the ORB strategy approach (Crabel, 1990; Williams, 1999; Fisher, 2002), identifying the range as a volatility predictor by itself and setting the range large enough so that only large volatility days are able to reach the thresholds.

This paper assesses the average daily returns when trading the ORB strategy out-of-sample, following the approach of Crabel (1990), Williams (1999), and Fisher (2002), i.e., setting the range large enough so that only large volatility days are able to reach the thresholds. We estimate the average daily returns with the regression \(R_{p,t}^{L\&S} = A_p + \omega_{p,t}\), where \(A_p\) is the average of the range large enough so that only large volatility days are able to be predicted.

\[^2\text{We tried various ARCH and GARCH specifications to predict the volatility state, but without improving the results in any significant way. We find that expansion days, which result in high ORB returns, tend to come unexpectedly after a number of contraction days. Further, expansion days do not typically appear two days in a row. Thus, the volatility prediction models do not have time to react. This is perhaps the reason why the ARCH and GARCH specifications are unable to improve the trading results.}\]
average daily return of the ORB strategy during days with predicted high volatility, and $\omega_t$ is the error term, given a certain range.

The results for both assets are given in Table 2:

**Table 2.** Daily returns when trading the ORB strategy out-of-sample. $\rho$ is the per cent distance added to and subtracted from the opening price. $T$ is the number of trades. $freq$ gives the proportion of trades that result in positive returns, while $A$ gives the average daily return. The p-values are calculated based on the HAC standard errors. No trading costs are included.

<table>
<thead>
<tr>
<th>$\rho$(%)</th>
<th>$T$</th>
<th>freq.</th>
<th>$A$</th>
<th>$p$</th>
</tr>
</thead>
<tbody>
<tr>
<td>crude oil</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5</td>
<td>2827</td>
<td>0.57</td>
<td>0.0013</td>
<td>0.0000</td>
</tr>
<tr>
<td>1.0</td>
<td>1044</td>
<td>0.58</td>
<td>0.0020</td>
<td>0.0000</td>
</tr>
<tr>
<td>1.5</td>
<td>423</td>
<td>0.61</td>
<td>0.0027</td>
<td>0.0000</td>
</tr>
<tr>
<td>2.0</td>
<td>189</td>
<td>0.67</td>
<td>0.0036</td>
<td>0.0001</td>
</tr>
<tr>
<td>S&amp;P 500</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5</td>
<td>3314</td>
<td>0.49</td>
<td>0.0004</td>
<td>0.0057</td>
</tr>
<tr>
<td>1.0</td>
<td>1572</td>
<td>0.53</td>
<td>0.0006</td>
<td>0.0267</td>
</tr>
<tr>
<td>1.5</td>
<td>749</td>
<td>0.52</td>
<td>0.0006</td>
<td>0.1755</td>
</tr>
<tr>
<td>2.0</td>
<td>368</td>
<td>0.52</td>
<td>0.0006</td>
<td>0.4937</td>
</tr>
</tbody>
</table>

Table 2 shows mixed results when trading the ORB strategy out-of-sample. We find significantly positive returns for all ranges at the 95% confidence level when trading crude oil futures out-of-sample, and it seems that returns increase with $\rho$. When trading S&P 500 futures out-of-sample, however, we find significantly positive returns only for the two smaller ranges, $\rho = 0.5$ and $\rho = 1.0$, at the 95% confidence level. For ranges larger than $\rho = 1.0$, e.g., $\rho = 1.5$ and $\rho = 2.0$, we cannot reject the null hypothesis of zero returns on average.

When separating the (Long Strangle) returns between long and short trades when trading S&P 500, we find that the average returns of short trades, initially positive, are reduced for $\rho > 1.0\%$ while the returns of long trades seem to increase with $\rho$, as in the crude oil example. This difference in average returns between long and short ORB trades drives the results although this is not explicitly shown. Regardless of the reasons why, it is clear that not all ranges are profitable when trading the S&P 500 out-of-sample. Thus, profitability when trading the ORB strategy out-of-sample depends on the choice of asset and range. Using the “wrong” range for a particular asset, for example, using $\rho = 1.5$ or $\rho = 2.0$ when trading...
S&P 500, the ORB strategy does not necessarily yield a daily return significantly larger than zero on average.

To compare these returns with the returns of an alternative investment strategy, we also study the difference between the return of the ORB strategy ($R_t^{L&S}$) for day $t$ and the corresponding return of the so-called buy and hold strategy ($R_t^{B&H} = P_t^c - P_{t-1}^c$). The buy and hold strategy is a straightforward strategy where the trader buys the asset and holds it until the expiration of the future contract, at which point the position is “rolled over” onto the next contract. As it turns out, the buy and hold strategy returns are close to zero; when running the regression $R_t^{L&S} - R_t^{B&H} = \tilde{A} + \tilde{\alpha}_t$, we find qualitatively the same results as illustrated in Table 2, for both assets, although not explicitly shown. That is, when trading crude oil futures out-of-sample, we find empirical support that the ORB strategy yields a larger average daily return for all ranges compared to the buy and hold strategy. When trading S&P 500 futures out-of-sample, on the other hand, we find empirical support that the ORB strategy yields a larger average daily return only for $\rho = 0.5$ and $\rho = 1.0$, compared to the buy and hold strategy.

We now investigate what a day trader can expect in terms of accumulated annual returns when trading the ORB strategy out-of-sample. We start by plotting the wealth accumulation over time starting at 1991-01-01 with a value of 1 000 000 USD, for all ranges, and for both assets. Profit is reinvested on to the next trade. The wealth accumulation of the buy and hold (B&H) strategy is included as a reference. Figures 14-15 plot the wealth accumulation over time when applying the B&H and the ORB strategy to trade crude oil futures and S&P 500 futures, respectively, out-of-sample. Table 3 presents the corresponding out-of-sample annual returns statistics (calendar year).
Figure 14. Wealth over time, starting with 1 000 000 USD (expressed in log levels), when trading crude oil futures out-of-sample using ORB strategies for all ranges from January 1, 1991 to January 26, 2011. B&H refers to the buy and hold strategy, and ORB refers to the ORB strategy given a particular range. No trading costs are included.

Figure 15. Wealth over time, starting with 1 000 000 USD (expressed in log levels), when trading S&P 500 futures out-of-sample using ORB strategies for all ranges from January 1, 1991 to November 29, 2010. B&H refers to the buy and hold strategy, and ORB refers to the ORB strategy for a particular range. No trading costs are included.
Table 3. Annual returns (calendar year) when trading the B&H strategy and the ORB strategy out-of-sample. $\rho$ is the per cent distance added to and subtracted from the opening price, where N/A refers to the B&H strategy. Mean/Std.Dev gives the average annual return per unit of annual volatility and Mean/-Min gives the average annual return over the largest annual loss. No trading costs are included.

<table>
<thead>
<tr>
<th>$\rho$ (%)</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std.Dev</th>
<th>Min</th>
<th>Max</th>
<th>Mean/Std.Dev</th>
<th>Mean/-Min</th>
</tr>
</thead>
<tbody>
<tr>
<td>N/A</td>
<td>19</td>
<td>0.0530</td>
<td>0.1672</td>
<td>-0.2505</td>
<td>0.3864</td>
<td>0.32</td>
<td>0.21</td>
</tr>
<tr>
<td>crude oil</td>
<td>0.5</td>
<td>0.3055</td>
<td>0.7110</td>
<td>-0.0493</td>
<td>2.5527</td>
<td>0.43</td>
<td>6.19</td>
</tr>
<tr>
<td></td>
<td>1.0</td>
<td>0.1568</td>
<td>0.4244</td>
<td>-0.0758</td>
<td>1.3994</td>
<td>0.37</td>
<td>2.07</td>
</tr>
<tr>
<td></td>
<td>1.5</td>
<td>0.0725</td>
<td>0.2180</td>
<td>-0.0214</td>
<td>0.7740</td>
<td>0.33</td>
<td>3.39</td>
</tr>
<tr>
<td></td>
<td>2.0</td>
<td>0.0391</td>
<td>0.1179</td>
<td>-0.0189</td>
<td>0.3866</td>
<td>0.33</td>
<td>2.07</td>
</tr>
<tr>
<td>S&amp;P 500</td>
<td>N/A</td>
<td>0.0250</td>
<td>0.1061</td>
<td>-0.1791</td>
<td>0.2665</td>
<td>0.24</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>0.5</td>
<td>0.0661</td>
<td>0.1655</td>
<td>-0.0784</td>
<td>0.6995</td>
<td>0.40</td>
<td>0.84</td>
</tr>
<tr>
<td></td>
<td>1.0</td>
<td>0.0562</td>
<td>0.1876</td>
<td>-0.1222</td>
<td>0.7946</td>
<td>0.30</td>
<td>0.46</td>
</tr>
<tr>
<td></td>
<td>1.5</td>
<td>0.0243</td>
<td>0.0848</td>
<td>-0.0557</td>
<td>0.3673</td>
<td>0.29</td>
<td>0.44</td>
</tr>
<tr>
<td></td>
<td>2.0</td>
<td>0.0087</td>
<td>0.0253</td>
<td>-0.0208</td>
<td>0.0720</td>
<td>0.34</td>
<td>0.42</td>
</tr>
</tbody>
</table>

Figures 14-15 illustrate that wealth accumulates unevenly over time and primarily during time periods connected to market crisis events with high volatility, for both assets. Even when ORB traders profit in the long run, we observe long periods of negative growth in wealth for both assets. Hence, profitability is not robust to time. Moreover, Figures 14-15 graphically show that long-run profit using ORB strategies is the result of relatively infrequent trades of a relatively large magnitude, associated with the infrequent time periods of market crisis, i.e., periods of high volatility.

Table 3 shows that the optimal levels of the range for maximizing annual returns are the relatively small range, $\rho = 0.5\%$, for both assets. Table 3 illustrates further that traders using the B&H strategy can achieve larger annual returns on average (Mean) than traders using ORB strategies for some ranges ($\rho = 2.0\%$ for crude oil, and $\rho = 1.5\%$ and $\rho = 2.0\%$ for S&P 500). One reason for the relatively low annual returns when trading ORB strategies is the relatively low frequency of trading (especially when using large ranges). As we increase the range, we remember from Table 2 that the number of trades ($T$) decreases. Fewer trades, in turn, decreases annual returns, ceteris paribus. We note that low annual returns due to few trades can, to some extent, be offset by trading many assets simultaneously, but this is not studied in this paper.
Table 3 further shows that ORB strategies yield larger risk-adjusted returns (measured by Mean/Std.Dev and Mean/-Min) than the buy and hold strategy, for all ranges and for both assets. This is interesting from a risk-return point of view because risk-averse day traders could benefit from using ORB strategies compared to the buy and hold strategy. ORB strategies seem especially attractive in terms of high Mean/-Min due to relatively moderate largest annual losses (min).

### 3.3.1 Sensitivity analysis regarding price jumps

Prices are not always continuous within a trading day but may experience so-called price jumps in the direction of the most recent price movement (e.g., Mandelbrot, 1963; Fama and Blume, 1966). Because of the price jumps, the trader may experience an order fill at worse prices than expected. Consequently, we may over-estimate the actual return from trading if the effects of price jumps are not taken into account when assessing the returns of technical trading strategies based on intraday thresholds (see, for example, the technical trading strategy in Alexander, 1961). This paper recognizes that possible price jumps will affect the returns of trading, but not necessarily in a negative way when we consider the ORB strategy.

This paper estimates the effects of price jumps on ORB returns in two stages of the trade. First, we model the price jump effect in market entries and, second, in market exits. First, because price jumps occur in the direction of the most recent price movement, the ORB traders’ entry prices are sometimes filled at some other price than the threshold. If $\tilde{\psi}_t$ denotes the actual entry price on day $t$, we may write the price jump effects for long trades as $\tilde{\psi}_t^e > \psi_t^e$, and for short trades as $\tilde{\psi}_t^l < \psi_t^l$, where the actual trading price is based on the range plus a price jump, $\tilde{\rho} = \rho + \epsilon$, where $\epsilon > 0$ is the size of the price jump. We consider here a reasonable estimate of $\epsilon = 2$ basis points when trading crude oil and S&P 500 futures (based on empirical observations when trading futures with the ORB strategy using an account size of around 1 000 000 USD, Interactive Brokers, www.interactivebrokers.com, February 2, 2010 to November 29, 2010).

Second, because ORB traders exit the market at the market close, there cannot be a jump to some other level. Thus, $P_t^c$ is the actual closing price of day $t$. Moreover, in contrast to the technical trading strategy of Alexander (1961), where both market entry and exit are based on intraday threshold crossing, the ORB strategy is only affected by possible price jumps at the
market entry level. From Figures 6-13 and Table 2, we observe that the effect of price jumps of $\varepsilon = 2$ basis points on returns is not necessarily negative when trading the ORB strategy. In fact, we find that the price jump effect on the average returns is positive for larger $\rho$ when trading crude oil, and either negative or positive, depending on the initial level of $\rho$, when trading S&P 500.

From this reasoning, we do not expect price jumps to qualitatively change the results shown in Figures 6-13 and Table 2, i.e., returns significantly larger (smaller) than zero will most likely remain significantly larger (smaller) than zero.

3.3.2 Sensitivity analysis regarding trading costs

Trading costs in terms of commission fees and bid-ask spreads will consume some of the profits. For the assets under consideration, these costs are relatively small during the trading hours of the US markets. We estimate that we need to subtract 4 basis points per trade, or 8 basis points roundtrip daily cost, for crude oil futures. For the S&P 500, we need to subtract 1.5 basis points per trade, or 3 basis points roundtrip daily cost (based on empirical observations when trading futures with the ORB strategy, using an account size of around $1 \ 000 \ 000$; USD Interactive Brokers, www.interactivebrokers.com, February 2, 2010 to November 29, 2010).

We recognize that these levels of trading costs are not large enough to qualitatively change the results for the average daily returns shown in Figures 6-13 or in Table 2; that is, returns significantly (insignificantly) larger than zero will remain significantly (insignificantly) larger than zero even if trading costs are included. We find, however, that even small levels of trading costs have a large effect on the accumulation of wealth over time and on the corresponding annual returns, when trading ORB strategies out-of-sample.

Figures 16-17 graphically show the accumulation of wealth over time when trading ORB strategies out-of-sample, adjusted for trading costs, applied to crude oil and S&P 500, respectively. Table 4 gives the corresponding annual returns statistics for both assets.
Figure 16. Wealth over time, starting with 1 000 000 USD (expressed in log levels), when trading crude oil futures out-of-sample, with trading costs included, from January 1, 1991 to January 26, 2011. B&H refers to the buy and hold strategy, and ORB refers to the ORB strategy given a particular range. We subtract 8 basis points roundtrip daily cost during trading days for ORB strategies, and a roundtrip daily cost of 8/20 basis points for the B&H strategy (we assume that contracts are rolled each month and that each month consists of 20 trading days).

Figure 17. Wealth over time, starting with 1 000 000 USD (expressed in log levels), when trading S&P 500 futures out-of-sample, with trading costs included, from January 1, 1991 to November 29, 2010. B&H refers to the buy and hold strategy, and ORB refers to the ORB strategy for a particular range. We subtract 3 basis points roundtrip daily cost during trading days for ORB strategies, and a roundtrip daily cost of 3/20 basis points for the B&H strategy (we assume that contracts are rolled each month and that each month consists of 20 trading days).
Table 4. Annual returns statistics (calendar year) when trading the B&H strategy and the ORB strategy out-of-sample when trading costs are included. \( \rho \) is the per cent distance added to and subtracted from the opening price, where N/A refers to the B&H strategy. Mean/Std.Dev gives the average annual return per unit of annual volatility and Mean/-Min gives the average annual return over the largest annual loss. When trading crude oil futures, we subtract 8 basis points roundtrip daily cost during trading days for ORB strategies, and a roundtrip daily cost of 8/20 basis points for the B&H strategy. When trading S&P 500 futures, we subtract 3 basis points roundtrip daily cost during trading days for ORB strategies, and a roundtrip daily cost of 3/20 basis points for the B&H strategy (we assume that contracts are rolled each month and that each month consists of 20 trading days).

<table>
<thead>
<tr>
<th>( \rho ) (%)</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std.Dev.</th>
<th>Min</th>
<th>Max</th>
<th>Mean/Std.Dev.</th>
<th>Mean/-Min</th>
</tr>
</thead>
<tbody>
<tr>
<td>N/A</td>
<td>19</td>
<td>0.0429</td>
<td>0.1658</td>
<td>-0.2580</td>
<td>0.3739</td>
<td>0.26</td>
<td>0.17</td>
</tr>
<tr>
<td>0.5</td>
<td>19</td>
<td>0.1568</td>
<td>0.5930</td>
<td>-0.2016</td>
<td>2.0990</td>
<td>0.26</td>
<td>0.78</td>
</tr>
<tr>
<td>crude oil</td>
<td>1.0</td>
<td>0.0993</td>
<td>0.3490</td>
<td>-0.1128</td>
<td>1.1638</td>
<td>0.28</td>
<td>0.88</td>
</tr>
<tr>
<td></td>
<td>1.5</td>
<td>0.0505</td>
<td>0.1798</td>
<td>-0.0718</td>
<td>0.6123</td>
<td>0.28</td>
<td>0.70</td>
</tr>
<tr>
<td></td>
<td>2.0</td>
<td>0.0298</td>
<td>0.0980</td>
<td>-0.0221</td>
<td>0.3315</td>
<td>0.30</td>
<td>1.35</td>
</tr>
<tr>
<td>S&amp;P 500</td>
<td>N/A</td>
<td>0.0212</td>
<td>0.1057</td>
<td>-0.1822</td>
<td>0.2617</td>
<td>0.20</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>0.5</td>
<td>0.0135</td>
<td>0.1482</td>
<td>-0.1416</td>
<td>0.5779</td>
<td>0.09</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
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<td>0.0300</td>
<td>0.1687</td>
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<td>0.6954</td>
<td>0.18</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>1.5</td>
<td>0.0123</td>
<td>0.0738</td>
<td>-0.0670</td>
<td>0.3120</td>
<td>0.17</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>2.0</td>
<td>0.0031</td>
<td>0.0239</td>
<td>-0.0212</td>
<td>0.0681</td>
<td>0.13</td>
<td>0.15</td>
</tr>
</tbody>
</table>

Figures 16-17 graphically show considerably reduced wealth levels for both assets when trading costs are included, compared to the wealth levels in Figures 14-15. When trading crude oil, terminal wealth is reduced 49% (\( \rho = 0.5\% \)), 37% (\( \rho = 1.0\% \)), 30% (\( \rho = 1.5\% \)), and 24% (\( \rho = 2.0\% \)). When trading S&P 500, terminal wealth is reduced 80% (\( \rho = 0.5\% \)), 47% (\( \rho = 1.0\% \)), 49% (\( \rho = 1.5\% \)), and 64% (\( \rho = 2.0\% \)). For the buy and hold strategy, wealth is reduced 19% and 15%, for crude oil and S&P 500, respectively.

Table 4 shows that annual returns and risk-adjusted returns decrease considerably for both assets when trading costs are included. Further, we find that the optimal range for maximizing annual returns remains at \( \rho = 0.5\% \) for crude oil but increases to \( \rho = 1.0\% \) for S&P 500 due to the increase in trading costs. In sum, trading costs decrease wealth accumulation and annual returns considerably but do not affect average daily returns shown in Table 2 in a qualitative way.
4. Concluding discussion

This paper assesses the returns of the Opening Range Breakout (ORB) strategy across volatility states. We calculate the average daily returns of the ORB strategy for each volatility state of the underlying asset when applied on long time series of crude oil and S&P 500 futures contracts. This paper contributes to the literature on day trading profitability by studying the returns of a day trading strategy for different volatility states. As a minor contribution, this paper improves the HLL (2013) approach of assessing ORB strategy returns by allowing the ORB trader to trade both long and short positions and to use stop loss orders, in line with the original ORB strategy in Crabel (1990) and in trading practice.

When empirically tested on long time series of crude oil and S&P 500 futures contracts, this paper finds that the average ORB return increases with the volatility of the underlying asset. Our results relate to the findings in Gencay (1998), in that technical trading strategies tend to result in higher profits when markets “trend” or in times of high volatility. This paper finds that the differences in average returns between the highest and lowest volatility state are around 200 basis points per day for crude oil, and around 150 basis points per day for S&P 500. This finding explains the significantly positive ORB returns in the period 2001-10-12 to 2011-01-26 found in HLL (2013) but also, perhaps more importantly, relates to the way we view profitable day traders. When reading the trading literature (e.g., Crabel, 1990; Williams, 1999; Fisher, 2002) and the account studies literature (e.g., Coval et al., 2005; Barber et al., 2011; Kuo and Lin, 2013), one may get the impression that long-run profitability in day trading is the same as earning steady profit over time. The findings of this paper suggest instead that long-run profitability in day trading is the result of trades that are relatively infrequent but of relatively large magnitude and are associated with the infrequent time periods of high volatility. Positive returns in day trading can hence be seen as a tail event during periods of high volatility of an otherwise efficient market. The implication is that a day trader, profitable in the long run, could still experience time periods of zero, or even negative, average returns during periods of normal, or low, volatility. Thus, even if long-run profitability in day trading could be achieved, it is achieved only by the trader committed to trade every day for a very long period of time or by the opportunistic trader able to restrict his trading to periods of high volatility. Further, this finding highlights the need for using a relatively long time series that contains a wide range of volatility states when evaluating the returns of day traders, in order to avoid possible volatility bias.
With trading ORB strategies out-of-sample, we find that profitability depends on the choice of asset and range, and that not all ranges are profitable. We find that the ORB strategy is profitable for all ranges when trading crude oil, but, when trading the S&P 500, the ORB strategy does not necessarily yield a daily return significantly larger than zero on average for some of the ranges. Further, we find that profitability is not robust to time. Even when ORB strategies are profitable in the long run, ORB strategies still lose money during periods of time when volatility is normal or low. If the trader, for example, is unfortunate enough to start trading the ORB strategy after a market crisis event, when the volatility has moved back to a low volatility state, it could take a long time, sometimes years, of day trading until the trader starts to profit. We believe this finding to be worrisome news for a trader looking to day trading as an alternative source of regular income instead of employment. A point to note is that ORB strategies result in relatively few trades, which restricts potential wealth accumulation over time. Most likely, the ORB trader simultaneously monitors and trades on several different markets, thereby increasing the frequency of trading. Further, this paper studies profitability when trading the ORB strategy without leverage (leverage means that the trader could have a market exposure larger than the value of trading capital), which also may restrict potential wealth accumulation over time. Most likely, the ORB trader uses leverage to increase the returns from trading. Moreover, we find that trading costs do not affect average daily returns in a qualitative way but decrease annual returns considerably.

For future research, it would be of interest to study whether the returns of other strategies used by day traders also correlate with volatility. In addition, it would be of interest to study whether the returns of momentum-based strategies with longer investment periods than intraday (see, for example, the strategies in Jegadeesh and Titman, 1993; Erb and Harvey, 2006; Miffre and Rallis, 2007) correlate with volatility.
References


