On the Returns of Trend-Following Trading Strategies

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To Myself

Abstract

Paper [I] tests the success rate of trades and the returns of the Opening Range Breakout (ORB) strategy. A trader that trades on the ORB strategy seeks to identify large intraday price movements and trades only when the price moves beyond some predetermined threshold. We present an ORB strategy based on normally distributed returns to identify such days and find that our ORB trading strategy result in significantly higher returns than zero as well as an increased success rate in relation to a fair game. The characteristics of such an approach over conventional statistical tests is that it involves the joint distribution of low, high, open and close over a given time horizon.

Paper [II] 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.

Paper [III] performs empirical analysis on short-term and long-term Commodity Trading Advisor (CTA) strategies regarding their exposures to unanticipated risk shocks. Previous research documents that CTA strategies offer diversification opportunities during equity market crisis situations when evaluated as a group, but do not separate between short-term and long-term CTA strategies. When separating between short-term and long-term CTA strategies, this paper finds that only short-term CTA strategies provide a significant, and consistent, exposure to unanticipated risk shocks while long-term CTA strategies do not. For the purpose of diversifying a portfolio during equity market crisis situations, this result suggests that an investor should allocate to short-term CTA strategies rather than to long-term CTA strategies.

Keywords: Bootstrap, Commodity Trading Advisor funds, Contraction-Expansion principle, Crude oil futures, Futures trading, Opening Range Breakout strategies, S&P 500 futures, Technical analysis, Time series momentum, Time-varying market inefficiency.

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Christian Lundström

Stockholm, March 2017

Contents

This thesis consists of an introduction and the following self-contained papers related to the returns of trend-following trading strategies:

Paper [I]

Holmberg, U., C. Lönnbark, and C. Lundström (2013): "Assessing the Profitability of Intra-day Opening Range Breakout Strategies," *Finance Research Letters*, 10, 27-33.

Paper [II]

Lundström, C. (2013): "Day trading returns across volatility states," *Umeå Economic Studies No.* 861. (Revised March 3, 2017)

Paper [III]

Lundström, C. and J. Peltomäki (2016): "Beyond Trends: The Reconcilability of Short-Term CTA Strategies with Risk Shocks," *Journal of Alternative Investments*, 18, 74-83.

1. Introduction

Futures have become mainstream investment vehicles among both traditional and alternative asset managers (e.g., Fuertes *et al.*, 2010). Through futures contracts, an investor may gain exposure to a wide range of asset classes, such as commodities, fixed income, currencies, debt, and stock market indices. Besides hedging, futures may be used as an inflation hedge (e.g., Greer, 1978; Bodie and Rosansky, 1980; Bodie, 1983), in portfolio diversification (e.g., Jensen *et al.*, 2000; Erb and Harvey, 2006), and in trading, where a trader actively initiates long or short positions of futures contracts in an attempt to profit from price trends (e.g., Crabel, 1990; Williams, 1999; Chan *et al.*, 2000; Fisher, 2002; Jensen *et al*., 2002; Wang and Yu, 2004; Erb and Harvey, 2006; Miffre and Rallis, 2007; Marshall *et al*., 2008a; Basu *et al.*, 2010; Fuertes *et al.*, 2010; Moskowitz *et al.*, 2012). When trading a certain strategy, the trader initiates trades following the buy and sell signals generated by a trading strategy to predict and profit from price trends. A *technical* trading strategy is a strategy based solely on past information (technical trading strategies are also known as filter rules, systematic strategies, or simply technical analysis). Technical trading strategies are typically based on past prices but could include trading volume and other quantifiable information (for an overview of technical trading strategies and the information that they use, see Katz and McCormick, 2000).

Trading futures for profit using technical trading strategies is a multi-billion US dollar industry. The Commodity Trading Advisor (CTA) funds, or Managed Futures funds, constitute a particular class of hedge funds that trade futures contracts for profit, not for hedging purposes, using trend-following strategies (e.g., Moskowitz *et al.*, 2012). Barclay Hedge estimates that CTA funds manage over USD 337 billion in 2016 and that more than 90% of the CTA funds are classified as technical trading strategies (BarclayHedge.com 2017-02-15). CTA funds are not limited to trading only commodity futures, but can also trade futures contracts for fixed income, currencies, debt, and stock market indices. Similar to other hedge funds, CTA funds are absolute return funds, which aim to generate positive returns net of costs. This can be contrasted to relative return funds, which aim to generate positive returns net of cost *relative* to the returns of a particular index, such as ordinary mutual funds invested in stocks that aim to generate positive returns relative to a stock market index. Given the sizable amount of capital invested in CTA funds, a relevant question is whether CTA funds and other futures traders are able to achieve their aim of generating positive returns net of costs by using technical trading strategies.

This thesis addresses the specific research question: "*Can technical trading strategies generate positive returns net of costs in futures trading?*" To shed some light on why technical trading strategies are able to attract multi-billion USD in assets under management, we restrict the study of this thesis to strategies actually used among futures traders and CTA funds.

The answer to our research question essentially depends on the underlying process that generates futures prices: trends or random walks? The Efficient Market Hypothesis (EMH) of Fama (1965, 1970) asserts that current asset prices fully reflect available information, implying that asset prices evolve as random walks over time and that technical trading strategies should generate zero returns over time (see also Fama and Blume, 1966). Trends in asset prices imply that prices deviate from random walks, creating possible profit opportunities for traders who may use technical trading strategies to exploit such trends (e.g., Alexander, 1961). A profitable trend-following trading strategy should generate a positive expected return net of costs either from a success rate greater than 50%, and/or from larger wins than losses on balance. The explanation of why trends may appear in asset prices is typically motivated from a psychological perspective and rests upon the assumption that at least some traders systematically commit behavioral errors that causes them to trade coordinately, thus creating a trend. The field of economics that studies behavioral errors is referred to as "behavioral finance," and notable work includes Kahneman and Tversky (1979), Barberis *et al.* (1998), Daniel *et al*. (1998) and Lo (2004).

This thesis studies technical trading strategies developed to profit from one specific behavioral error known as *momentum*. Momentum is the tendency for rising asset prices to keep rising and falling prices to keep falling, which causes prices to trend (e.g., Jegadeesh and Titman, 1993). Trading strategies based on momentum is typically referred to as trend-following strategies in the asset management industry (e.g., Moskowitz *et al.*, 2012). Empirical evidence of momentum in asset prices is reported by many (e.g., Jegadeesh and Titman, 1993; Chan *et al.*, 2000; Erb and Harvey, 2006; Miffre and Rallis, 2007; Fuertes *et al.*, 2010; Moskowitz *et al.*, 2012; Kaminski and Lo, 2013; Pettersson, 2014; and others). The behavioral finance literature has proposed a number of reasons why momentum could appear in the markets; it is typically attributed to cognitive biases from irrational investors and traders, such as investor over- or under-reaction to news. Over-reaction can be caused by herding (e.g., Bikhchandani *et al.*, 1992), over-confidence and self-attribution confirmation biases (e.g., Daniel *et al*., 1998), the representativeness heuristic (e.g., Barberis *et al.*, 1998), positive feedback trading (e.g., Hong and Stein, 1999), or investor sentiment (e.g., Baker and Wurgler, 2006). Under-reaction can result from the disposition effect to realize the wins of winning trades too soon and hold on to losing trades too long (e.g., Shefrin and Statman, 1985), conservativeness and anchoring biases (e.g., Barberis *et al.*, 1998), or slow diffusion of news (e.g., Hong and Stein, 1999). As discussed in Crombez (2001), however, momentum also can be observed with perfectly rational traders if we assume noise in the experts' information.

Regardless of the reasons why momentum may occur, we may separate momentum into two major types: *cross-sectional* momentum and *time series* momentum. Cross-sectional momentum focuses on the *relative* performance of assets in the cross-section, based on findings that assets that outperformed their peers over the most recent 3 to 12 months continue to outperform their peers on average during the next month, for both stocks and futures contracts (e.g., Jegadeesh and Titman, 1993; Chan *et al.*, 2000; Erb and Harvey, 2006; Miffre and Rallis, 2007; Fuertes *et al.*, 2010). Time series momentum (introduced for the first time in Moskowitz *et al.*, 2012) focuses instead on the asset's *own* past performance. Moskowitz *et al.* (2012) find that futures contracts that increased (decreased) in price over the most recent 12 months continued to increase (decrease) on average during the next month, for nearly every contract tested out of 58 different contracts, including equity indices, currencies, and commodities, over more than 25 years of data (see also Kaminski and Lo, 2013, and Pettersson, 2014). Cross-sectional momentum portfolios are constructed differently from time series momentum portfolios. A cross-sectional momentum strategy is a zero-investment portfolio in terms of market exposure; it is invested long in half of the assets *and* short-sells the other half, netting the market exposure to roughly zero. By contrast, a time series momentum portfolio is a portfolio of asset-specific momentum strategies, usually with a non-negative market exposure; it is either invested long in assets that have increased in value during the past year *or* it short-sells assets that have decreased in value during the past year. Thus, we would expect the market exposure of a time series momentum portfolio to vary over time, depending on the number of long and short trades.

We restrict the study of this thesis to technical trading strategies based solely on time series momentum. We recognize that CTA funds are time series momentum portfolios (e.g., Moskowitz *et al.* 2012) and that time series momentum, rather than cross-sectional momentum, more directly matches the predictions of these behavioral and rational asset-pricing theories. Barberis *et al.* (1998), Daniel *et al*. (1998), and Hong and Stein (1999) all focus on a single asset, and therefore have implications for time series momentum rather than cross-sectional momentum. Likewise, rational theories of momentum such as Crombez (2001) also relate to a single asset. Henceforth, we shall refer to momentum as time series momentum if not otherwise stated. How should we then go about testing whether technical trading strategies generate positive returns net of costs?

1.1 Assessing the returns of technical trading strategies

Assessing the returns of technical trading strategies has a long history and includes, among others, Alexander (1961), Fama and Blume (1966), Brock *et al.* (1992), Caginalp and Laurent (1998), Gencay (1998), Sullivan *et al.* (1999), Neely (2003), Park and Irwin (2007), Marshall *et al*. (2008a; 2008b), Schulmeister (2009), and Yamamoto (2012). Fama and Blume (1966) argue that, because information on prices is readily available to anyone, the null hypothesis is that a technical trading strategy should generate a zero return on average when markets are efficient. If a technical trading strategy generates an average return significantly larger than the associated trading cost, this would consequently reject the null hypothesis of efficient markets (e.g., Fama and Blume, 1966). Thus, CTA funds and futures traders should not be able to achieve positive returns net of costs by using technical trading strategies.

In the massive literature on the subject, we find both acceptance and rejection of the EMH (for an overview, see Park and Irwin, 2007). Recent studies argue, however, that significantly positive returns net of costs are not enough to reject the EMH, for a number of reasons. For example, it is argued that the returns of a technical trading strategy should also, when applicable, be larger than the returns from buying and holding the underlying asset (e.g., Park and Irwin, 2007) and also when adjusted for risk/volatility (e.g., Neely, 2003). As futures trading inherently involves risk, one could argue from a risk-return perspective that traders and CTA funds can actually achieve positive returns net of costs, even when markets are efficient, if they are rewarded for carrying high risk (see the discussion in Neely, 2003). Further, when assessing the returns of a technical trading strategy, the researcher could potentially over-fit the strategy parameters to the data and, in turn, over-estimate the actual strategy returns. This is related to the problem of data snooping (e.g., Sullivan *et al*. 1999; White, 2000). Thus, to reject the EMH, the profit of the technical trading strategy must also be robust to changes in parameters (e.g., Park and Irwin, 2007). Moreover, if a technical trading strategy is indeed profitable, such a strategy would soon be used by other traders, the profit would diminish and the strategy would self-destruct. This argument leads some authors to suggest that the technical trading strategy able to achieve significantly positive returns net of costs must also be known to, as well as used by, traders at the time of their trading decisions, in order to reject the EMH (see the discussion in Coval *et al*., 2005).

One way to assess the returns of momentum-based (trend-following) technical trading strategies actually used by traders is to analyze the historical returns of CTA funds. Another way is to assess the returns of a hypothetical trader by applying a momentum-based technical trading strategy that is actually used among traders on empirical asset prices. As CTA funds are naturally secretive of what strategies they use, we cannot definitely say that only strategies based on momentum are generating the returns. Assessing the returns of a hypothetical trader therefore has the advantage that we know whether or not the trading strategy is based on momentum. We must, however, verify that that the strategy is actually used among traders and ensure that the strategy is robust in parameters to avoid the problem of data snooping.

Papers [I] and [II] study the returns of a particular momentum-based technical trading strategy used among day traders, and Paper [III] studies the returns of short-term (weekly) and long-term (monthly) CTA strategies and their relationship to market volatility. We summarize the literature on the returns of day traders and the literature on the returns of CTA funds.

1.1.1 The returns of day traders

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 profitable, i.e., 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 fewer (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.

The empirical observation that day traders are able to achieve average returns significantly larger than zero after adjusting for transaction costs is interesting considering that day traders should lose money on average after adjusting for transaction costs when markets are efficient with respect to information (Statman, 2002). 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. Can day traders use technical trading strategies to generate positive returns net of costs from day trading?

Papers [I] and [II] study the returns of a particular momentum-based technical trading strategy used among day traders. The returns of technical trading strategies applied intraday can be found in, for example, Marshall *et al*. (2008b), Schulmeister (2009) and Yamamoto (2012) but these strategies are developed by researchers and not necessarily used among day traders during the tested time period. On a methodological note, we recognize three advantages of assessing the returns of technical trading strategies 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 those of account studies, thereby avoiding possible small sample biases. Second, we also may use powerful data-generating techniques such as the bootstrapping technique used in Brock *et al*. (1992) to generate even longer time series, with more observations, than the actual series of empirical data when testing the profitability of technical trading strategies. Third, we are able to study the returns of trading strategies that are used solely to generate profits, in contrast to the recorded returns of trading accounts. This is because trading accounts may also include trades initiated for reasons other than profit, such as consumption, liquidity, portfolio rebalancing, diversification, hedging, tax motives, etc., creating potentially noisy estimates (see the discussion in Kuo and Lin, 2013).

1.1.2 The returns of CTA funds

Paper [III] studies the returns of short-term (weekly), and long-term (monthly) CTA strategies and their relationship to market volatility. Kaminski (2011a; 2011b; 2011c) classify CTA strategies as long volatility investment strategies generating positive average returns during equity market crisis situations, i.e., crisis alpha (see also the results in Moskowitz *et al.* 2012). As an asset class, CTA strategies are therefore interesting in portfolio construction from a diversification perspective because of their capacity to hedge equity tail risk during periods of equity market crisis (for a discussion of equity tail risk, see Bhansali, 2008). Further, we note that CTA funds are time series momentum portfolios that we actually can observe empirically, providing a valuable complement to the studies of time series momentum in Moskowitz *et al.* (2012), Kaminski and Lo (2013), and Pettersson (2014), where the momentum strategies employed are developed by researchers.

We note that the relationship between CTA returns and volatility is not clear-cut. Recognizing that CTA strategies are trend-following strategies, positioned either long or short in price trends, we argue that the path properties of the trend, i.e., the volatility of the trend, matters. If the volatility of the trend is too high, many CTA strategies will suffer from losses due to stopped-out trades. Further, CTA strategies may vary considerably in their ability to deliver crisis alpha, and, in turn, in their capacity to hedge equity tail risk, depending on the strategy of the fund, the frequency of the trading (short-term, long-term), and so on. So, even if the returns of CTA strategies evaluated as a group yield a significant crisis alpha on average, as reported in Kaminski

(2011c), the individual contribution of alpha may vary among different sub-classes of CTA strategies. It could be the case that one CTA strategy may serve as a decent hedge of equity tail risk while another CTA strategy does not. We note that Pettersson (2014) reports that (time series) momentum portfolios produce *lower* average returns during periods of high volatility. Recognizing that CTA strategies are time series momentum portfolios, this finding goes against the result in Kaminski (2011c). The contradictory empirical results of Kaminski (2011c) and Pettersson (2014) highlight the need for further study of the returns of trend-following trading strategies and volatility. Selecting CTA strategies able to quickly adjust to the increase in market volatility and successfully offer diversification opportunities would certainly add value for investors searching beyond the traditional asset classes to counterbalance the poorly performing traditional assets during equity market crises situations.

2. Summary of the papers

Paper [I]: Assessing the profitability of intra-day opening range breakout strategies

This paper links 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 move until the closing price 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. To determine the thresholds from the opening price in the ORB strategy, the trader uses a so-called range, which is added to (subtracted from) the opening price for long (short) trades. As positive ORB returns are based on intraday 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. The advantage of testing the returns of the ORB strategy, relative to the returns of the day trading strategies reported in previous studies, is that the ORB strategy is documented as being used among profitable day traders and not developed by researchers.

This paper presents an ORB strategy where the range is based on normally distributed returns and proposes an approach of assessing the returns of such a strategy when long records of daily opening, high, low, and closing prices are available. The advantage of such an approach over conventional statistical tests is that it involves the joint distribution of low, high, open and close over a given time horizon. To assess statistical significance, we rely on a bootstrap approach. Here, we face additional challenges compared to previous studies assessing the returns of technical trading strategies because the case at hand is multivariate, with natural ordering of the level series: low, high, open and close. To meet these additional challenges, this paper expands the traditional bootstrap approach used in previous studies to test the profit of technical trading strategies to suit this multivariate setting. In an empirical application, we apply our test to a long time series of US crude oil futures from 1983-03-30 to 2011-01-26. Using the full sample of years, we find remarkable success of the ORB trading strategy, resulting in significantly higher returns than zero, as well as an increased success rate relative to a fair game. When we split the data series into shorter time periods, we find significantly positive returns only in the last time period, ranging from 2001-10-12 to 2011-01-26. This time period includes the sub-prime market crisis, which leads us to suggest that positive ORB returns, and in turn intraday momentum, are perhaps positively correlated with market volatility.

Paper [II]: Day trading returns across volatility states

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 to a 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 approach of assessing ORB strategy returns used in Paper [I] by allowing the ORB trader to trade both long and short positions and to use stop loss orders, in line with trading practice. Further, this paper uses a larger data set than in Paper [I] and also studies the returns when applying the ORB strategy out-of-sample. Because the ORB strategy is defined by only one parameter – the range – this paper avoids the problem of data snooping by assessing the strategy returns for a large number of ranges. Also, the range used in this paper is not restricted to any particular returns density function assumption.

This paper finds that the differences in average returns between the highest and lowest volatility states 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 that were found in Paper [I]. Perhaps more importantly, it affects how we view profitable day traders. When reading the trading literature and the account studies literature, 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, in 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.

When we study 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. Further, we find that profitability is not robust to time. 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.

Paper [III]: Beyond Trends: The Reconcilability of Short-Term CTA Strategies with Risk Shocks

This paper performs empirical analysis on the returns of short-term and long-term Commodity Trading Advisor (CTA) strategies and their exposures to unanticipated risk shocks. This paper calculates the unanticipated risk shocks based on the VIX index and uses such shocks as a proxy for market risk. Previous research documents that CTA strategies offer diversification opportunities during equity market crisis situations when evaluated as a group, but these earlier studies do not separate between short-term and long-term CTA strategies. This paper recognizes that CTA strategies may vary considerably in their ability to deliver crisis alpha, and, in turn, in their capacity to hedge equity tail risk, depending on the strategy of the fund, the frequency of the trading, and so on. So, even if CTA strategies produce a significant crisis alpha on average when evaluated as a group, the individual contribution of alpha may vary considerably among different sub-classes of CTA strategies.

When separating between short-term CTA strategies and long-term CTA strategies, this paper finds that only short-term CTA strategies provide a significant, and consistent, exposure to unanticipated risk shocks, while long-term CTA strategies do not. "Consistent" means that the exposures to risk shocks are prevalent in different states of the risk cycle. This finding contributes to the CTA literature by showing that only short-term CTA strategies offer diversification opportunities during equity market crisis situations. This finding also relates to the findings in Papers [I] and [II] that the returns of momentum-based trading strategies are positively correlated to volatility.

The result of this paper suggests that, for the purpose of diversifying a portfolio during equity market crisis situations, an investor should allocate to short-term CTA strategies rather than to long-term CTA strategies. The implication of this finding differs depending on whether the investor is passive or active. A passive investor should buy and hold short-term CTA funds for a part of the portfolio assets to hedge equity tail risk. An active investor should instead try to allocate to short-term CTA funds in an early state of the risk cycle, when the risk level trends up, and should reallocate the assets to, for example, long-term CTA funds or (more) equities in a later state of the risk cycle, when the risk level trends down.

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I

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Assessing the profitability of intraday opening range breakout strategies

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A B S T R A C T

Is it possible to beat the market by mechanical trading rules based on historical and publicly known information? Such rules have long been used by investors and in this paper, we test the success rate of trades and profitability of the Open Range Breakout (ORB) strategy. An investor that trades on the ORB strategy seeks to identify large intraday price movements and trades only when the price moves beyond some predetermined threshold. We present an ORB strategy based on normally distributed returns to identify such days and find that our ORB trading strategy result in significantly higher returns than zero as well as an increased success rate in relation to a fair game. The characteristics of such an approach over conventional statistical tests is that it involves the joint distribution of low, high, open and close over a given time horizon.

1. Introduction

The Efficient Market Hypothesis (EMH) of Fama (1965, 1970) asserts that current asset prices fully reflect available information (see also Fama, 1991) implying that asset prices evolve as random walks in time. Consequently, tests of the EMH have traditionally been designed to catch deviations from random walk prices and in the massive literature on the subject one is bound to find support for both acceptances and rejections of the hypothesis (e.g., Malkiel, 1996; Lo, 2001). In particular, an assertion of the EMH is that it should not be possible to base a trading strategy on historical prices (so-called

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filter rules or technical trading) and earn positive expected returns. However, the fact remains that the use of filter rules is a widespread phenomenon. Barclay Hedge estimates that filter based Hedge Funds within the Managed Futures category manage over 300 Billion USD in 2011 and is today the largest hedge fund category with respect to assets under management. Indeed, some filter rule traders appear to consistently outperform the market (see Schwager (1989), for a classic reference) and the subject has been given due attention in the literature (e.g. Brock et al., 1992; Gençay, 1996, 1998). Testing of the profitability of trading rules has traditionally been carried out based on a (at least) daily investment horizon. However, as discussed in Taylor and Allen (1992) the use of filter rules among practitioners appears to increase with the frequency of trading (see also Schulmeister, 2006, 2009). In particular, many strategies are typically employed intraday and to assess their potential profitability one would typically require intraday data. The relative unavailability of intraday data may thus be a possible explanation for the apparent lagging behind of the research community.

In this paper we remove this obstacle and propose a quite novel approach on how to assess the profitability when only records of daily high, low, opening and close are available. Obviously, there is a plethora of filter rules out there and the one we have in mind in the present paper is the so-called Opening Range Breakout (ORB), which is typically adopted intraday. This rule is based on the premise that if the market moves a certain percentage from the opening price level, the odds favor a continuation of that move. An ORB filter suggests that, long (short) positions are established at some predetermined price threshold a certain percentage above (below) the opening price.

To evoke the testing strategy and gain intuition on the way we first note that the rationale behind using an ORB filter is the believe in so-called momentum in prices (e.g. Jegadeesh and Titman, 1993). That is, the tendency for rising asset prices to rise further and falling prices to keep falling. In the behavioral finance literature the appearance of momentum is often attributed to cognitive biases from irrational investors such as investor herding, investor over- and under-reaction, and confirmation bias (see Barberis et al., 1998; Daniel et al., 1998). However, as discussed in Crombez (2001) momentum can also be observed with perfectly rational traders. In pioneering the ORB strategy Crabel (1990) presented the so-called Contraction–Expansion (C–E) principle. The principle asserts that markets alternates between regimes of contraction and expansion, or, periods of modest and large price movements, respectively. An ORB strategy may be viewed as a strategy of identifying and profiting from days of expansion. In passing we note the resemblance with the stylized fact of volatility clustering in financial return series (e.g. Engle, 1982).

Now, a seemingly quite reasonable assumption is that markets for the most part are relatively efficient with prices evolving as random walks in time, or equivalently, returns are martingales. Thus, a heuristic use of the law of large number implies normally distributed returns. According to the (C–E) principle these calm days could be considered as periods of contraction during which the returns are normally distributed. Now, during periods of expansions traders activates ORB strategies and the profitability of them implies that the martingale property breaks down with non-normality as a consequence. Building on this reasoning our testing strategy is simply based on identifying days of large intraday movements and evaluating the expected return on these days. In particular, if on a given day the price threshold implied by the rule is above (below) the high (low) price we deduce that a long (short) position was established at some point during this day. To assess statistical significance we build on Brock et al. (1992) and use a bootstrap approach adapted to the present case.

The remainder of the paper is organized as follows: In Section 2 we briefly review the underlying theory and give an account of the ORB strategy. In this section we also outline our proposed test for profitability. Section 3 gives results for the empirical application and the fourth section concludes.

2. Martingale prices and momentum based trading strategies

We denote by P_t^o, P_t^h, P_t^l and P_t^c the opening, high, low and, closing price on day t, respectively. A point in time on day t is given by $t + \delta$, $0 \leqslant \delta \leqslant 1$. Note that $P_t^o = P_t$ and $P_t^c = P_{t+1}$. The set $\Psi_{t+\delta}$ contains the information available at time $t + \delta$. Furthermore, let $\psi^u(\psi^l)$ denote a certain threshold price level that is such that if the price crosses it from below (above) a momentum investor acts, i.e. takes a long (short) position. For ORB investors, these threshold price are often set in terms of some predetermined (large) relative change, ρ, from the opening price such that $\psi_t^u = (1+\rho)P_t^o$ and $\psi_t^l = (1-\rho)P_t^o$. For the purpose of this paper we assume that all positions are closed at the end of the trading day. Hence, no type of money management techniques such as a stop loss, trailing loss, and profit stop are considered.

Within the context of the present paper it is natural to involve the martingale pricing model (MPT) of Samuelson (1965). If capital markets are efficient with respect to $\Psi_{t+\delta}$ some prescribed formula based on $\Psi_{t+\delta}$ should not result in systematic success implying that prices are martingales with respect to this information set. In particular,

$$E\left[P_t^c|\Psi_{t+\delta}\right] = P_{t+\delta}. \quad (1)$$

A direct consequence of martingale pricing is that any investment should earn a zero expected return

$$E\left[R_{t+\delta}^c|\Psi_{t+\delta}\right] = 0, \quad (2)$$

where $R_{t+\delta}^c = \log\left(P_t^c/P_{t+\delta}\right)$. As such, any investment within the MPT framework is a "fair game" and from the martingale central limit theorem it follows that the returns are normally distributed (Brown, 1971).

Now, momentum investments are based on the premise that, if the market moves a certain percentage from the opening price level, the odds favor a continuation of that move. More specifically, a profitable momentum based trading strategy implies that

$$E\left[P_t^c|P_{t+\delta} > \psi_t^u\right] > P_{t+\delta} \text{ and/or } E\left[P_t^c|P_{t+\delta} < \psi_t^l\right] < P_{t+\delta}. \quad (3)$$

As such, the breaking down of the martingale property implies that the martingale central limit theorem no longer applies. Thus, it is natural to define ρ as a daily return that is unlikely to occur given normally distributed returns

$$\rho_\alpha = \hat{\mu} + \hat{\sigma} q_\alpha, \quad (4)$$

where $\hat{\mu}$ and $\hat{\sigma}$ are estimates of the mean and standard deviation of $R_t^c = \log\left(P_t^c/P_t^o\right)$, respectively, and q_α the inverse of the standard normal cumulative distribution function evaluated at α. Fig. 1 illustrates a profitable intraday trade based an ORB strategy. The price opens at P_t^o and as long as the price stays within "normal bounds", i.e. within $\left(\psi_t^u, \psi_t^l\right)$, the trader refrains from action but as soon as $P_{t+\delta} = \psi_t^u$, the trader initiates a long position, anticipating a continuation of the price moving in the same direction.

Given that an ORB strategy is based on intraday price movements, as illustrated in Fig. 1, it is clear that a perfect test of profitability requires information on the intraday price paths. The challenge we take on here is that of designing a test with access only to records of daily opening, high, low and closing prices. Our basic observation is that if the daily high (low) is higher (lower) than the set $\psi_t^u\left(\psi_t^l\right)$, we know with certainty that a buy (sell) signal was triggered at some point during the day and that a position was initiated at $\psi_t^u\left(\psi_t^l\right)$. For the purpose of this paper we assume a perfect order fill at the

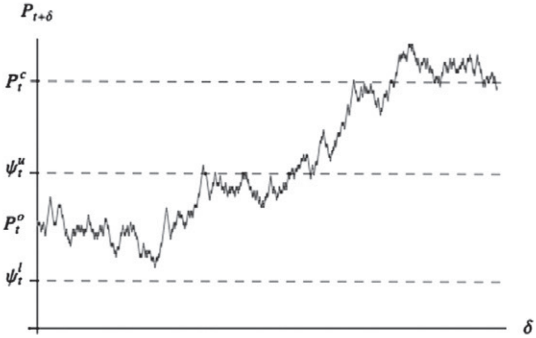

Fig. 1. An ORB strategy trader enters a long position if the intraday price exceeds ψ_t^u.

threshold price, a zero bid ask spread, as well as zero commissions. Consequently, real-life trading produce slightly different results.

Upon defining the return series $R_t^{long} = \log\left(P_t^c/\psi_t^u\right)$ and $R_t^{short} = \log\left(P_t^c/\psi_t^l\right)$ we may consider the averages

$$\overline{R}^{long} = \frac{\sum \mathbf{1}\left(P_t^h > \psi^u\right) R_t^{long}}{\sum \mathbf{1}\left(P_t^h > \psi^u\right)}, \tag{5}$$

$$\overline{R}^{short} = -\frac{\sum \mathbf{1}\left(P_t^l < \psi^l\right) R_t^{short}}{\sum \mathbf{1}\left(P_t^l < \psi^l\right)}, \tag{6}$$

where $\mathbf{1}(\cdot)$ is the indicator function. If strategies based on ORB filters are profitable then $\overline{R}^{long}$ and $\overline{R}^{short}$ should be significantly larger than zero. To assess statistical significance we rely on the bootstrap approach suggested in Brock et al. (1992). Here, we face additional challenges compared to their work as the case at hand is multivariate with a natural ordering of the level series. A reasonable procedure that accommodates this restriction proceeds as follows.

Assume that the level series share a common trend (cf. co-integration). Hence, considering a "benchmark" series to bootstrap the general levels appears reasonable. The other series may then be obtained as bootstrapped deviations from the benchmark series. To this end we consider the daily opening price as the benchmark series and define $R_t^o = \log\left(P_t^o/P_{t-1}^o\right),\ t = 2, \ldots, T$. Also define deviations $R_t^i = \log\left(P_t^i/P_t^o\right)$ for $i = \{h, l, c\}$ and $t = 1, \ldots, T$. Collect these returns in $\mathbf{R}_t = \left(R_t^o, R_t^h, R_t^l, R_t^c\right)$ are then drawn randomly with replacement, generating an pseudo-sample of returns. Based on this sample, an alternative realization of the level series is then generated. This procedure is repeated N times to generate sampling distributions of $\overline{R}^{long}$ and $\overline{R}^{short}$ respectively. The sampling distributions are then used in the standard way to test the null of zero expected returns against the alternative of positive ones.

3. Application

We apply the testing strategy presented above to a time series of US crude oil futures prices obtained from Commodity Systems Inc covering the period March 30, 1983–January 26, 2011. When constructing the time series the switch from the near-by contract to the next typically occur around

Fig. 2. The evolution of the daily open price for US crude oil futures adjusted for roll-over effects from March 30, 1983 to January 26, 2011. Source: Commodity Systems Inc.

Table 1
Descriptives of the daily return series.

Obs.	Mean	Std. dev.	Min	Max	Skewness	Kurtosis	Jarque–Bera
6976	0.02	0.72	−6.06	9.90	0.16	10.26	30,668

Table 2
Empirical results. The α is the tail probability, and ρ gives the associated percentage return. N is the number of trades. Freq. gives the proportion of trades that result in positive returns, while $\overline{R}$ gives the average returns.

	Long						Short				
	α (%)	ρ	N	*Freq.*	$\overline{R}_{long}$	p	ρ	N	*Freq.*	$\overline{R}_{short}$	p
Full sample	10	0.9388	738	0.6057	0.2019	0.0000	−0.9013	826	0.5424	0.1439	0.0000
	5	1.1996	439	0.6036	0.2180	0.0000	−1.1621	497	0.5714	0.1784	0.0000
	1	1.6889	188	0.6117	0.2583	0.0001	−1.6513	224	0.6205	0.2442	0.0003
	0.5	1.8680	141	0.6028	0.3108	0.0002	−1.8304	172	0.6454	0.2527	0.0008
	0.1	2.2373	80	0.7125	0.4027	0.0010	−2.1997	98	0.6225	0.2489	0.0147
1983-03-30 to 1992-06-29	10	0.7840	260	0.4923	0.0334	0.2539	−0.7574	272	0.5368	0.0871	0.0430
	5	1.0024	159	0.5157	0.0711	0.1350	−0.9759	156	0.5192	0.1313	0.0401
	1	1.4122	72	0.4861	0.1140	0.1246	−1.3857	73	0.5753	0.1978	0.0563
	0.5	1.5623	57	0.4912	0.0799	0.2467	−1.5357	56	0.5893	0.2420	0.0494
	0.1	1.8716	33	0.5758	0.1656	0.1448	−1.8451	41	0.6342	0.1026	0.2859
1992-06-30 to 2001-10-11	10	0.6069	373	0.5657	0.0374	0.0357	−0.5947	371	0.5148	0.0307	0.0734
	5	0.7772	195	0.5795	0.0634	0.0196	−0.7650	214	0.5327	0.0228	0.2172
	1	1.0966	62	0.5807	0.0843	0.0357	−1.0845	79	0.5317	−0.0258	0.6814
	0.5	1.2136	53	0.3962	0.0068	0.4546	−1.2015	57	0.5790	−0.0608	0.8091
	0.1	1.4548	20	0.5000	0.0254	0.4061	−1.4426	27	0.3333	−0.0290	0.6420
2001-10-12 to 2011-01-26	10	1.2956	245	0.6612	0.2813	0.0000	−1.2216	300	0.5967	0.2483	0.0000
	5	1.6524	138	0.6522	0.3405	0.0004	−1.5784	177	0.6328	0.2734	0.0001
	1	2.3216	50	0.8000	0.5155	0.0063	−2.2477	64	0.6406	0.3879	0.0006
	0.5	2.5667	44	0.7500	0.4926	0.0062	−2.4927	48	0.6667	0.3892	0.0008
	0.1	3.0718	23	0.8261	0.6397	0.0096	−2.9979	28	0.7143	0.3763	0.0054

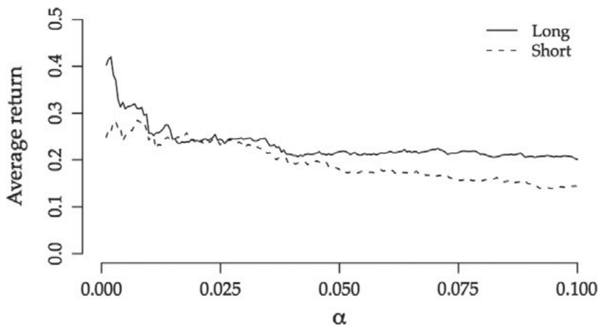

Fig. 3. Average returns on the tail probability (α).

the 20th each month, one month prior to the expiration month (see Pelletier (1997), for details on the adjustment of roll-over effects). Commodity futures are as easily sold short as bought long, and are not subject to short-selling restrictions while the costs associated with trading (e.g. slippage, bid ask spreads, and commissions) are often relatively low. In Fig. 2 we plot the evolution of the level series. The series exhibit a cyclical pattern and follows a positive long run trend reasonably due to inflation. Notable is also the sharp drop during the 2008 sub-prime crisis.

In Table 1 we give some descriptives for the daily returns series, i.e. R_t^c. The series exhibit positive skewness and excess kurtosis and consequently the Jarque–Bera test strongly rejects normality.

The values of the ρ's (and consequently the threshold prices) are derived from the sample. We thus check ex post for the existence of intraday trending of oil futures prices.

As can be read in Table 2, the ORB strategy results in significant positive average returns suggesting that the "fair game" argument embedded in the Martingale pricing theory does not hold true for adverse price movements. Interestingly, as we tighten the criterion used to determine entry, i.e. if we move further down the tail of a normal distribution, both the success rate and average returns increase. Fig. 3 clarifies this relationship. However, it should be noted that by moving down the tail of the normal distribution, we also reduce the number of trades, reducing the investors potential profits.

Dividing the full data set into three sub-samples, 1983-03-30 to 1992-06-29, 1992-06-30 to 2001-10-11, and finally 2001-10-12 to 2011-01-26 we find that the most recent time period drives the result. Given the possible resemblance between the ORB strategy and the stylized fact of volatility clustering in financial returns series, one plausible explanation is the relatively high volatility in the 2001-10-12 to 2011-01-26 period. After all, ORB is a directional strategy in the sense that either a long or a short position is established and hence it is basically long volatility in contrast to hedge fund strategies such as Long Short Equity, Market Neutral strategies or different variants of Arbitrage strategies to mention a few. Market volatility and ORB profitability should be expected to go hand in hand.

4. Concluding discussion

We proposed a way of assessing the profitability of intraday ORB strategies when long records of daily opening, high, low and closing prices are available. In an empirical application we employ our testing strategy to US crude oil futures. Using the full sample we find a remarkable success of the of ORB strategies. However, splitting up the full sample into three sub-periods reveals that this finding is not robust to time and to a large extent explained by the most recent (and most volatile) period. In this sense, our results relate to the findings in Gençay (1998), that mechanical trading rules tend to result in higher profits when markets "trend" or in times of high volatility.

A point to note is that our testing strategy will underestimate the actual profits since the closing of the positions is assumed to occur at the daily close. Thus, days when the momentum does not carry through to the end of the day or even reverses intraday will be included. In practice, the losses on these days will be limited by so-called stop losses.

Notable is also the our filter results in relatively few trades, which restricts potential profits. Most likely though the orb trader simultaneously monitors and acts on several markets.

Admittedly, transaction costs in terms of commission fees and bid-ask spreads will consume some of the profits. However, for the market under consideration these are relatively small. A reasonable estimate is 0.04%, or 0.08% round trip.

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II

Day trading returns across volatility states[1]

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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

500. 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: $P_t^o = P_t$, $P_t^c = P_{t+1}$, $P_t^h = \max_{0\leq\delta\leq1} P_{t+\delta}$, and $P_t^l = \min_{0\leq\delta\leq1} P_{t+\delta}$. Further, we let ψ_t^u and ψ_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 ρ 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 *ex ante* bias regarding future price trend direction and, in line with HLL (2013), uses symmetrically placed thresholds with the same ρ 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;

$$E_{t+\delta}[P_{t+1}|\Psi_{t+\delta}] = P_{t+\delta} \tag{1}$$

$$E_{t+\delta}[R_{t+1}|\Psi_{t+\delta}] = E_{t+\delta}[P_{t+1}|\Psi_{t+\delta}] - P_{t+\delta} = 0 \tag{2}$$

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, ψ_t^u and (ψ_t^l), such that:

$$E_{t+\gamma}\left[P_{t+1}\middle|P_{t+\gamma} = \psi_t^u\right] > \psi_t^u \; or \; E_{t+\gamma}\left[P_{t+1}\middle|P_{t+\gamma} = \psi_t^l\right] < \psi_t^l \tag{3}$$

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 ψ_t^u, or if the daily low (P_t^l) is equal to or lower than ψ_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 $R_t^L = P_t^c - \psi_t^u \middle| P_t^h \geq \psi_t^u$, and for short ORB trades by $R_t^S = \psi_t^l - P_t^c \middle| P_t^l \leq \psi_t^l$, 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 ψ_t^u or ψ_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.

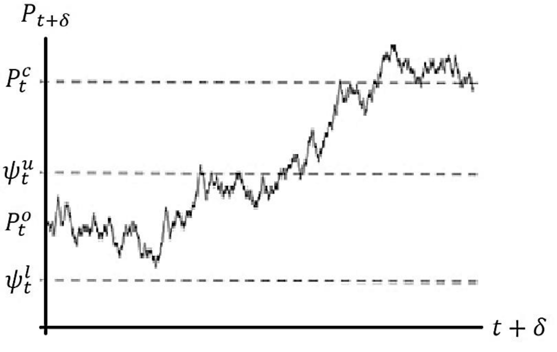

Figure 1. An ORB strategy trader initiates a long position when the intraday price reaches ψ_t^u and then closes the position at P_t^c, with the profit $P_t^c - \psi_t^u > 0$.

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 ψ_t^u and a short position at ψ_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:

$$R_t^{L\&S} = \begin{cases} P_t^c - \psi_t^u \gtreqless 0, if\ (P_t^h \geq \psi_t^u) \cap (P_t^l > \psi_t^l) \\ \psi_t^l - P_t^c \gtreqless 0, if\ (P_t^h < \psi_t^u) \cap (P_t^l \leq \psi_t^l) \\ \psi_t^l - \psi_t^u < 0, if\ (P_t^h \geq \psi_t^u) \cap (P_t^l \leq \psi_t^l) \end{cases} \tag{4}$$

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 ρ:

$$R_{\rho,t}^{L\&S} = \sum_{\tau=1}^{10} a_{\rho,\tau} D_{\rho,\tau} + v_{\rho,t} \tag{5}$$

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 σ_{t+1} by tracking the daily absolute return (log-difference of prices) of day t:

$$\sigma_t^c = +\sqrt{(P_t^c - P_t^o)^2} = |P_t^c - P_t^o| \tag{6}$$

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 σ_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 σ_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 $R_t^{L\&S} = -\left(P_t^c - \psi_t^l\right) = -(P_t^c - P_t^o + \rho) = -(-\sigma_t^c + \rho) = \sigma_t^c - \rho$ because $R_t^{L\&S} = -\left(P_t^c - \psi_t^l\right) > 0$ 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 ($\varsigma_t = P_t^h - P_t^l > 0$) could also serve as a suitable measure of the daily volatility. To strengthen the empirical results, this paper also estimates daily volatility σ_{t+1} by the price range of day t, i.e., ς_t. Finding qualitatively identical results whether we use ς_t or σ_t^c, we report only the empirical results when using σ_t^c.

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.

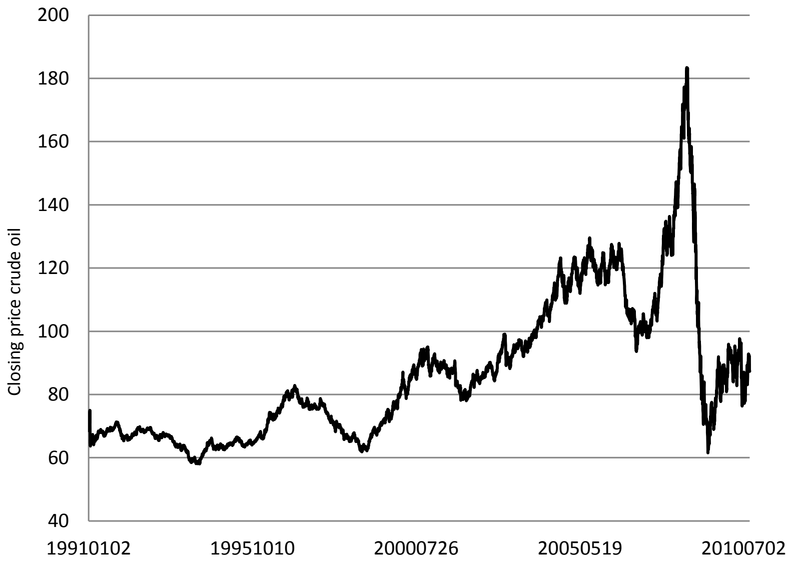

Figure 2. The daily closing prices for crude oil futures over time, adjusted for roll-over effects, from January 2, 1991 to January 26, 2011. Source: Commodity Systems Inc.

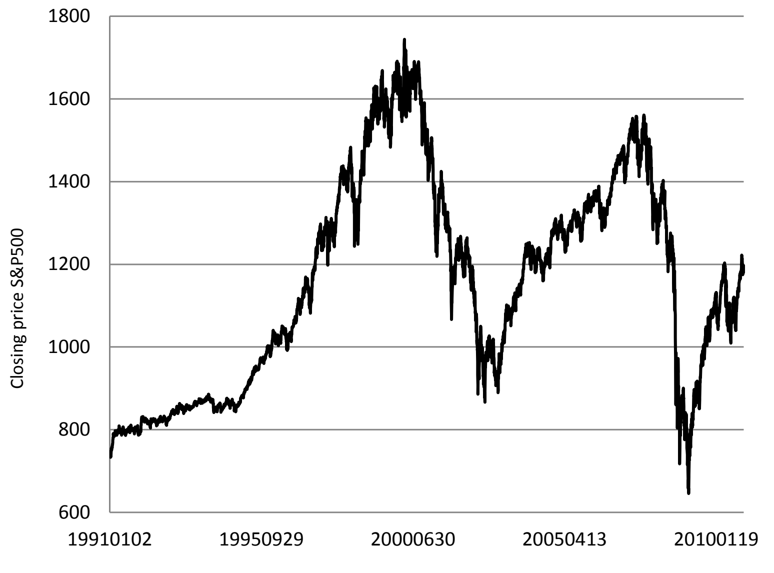

Figure 3. The daily closing prices for S&P 500 futures over time, adjusted for roll-over effects, from January 2, 1991 to November 29, 2010. Source: Commodity Systems Inc.

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 1. Descriptive statistics of the daily price returns

	Obs.	Mean	Std.Dev.	Min	Max	Skewness	Kurtosis
crude oil	4845	0.0002	0.0077	-0.0606	0.0902	0.22	9.67
S&P 500	5018	0.0001	0.0093	-0.0912	0.0808	-0.06	11.73

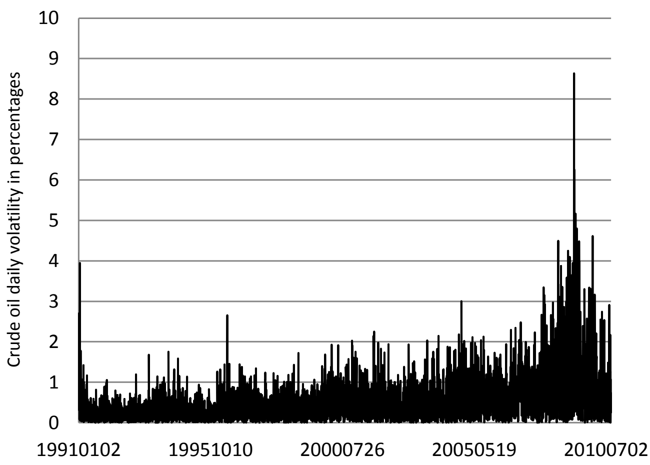

Figure 4. The daily price returns volatility (%) for crude oil futures over time, from January 2, 1991 to January 26, 2011.

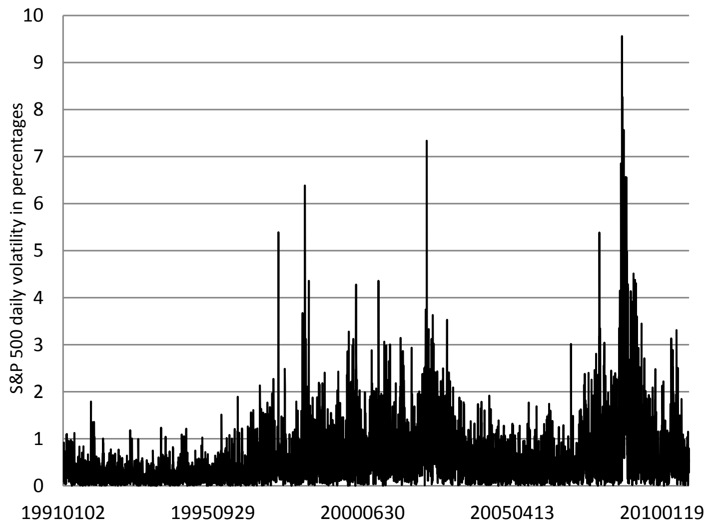

Figure 5. The daily price returns volatility (%) for S&P 500 futures over time, from January 2, 1991 to November 29, 2010.

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 ρ, 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 $\rho \epsilon \{0.5\%, 1.0\%, 1.5\%, 2.0\%\}$, 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 (%%), $(a \cdot 10\ 000)$, 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.

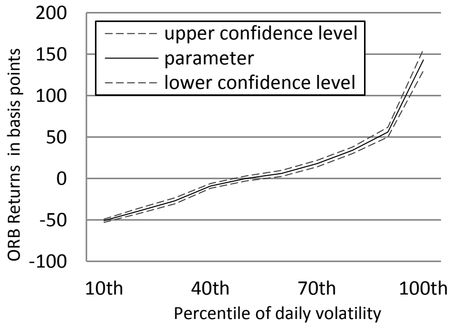

Figure 6. Average returns (bp:s) across volatility states (τ) when trading crude oil futures using $\rho = 0.5\%$. We use 95% confidence intervals based on the HAC standard errors.

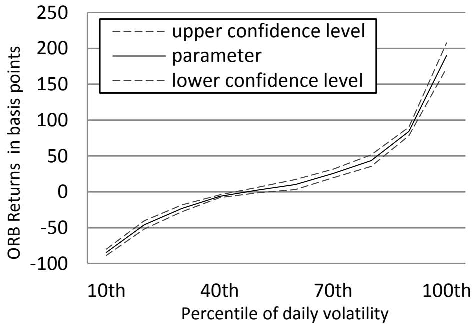

Figure 7. Average returns (bp:s) across volatility states (τ) when trading crude oil futures using $\rho = 1.0\%$. We use 95% confidence intervals based on the HAC standard errors.

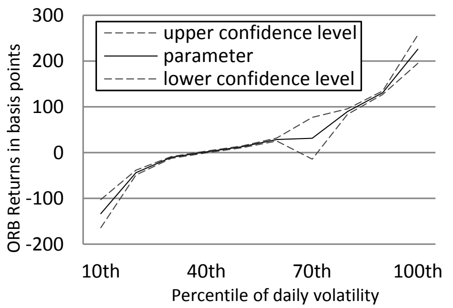

Figure 8. Average returns (bp:s) across volatility states (τ) when trading crude oil futures using $\rho = 1.5\%$. We use 95% confidence intervals based on the HAC standard errors.

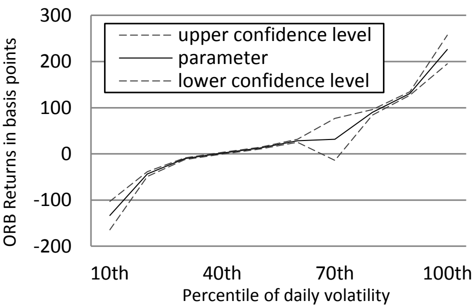

Figure 9. Average returns (bp:s) across volatility states (τ) when trading crude oil futures using $\rho = 2.0\%$. We use 95% confidence intervals based on the HAC standard errors.

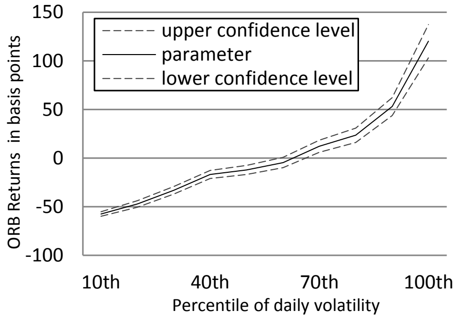

Figure 10. Average returns (bp:s) across volatility states (τ) when trading S&P 500 futures using $\rho = 0.5\%$. We use 95% confidence intervals based on the HAC standard errors.

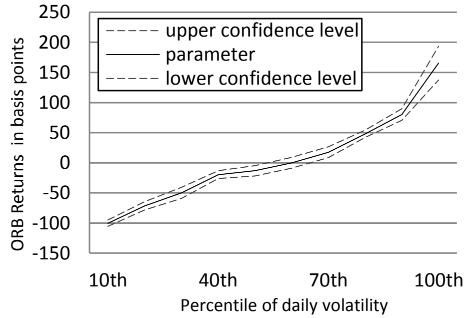

Figure 11. Average returns (bp:s) across volatility states (τ) when trading S&P 500 futures using $\rho = 1.0\%$. We use 95% confidence intervals based on the HAC standard errors.

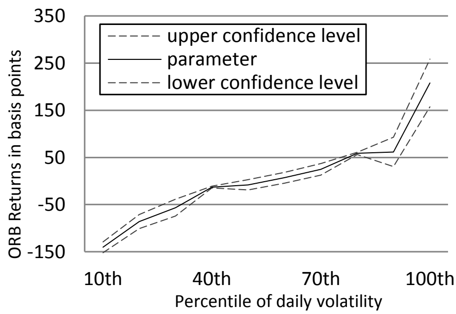

Figure 12. Average returns (bp:s) across volatility states (τ) when trading S&P 500 futures using $\rho = 1.5\%$. We use 95% confidence intervals based on the HAC standard errors.

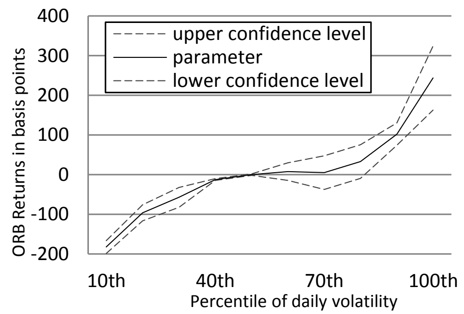

Figure 13. Average returns (bp:s) across volatility states (τ) when trading S&P 500 futures using $\rho = 2.0\%$. We use 95% confidence intervals based on the HAC standard errors.

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 *a priori* knows the volatility state; in this respect, these are in-sample results. In actual trading, traders do not *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 *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 *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,[2] 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 $R_{\rho,t}^{L\&S}=A_\rho+\omega_{\rho,t}$, where A_ρ is the

[2] 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 ω_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. ρ 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.

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

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 ρ. 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 ρ, 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 $R_t^{L\&S} - R_t^{B\&H} = \tilde{A} + \widetilde{\omega}_t$, 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).

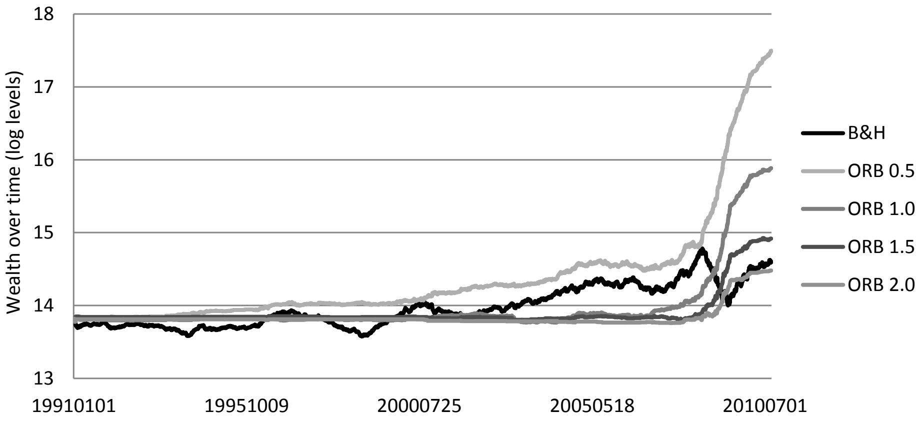

Figure 14. Wealth over time, starting with 1 000 000 USD (expressed in log levels), when trading crude oil futures out-of-sample using ORB strategies for all ranges from January 1, 1991 to January 26, 2011. B&H refers to the buy and hold strategy, and ORB refers to the ORB strategy given a particular range. No trading costs are included.

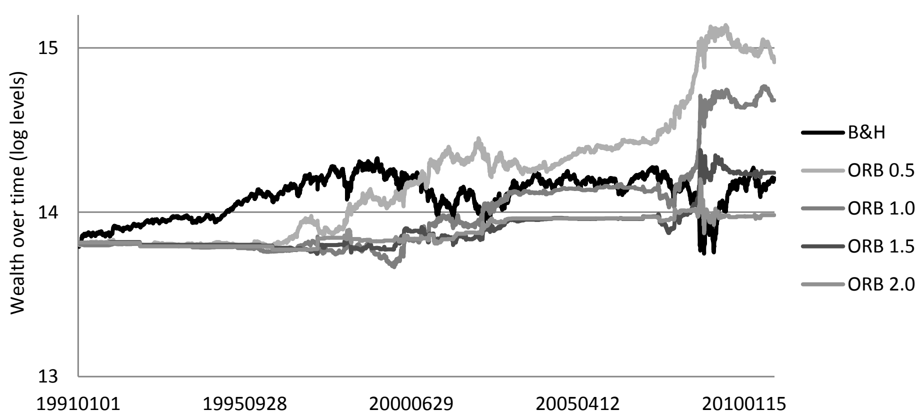

Figure 15. Wealth over time, starting with 1 000 000 USD (expressed in log levels), when trading S&P 500 futures out-of-sample using ORB strategies for all ranges from January 1, 1991 to November 29, 2010. B&H refers to the buy and hold strategy, and ORB refers to the ORB strategy for a particular range. No trading costs are included.

Table 3. Annual returns (calendar year) when trading the B&H strategy and the ORB strategy out-of-sample. ρ 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.

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

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 $\tilde{\psi}_t^u > \psi_t^u$, 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, $\tilde{\rho} = \rho + \varepsilon$, where $\varepsilon > 0$ is the size of the price jump. We consider here a reasonable estimate of $\varepsilon = 2$ 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 ρ when trading crude oil, and either negative or positive, depending on the initial level of ρ, 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.

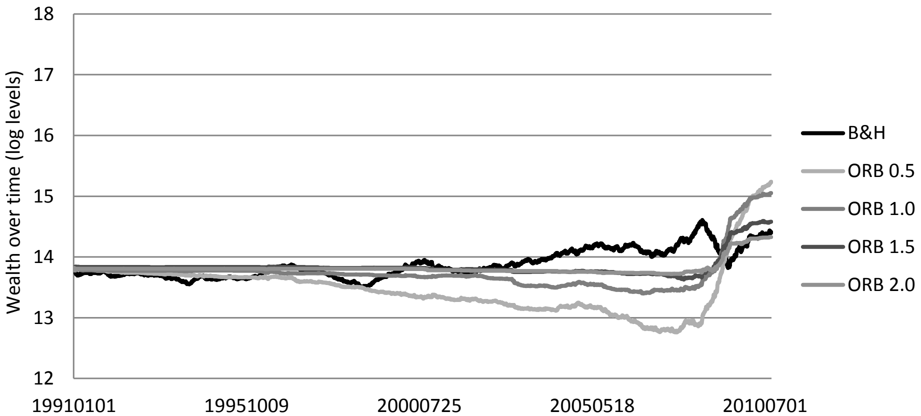

Figure 16. Wealth over time, starting with 1 000 000 USD (expressed in log levels), when trading crude oil futures out-of-sample, with trading costs included, from January 1, 1991 to January 26, 2011. B&H refers to the buy and hold strategy, and ORB refers to the ORB strategy given a particular range. 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).

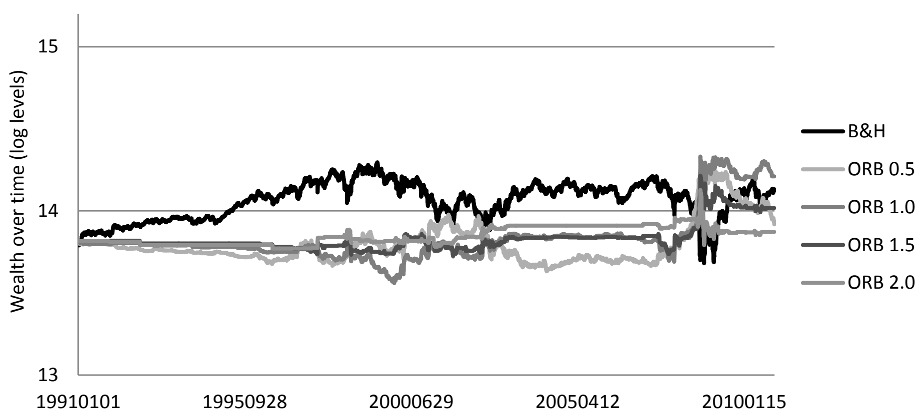

Figure 17. Wealth over time, starting with 1 000 000 USD (expressed in log levels), when trading S&P 500 futures out-of-sample, with trading costs included, from January 1, 1991 to November 29, 2010. B&H refers to the buy and hold strategy, and ORB refers to the ORB strategy for a particular range. We 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. ρ 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).

	ρ(%)	Obs.	Mean	Std.Dev.	Min	Max	Mean/Std.Dev.	Mean/-Min
	N/A	19	0.0429	0.1658	-0.2580	0.3739	0.26	0.17
	0.5	19	0.1568	0.5930	-0.2016	2.0990	0.26	0.78
crude oil	1.0	19	0.0993	0.3490	-0.1128	1.1638	0.28	0.88
	1.5	19	0.0505	0.1798	-0.0718	0.6123	0.28	0.70
	2.0	19	0.0298	0.0980	-0.0221	0.3315	0.30	1.35
	ρ(%)	Obs.	Mean	Std.Dev	Min	Max	Mean/Std.Dev	Mean/-Min
	N/A	19	0.0212	0.1057	-0.1822	0.2617	0.20	0.12
	0.5	19	0.0135	0.1482	-0.1416	0.5779	0.09	0.10
S&P 500	1.0	19	0.0300	0.1687	-0.1528	0.6954	0.18	0.20
	1.5	19	0.0123	0.0738	-0.0670	0.3120	0.17	0.18
	2.0	19	0.0031	0.0239	-0.0212	0.0681	0.13	0.15

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.

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III

Beyond Trends: The Reconcilability of Short-Term CTA Strategies with Risk Shocks

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It is common among institutional investors to go beyond traditional asset classes and add less conventional investments to their portfolios that counterbalance the poorly performing traditional assets during times of crisis. Despite the fact that such investment vehicles, able to maneuver rapidly between long and short positions and profit in a crisis, can be challenging to find; funds that specialize in trading futures are not impeded from taking positions to profit from crisis situations by following trends. Thus, it stands to reason that Kaminski [2011c] denotes crisis alpha opportunities as profits that are gained by exploiting the persistent trends that occur across markets during times of crisis.

Recent research isolates one particular subclass of hedge funds that actually thrives during equity market crises with relatively good performance during these time periods, providing an attractive diversification to other holdings (e.g., Fung and Hsieh [2001a], Kaminski [2011a, 2011b, 2011c]). This alternative investment subclass is the so-called commodity trading advisors (CTAs) or managed futures hedge funds, which are funds designed to capture and profit from reoccurring price patterns in the commodity futures markets. As a large part of these price patterns are based on price trends, CTAs are often found to follow trend-following investment strategies. The benefit of the CTA strategies is that they can switch their position from the long side to the short side, enabling them to be candidates for crisis alpha opportunities. In our study, we investigate the value addition of short-term CTAs whose more frequent trading and relatively fast adjustment from the long-side to the short-side positioning may be a compelling advantage in crisis situations.

To explore the nature of the performance of CTAs during equity market crises and to gain further insights into crisis alpha opportunities, we extract short-term risk shocks using short-term deviations from the expected level of market risk to represent unanticipated changes in risk environment and we examine its relation to the two different types of CTA strategy returns. Thus, we interpret crisis alpha as an exposure to unanticipated changes in risk, that is, risk shocks, which might not be exploitable by following long-term trends. Additionally, our approach means that we "factorize" crisis alpha as a factor exposure to short-term risk shocks, enabling us to explore whether it is possible to detect crisis alpha potentiality through the factor exposure. In our analysis, we test the factor exposures of the daily returns of the Newedge Short-Term Traders Index, the Newedge CTA Index, and the Newedge Trend Index to unanticipated risk shocks during the period from 2008 to 2014.

In contrast to previously presented alternative investment benchmarks such as the seven-factor model by Fung and Hsieh [2001b], this article uses a rolling second moment of equity returns (and its representatives) for extracting risk shocks from the level effects of market risk. We also consider the impact of risk shocks in different market states by taking into consideration the market states of upward and downward trending risk along with the states of high and low levels of risk. We refer to the market states of upward and downward trending risk as "risk cycles." While Kazemi and Li [2009] investigate market timing ability of discretionary and systematic CTA funds, we aim to use the ability of CTAs to quickly react to volatility events as an important and disjunctive feature of CTAs. We also propose a new approach to analyzing the ability of fund managers to capture and actually profit from crisis alpha opportunities.

The remainder of this study is organized as follows. The next section discusses risk cycles and risk shocks and their expected relation to the analysis of CTA returns. The third section discusses the methodology and data used in the study. The fourth section presents our empirical results, and the final section concludes the study.

EXPECTED HETEROGENEITY IN CTA EXPOSURES TO RISK SHOCKS

According to common usage in portfolio management and academic evidence, CTA strategies are typically classified as long-volatility investment strategies as they stand to gain from increases in volatility (see, e.g., Kaminski [2011c]). This point bears emphasizing and can, to some extent, be observed by replicating and benchmarking their returns using a long straddle portfolio (Fund and Hsieh [2001]) or in their exposure to changes in the VIX (e.g., Peltomäki [2007]). From a diversification standpoint, CTAs are hence interesting because they may provide a hedge of equity tail risk when included in portfolios during periods of equity market crisis (for equity tail risk, see Bhansali [2008]). However, the relation between CTA returns and volatility is not clear-cut. We note that most CTAs are long price trends, which means that the path properties of the trend, that is, the volatility of the trend, matters. If the volatility of the trend is too high, trend-following strategies will also suffer from large drawdowns or losses from stopped-out trades.

Furthermore, CTA funds may considerably vary in their ability to deliver crisis alpha and applicability as a hedge to equity tail risk depending on the strategy of the fund and, for example, the frequency of the trading. So, even if a CTA group (arranged by the Barclay CTA Index or the Newedge CTA Index) yields a significant crisis alpha on average, as reported in Kaminski [2011c], the individual contribution may potentially vary across CTA managers—one manager providing a suitable tail risk hedge while, perhaps, another manager does not.

This article recognizes CTAs as a nonhomogenous class of different investment strategies with two common denominators: being based on systematic directional trading, and involved in the futures markets. CTAs are nonhomogenous in other aspects, as they differ both in markets (agriculture, equities, currency, metals, and debt) and in the frequency of trading (short term to long term), consequently with relatively different return profiles and performance.[1] Following this observation, we expect that CTAs can be classified on the basis of their alpha capability during risk shocks and different states of market risk cycles. We note further that the crisis alpha proposed in Kaminski [2011c] is an ex post classification of returns into a Bernoulli state, Which may or may not belong to a time period of an equity market crisis. Although it captures the level effects in performance between states, such an approach does not capture the common variability of CTA fund returns with the sensitivities to unanticipated and anticipated risk changes.

Although the value addition of including CTAs into a diversified portfolio typically stems from downside protection during equity market crisis, we note that short-term CTA strategies trade more frequently and should hence be able to more quickly reconcile their positioning against rapid changes in market risk compared with the long-term, that is, trend-following, CTAs. In addition, the reconcilability of the short-term trading strategies implies that they should have superior performance characteristics in an early state of the risk cycle. Thus, we hypothesize that short-term CTA strategies could be a more suitable asset class compared with long-term, that is, trend-following, CTAs as they possibly adapt more quickly to risk shocks. Furthermore, we expect to be able to capture the performance of short-term CTA strategies by the returns of Newedge Short-Term Traders Index. In our analysis, we compare the performance of short-term CTAs, represented by the Newedge Short-Term Traders Index, with the performances of trend-following CTAs, represented by the Newedge Trend Index, and the broad CTA sector, represented by the Newedge CTA Index.

METHODOLOGY AND DATA

The three Newedge CTA indexes that we use in our study track the daily performances of the short-term trading and trend-following strategies and the performance of CTA composite returns.[2] We use daily returns data because we particularly focus on short-term CTA strategies. The Newedge Short Term Traders Index and the Newedge Trend Index are different from each other in that the Newedge Trend Index is designed to capture the net daily return for a pool of hedge fund managers using long-term trend-following strategies, whereas the Newedge Short-Term Traders Index tracks the performance of individual CTAs and global macro managers executing diversified trading strategies with less than 10-day average holding period. The Newedge CTA Index is an investable index that is equally weighted and reconstituted annually. It calculates the net daily rate of returns for a portfolio that consists of the largest managers open to new investments. We consider the Newedge CTA index as a composite index of CTA performance. In addition to the CTA index data, we use the VIX implied volatility index, which is the level of risk derived from option prices and typically used as an indicator of investors' risk appetite. We accessed all our index data from Datastream.

To analyze the exposure of the returns of CTA strategies to risk shocks, the first step of our analysis is to extract short-term shocks from stock market risk cycles. We consider the VIX implied volatility index as the proxy for market risk, which is often considered the investor gauge of fear. Furthermore, we define the variables of anticipated risk and risk shocks as the fitted values and the residuals from an AR(2) model for the VIX, and denote these variables of risk as *Expected* and *Shock*.[3,4] We apply an AR(2) model as it sufficiently captures both the level of risk, constant across the business cycle, and the autocorrelated structure we find in the VIX time series.[5] To calculate the variables "risk shocks" and "expected," we use the following AR(2) model for the VIX:

$$VIX_t = \alpha + \rho_1 VIX_{t-1} + \rho_2 VIX_{t-2} + \delta_t \qquad (1)$$

where we define the variable of "Shock" as $Shock_t = \delta_t$; and the variable of anticipated risk "Expected" as $Expected_t = VIX_t - Shock_t$.

By using this approach of calculating risk shocks, we exclude the level of risk that an investor could expect on average.

As the second step of our analysis, we apply time-series regression and model the exposure of the returns of the short-term, trend-following, and composite CTA indexes to the variables of risk as presented in Equation (2):

$$R_{CTA,t} = \alpha + \beta_1 Expected_t + \beta_2 Shock_t + \varepsilon_t \qquad (2)$$

where $R_{CTA,t}$ is the return of a CTA index (short-term, trend-following, or composite) on day *t*. The coefficient β_2 in Equation (2) measures a CTA strategy's reconcilability with risk shocks. According to our hypothesis, the returns of the short-term CTA strategy (the long-term trend-following strategy) should obtain positive and statistically significant (insignificant) values for the coefficient.

In addition to the model presented in Equation (2), we consider the possibility of an asymmetric relation between the CTA index returns and risk shocks by modeling the nonlinear relation between the returns of a CTA index and risk shocks as presented in Equation (3):

$$R_{CTA,t} = \alpha + \beta_1 Expected_t + \beta_2 Shock_t + \beta_3 Shock_t^2 + \varepsilon_t \qquad (3)$$

A compelling feature of our approach is that it does not attempt to generalize fund-level exposures to broad return-based style exposures, which is problematic with niche strategies, but it uses the ability of the fund to reconcile its positioning to *any* risk shock.

We also test this reconcilability in various market states measuring their response to risk shocks by regressing CTA returns against risk shocks from a market model approach using different samples. We consider two different sampling approaches. First, we estimate Equation (2) with *Shock* for samples on very high, high, and low levels of the VIX. This sampling enables us to observe whether the returns of the short-term and trend-following CTA strategies are consistently exposed to risk shocks at different levels of market risk. Second, we form samples for upward and downward trending risk as different states of the risk cycle. For determining these two

EXHIBIT 1
Descriptive Statistics

	VIX	Expected	Shock	CTA	Trend-Following	Short-Term
Mean	22.291	22.270	0.020	0.017	0.024	0.008
Median	19.060	19.108	-0.141	0.020	0.040	-0.010
Max.	80.86	79.17	17.06	1.87	3.20	1.57
Min.	10.32	10.48	-16.28	-2.44	-3.67	-1.53
Std. Dev.	10.61	10.42	2.03	0.44	0.69	0.30
Skewness	2.08	2.07	1.19	-0.35	-0.39	0.41
Kurtosis	8.28	8.20	19.01	5.03	5.10	6.16

Note: This exhibit presents the descriptive statistics for a sample period from January 1, 2008 to March 6, 2015. The sample includes 1,874 observations. The returns for the CTA indexes are presented in percentages.

EXHIBIT 2
Correlation Statistics

	VIX	Expected	Shock	CTA	Trend-Following	Short-Term
VIX	1.00					
Expected	0.98	1.00				
Shock	0.19	0.00	1.00			
CTA	0.00	-0.01	0.04	1.00		
Trend	-0.01	-0.01	0.00	0.96	1.00	
Short-term	0.03	-0.01	0.23	0.56	0.49	1.00

Note: This exhibit presents Pearson pairwise correlations between the variables of the study.

states of the risk cycle, we use the 10-day moving average of the VIX and define the risk cycle to be trending up (down) when the value of the VIX is above (below) its 10-day moving average from the previous trading day.[6] This risk cycle analysis enables us to observe whether the short-term and trend-following CTA strategies are consistent in their exposures to risk shocks in different states of the risk cycle. We interpret the regression betas as the strategy's ability to capture crisis alpha in different market states.

Exhibit 1 presents the descriptive statistics for the sample of our study. These statistics show that the risk shocks extracted from VIX range from −16.28 to 17.06, which is a considerably wide range in comparison with maximum and minimum values of VIX. It can be also noted from Exhibit 1 that the trend-following CTA strategy index obtains superior mean and median returns compared to the short-term CTA strategy index. In fact, the return performance of the short-term CTA strategy is relatively poor as the average return of the composite CTA index is more than twice that of the short-term CTA strategy index.

Exhibit 2 presents the correlation statistics for the variables of our sample. The statistics show that the pairwise linear correlation between the returns of the short-term and trend-following CTA strategies is moderate. However, the short-term CTA strategy is the only strategy that appears to be correlated with the risk shock variable, obtaining the value of 0.23 for the correlation coefficient. These statistics imply that short-term CTAs, unlike other CTAs, have an attractive relation to a critical risk component.

EXHIBIT 3
CTA Returns and the VIX

	VIX>30	VIX>20	VIX<20
Short-Term CTA	0.021	0.016	0.002
Trend-Following CTA	-0.030	-0.009	0.051
Composite CTA	-0.005	-0.001	0.033
Obs.	299	855	1019

Note: This exhibit presents the average daily returns for the Newedge Short-Term Traders Index, the Newedge Trend Index, and the Newedge CTA Index by different levels of the VIX implied volatility index. The returns are presented in percentages.

EXHIBIT 4
The Exposure of CTA Returns to Risk Shocks

	Short-Term CTA		Trend-Following CTA		CTA Composite	
	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.
C	0.015	*0.95*	0.034	*0.99*	0.023	*1.01*
Expected	0.000	*-0.57*	0.000	*-0.31*	0.000	*-0.30*
Shock	0.034***	*6.78*	-0.001	*-0.04*	0.009	*0.67*
Adj. R-squared	0.05		0.00		0.00	
F-statistic	35.51		3.03		3.58	
Prob(F-statistic)	0.000		0.028		0.013	

Note: This exhibit presents the estimates of the ordinary least squares (OLS) analysis of the exposures of CTA returns to expected risk and unexpected risk shocks. The analysis model is the following:

$$R_{CTA,t} = \alpha + \beta_1 Expected_t + \beta_2 Shock_t + \varepsilon_t$$

*where $R_{CTA,t}$ is the return of a CTA index (short-term, trend-following, or composite) on day t, $Expected_t$ is the measure of anticipated risk on day t, and $Shock_t$ is the measure of a risk shock on day t. The returns for the CTA indexes are presented in percentages. The standard errors are Newey–West heteroskedasticity and autocorrelation robust (the lag length is based on the Akaike Information Criterion (AIC)). The asterisks *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively. The sample includes 1,873 observations.*

Exhibit 3 presents the returns of the short-term, trend-following, and composite CTA indexes in three market states by very high, high, and low levels of the VIX. This analysis enables us to assess the relative return performance of different CTA strategies in different market states on the level of the VIX implied volatility. In comparison with the descriptive statistics in Exhibit 1, it can be seen from Exhibit 3 that the return performance of different CTA strategies depends on the level of risk; short-term CTAs demonstrate superior performance in high-volatility market states, while trend-following CTAs demonstrate better performance in low-volatility market states. This finding is also in line with the results in Exhibit 2, supporting the view that the return performance of short-term CTAs is aligned to higher levels of market risk.

RESULTS

We test the exposure of the returns of the short-term, trend-following, and composite CTA indexes to risk shocks by regressing the returns on our measures of anticipated risk and risk shocks. Exhibit 4 reports our estimation results of Equation (2) when using the full sample period of our study. The results show that the coefficient for risk shocks is statistically significant and

EXHIBIT 5

The Asymmetric Exposure of CTA Returns to Risk Shocks

	Short-Term CTA		Trend-Following CTA		CTA Composite	
	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.
C	0.035**	*2.36*	0.061*	*1.93*	0.042*	*1.93*
Expected	-0.002***	*-2.75*	-0.002*	*-1.68*	-0.001	*-1.63*
Shock	0.030***	*6.85*	-0.008	*-0.22*	0.005	*0.27*
$Shock^2$	0.002***	*3.87*	0.003***	*3.26*	0.002***	*3.31*
Adj. R-squared	0.06		0.01		0.01	
F-statistic	31.20		3.82		4.43	
Prob(F-statistic)	0.000		0.004		0.001	

Note: This exhibit presents the estimates of the ordinary least squares (OLS) analysis of the exposures of CTA returns to expected risk and unexpected risk shocks. The analysis model is the following:

$$R_{CTA,t} = \alpha + \beta_1 Expected_t + \beta_2 Shock_t + \beta_3 Shock_t^2 + \varepsilon_t$$

*where $R_{CTA,t}$ is the return of a CTA index (short-term, trend-following, or composite) on day t, $Expected_t$ is the measure of anticipated risk on day t, and $Shock_t$ is the measure of a risk shock on day t. The returns for the CTA indexes are presented in percentages. The standard errors are Newey–West heteroskedasticity and autocorrelation robust (the lag length is based on the AIC criterion). The asterisks *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively. The sample includes 1,873 observations.*

positive only for the returns of the short-term CTA index. More specifically, the coefficient value of 0.034 implies that the short-term CTA strategy index delivers a daily return of 0.34% when the value of *Shock* is 10. The coefficient values for *Expected* are all statistically insignificant, which suggests that the expected level of volatility does not affect the performance of short-term CTAs. The results in Exhibit 4 support our hypothesis that short-term CTA strategies are unique in that they have an attractive exposure to risk shocks. Considering the concept of crisis alpha (see Kaminski [2011b, 2011c]), the results suggest that short-term CTAs are superior at profiting from crisis situations, characterized as unanticipated risk shocks.

Exhibit 5 reports our estimation results of Equation (3), which is a nonlinear model for the relation between the returns of CTA indexes and risk shocks, when using the full sample period of our study. The results are in line with the results presented in Exhibit 4 but also reveal that *Shock* has an asymmetric impact on the returns of CTA indexes. More specifically, the positive and statistically significant coefficients at the 1% level for the square of *Shock* suggest that the relation between the returns of the three CTA indexes and risk shocks is nonlinear. Furthermore, it can be seen from the results that the relation between the returns of the trend-following and composite CTA indexes and *Shock* is U-shaped (or convex). *Expected*, in turn, has a negative and statistically significant impact on the returns of short-term and composite CTA index returns. Thus, the results in Exhibit 5 not only support the view that short-term CTAs are positively exposed to risk shocks but can be negatively affected by a high level of expected risk. An intuitive explanation for this can be that short-term CTAs, as short-term strategies implicitly imbed more frequent trading, may have to change their positioning in volatile market states, which increases their implicit and explicit trading costs.

As the dependence between CTA returns and *Shock* may differ across VIX levels, we present the estimation results of a single factor version of Equation (2) for subsamples on very high, high, and low levels of the VIX in Exhibit 6. While the results show that the returns of all the three CTA indexes have a positive exposure to *Shock* at high and very high levels of the VIX, only the short-term CTA strategy avoids a negative exposure to *Shock* at the low level of the VIX. These

EXHIBIT 6

Risk Shocks as an Explicator of CTA Performance in Volatility States

Panel A. Short-Term CTA

	VIX>30		VIX>20		VIX<20	
	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.
C	0.000	*0.00*	0.005	*0.55*	0.001	*0.08*
Shocks	0.036***	*7.22*	0.040***	*7.80*	-0.004	*-0.32*
Adj. R-squared	0.24		0.14		0.00	
Obs.	299		855		1019	

Panel B. Trend-Following CTA

	VIX>30		VIX>20		VIX<20	
Variable	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.
C	-0.065*	*-1.71*	-0.017	*-0.67*	0.014	*0.67*
Shocks	0.058***	*3.98*	0.031*	*1.90*	-0.204***	*-7.62*
Adj. R-squared	0.12		0.01		0.09	
Obs.	299		855		1019	

Panel C. CTA Composite

	VIX>30		VIX>20		VIX<20	
Variable	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.
C	-0.032	*-1.32*	-0.009	*-0.57*	0.011	*0.83*
Shocks	0.044***	*4.98*	0.030***	*3.18*	-0.118***	*-6.90*
Adj. R-squared	0.15		0.03		0.08	
Obs.	299		855		1019	

Note: This exhibit presents the estimates of the ordinary least squares (OLS) analysis of CTA performance and risk shocks in different volatility states. The analysis model is the following:

$$R_{CTA,t} = \alpha + \beta_1 Shock_t + \varepsilon_t$$

*where $R_{CTA,t}$ is the return of a CTA index (short-term, trend-following, or composite) on day t and $Shock_t$ is the measure of a risk shock on day t. The returns for the CTA indexes are presented in percentages. The standard errors are Newey–West heteroskedasticity robust. The asterisks *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively. The number of observations for each analysis is indicated below.*

results are in line with our hypothesis, suggesting that the short-term CTA strategy index obtains a different exposure to risk shocks than other CTAs. Thus, CTA strategies are nonhomogenous in their ability to hedge for equity tail risk.

It can be also seen from the results in Exhibit 6 that the exposures of the short-term CTA index returns to risk shocks increase for high and very high levels of the VIX, comparing with the results in Exhibit 5, because of the higher adjusted *R*-squares for the short-term strategy (at least the linear exposure). Taken together, the results presented in Exhibit 6 could imply that short-term CTAs can reconcile with changing market environments already when the equity market crises start developing and the value of the VIX has not risen yet. That is, do short-term CTAs adjust to changes in the risk cycle? To investigate this possible characteristic further, we study the relation between the returns of CTA indexes and risk shocks when we sort the returns belonging to either

EXHIBIT 7

CTA Performance and Risk Shocks in Risk Cycles

Panel A. Upward Risk Trend (Observations: 817)

	Short-Term CTA		Trend-Following CTA		CTA Composite	
	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.
C	0.005	*0.42*	-0.066**	*-2.49*	-0.038**	*-2.25*
Shock	0.035***	*6.13*	0.004	*0.16*	0.014	*1.11*
Adj. R-squared	0.07		0.00		0.00	

Panel B. Downward Risk Trend (Observations: 1057)

	Short-Term CTA		Trend-Following CTA		CTA Composite	
	Coef.	*t*-Stat.	Coef.	*t*-Stat.	Coef.	*t*-Stat.
C	0.008	*0.80*	0.112**	*5.76*	0.068**	*5.20*
Shock	0.033***	*4.12*	0.036**	*2.32*	0.028***	*2.74*
Adj. R-squared	0.02		0.01		0.01	

Note: This exhibit presents the estimates of the ordinary least squares (OLS) analysis of CTA performance and risk shocks in upward and downward risk cycles. The analysis model is the following:

$$R_{CTA,t} = \alpha + \beta_1 Shock_t + \varepsilon_t$$

*where $R_{CTA,t}$ is the return of a CTA index (short-term, trend-following, or composite) on day t and $Shock_t$ is the measure of a risk shock on day t. The returns for the CTA indexes are presented in percentages. The standard errors are Newey–West heteroskedasticity robust. The asterisks *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively. The sample for upward (downward) risk trends includes 817 (1,057) observations.*

an upward or a downward trending risk cycle. The results are presented in Exhibit 7.

In Exhibit 7, our estimation results of a single factor version of Equation (2) for the two samples based on risk cycles, indeed, suggest that trend-following CTAs and short-term CTAs are different from each other in that only short-term CTA show positive exposure to risk shocks when the risk cycle trends up. The results in Exhibit 7 suggest that short-term CTAs can reconcile their positioning in equity market crisis situations more quickly than the long-term trend-following CTA strategies.

In sum, the results in this section show consistent evidence that short-term CTAs are long-volatility investments that can profit from increases in the unanticipated component of market volatility. In relation to the evidence on time-varying volatility exposure of commonly known market anomalies, the exposure of short-term CTAs to unanticipated risk shocks appears to be persistent in different market states. For example, Daniel and Moskowitz [2014] show that momentum strategies experience infrequent and persistent strings of negative returns during panic states and market rebounds. In addition, the evidence of Peltomäki and Äijö [2015] shows that the volatility risk exposure of the value and momentum strategies can change from positive to negative in different economic and market cycles.

Regarding trend-following strategies, the results in Exhibits 6 and 7 show that, although their exposure to *Shock* is not statistically significant in Exhibit 4, they can also profit from unanticipated increases. Their long exposure to risk shocks, however, is neither prevalent in the different state of the risk cycle nor in the different states of market volatility.

CONCLUSION

While Fung and Hsieh [2001a] document that the performance characteristics of trend-followers resemble those of long "volatility" and "market risk event", we re-assess this presumed feature for short-term and trend-following CTAs using daily returns and unanticipated risk shocks to the VIX. Our results unfold that CTAs are heterogeneous in that short-term CTAs can reconcile better with unanticipated risk shocks. With regard to the differences between the short-term and trend-following CTA strategies, our results show an apparent difference between the strategies: trend-following CTAs are able to reconcile their positioning with risk shocks when the risk cycle is already trending down, while short-term CTAs can do it later when the risk cycle is trending up. Thus, our findings imply that a particularly attractive feature of short-term CTAs, and other short-term futures trading strategies, is their reconcilability with unanticipated risk shocks.

One more implication of our findings is that short-term trading strategies can offer considerable diversification opportunities in equity market crisis situations. For active multistrategy managers, our findings suggest that one should seek to diversify assets to short-term futures strategies in an early state of the risk cycle when the risk level trends up, and reallocate the assets to trend-following investment strategies when the risk cycle trends down. For passive multistrategy managers, our findings suggest that one could include short-term futures trading strategies as a hedge for equity tail risk during periods of equity market crisis. In further academic applications, one could address the impact of risk shocks in other ways, for example, using the approach of Asness, Moskowitz, and Pedersen [2013] to model global funding liquidity shocks.

ENDNOTES

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[1]For the profitability of short-term directional futures trading, see, for example, Lundström [2013], and for the profitability of longer term directional futures trading, see, for example, Miffre and Rallis [2007]. Being naturally secretive regarding the exact strategies used, and often considered a black box, the CTA funds probably differ in trading strategies and/or with different parameters as well.

[2]Detailed index methodology and constituents for these indexes can be downloaded at http://www.newedge.com/content/newedgecom/en/brokerage-services/prime-brokerage/newedge-indices.html.

[3]Our approach to defining risk shocks is comparable to the approach of Asness et al. [2013] to defining liquidity shocks.

[4]We use a more extensive data period to estimate the parameters for the AR(2) model. The estimation period starts from December 31, 1999.

[5]We also used the Hodrick–Prescott filter and found that we could have used it without qualitatively changing the results of this paper.

[6]For robustness test, we also tested moving averages with durations other than 10 days without qualitatively changing the results. We only report the results of the 10-day moving average in this article.

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