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.
References


