Soldiers, pigeons and shooting stars: Evaluating the profitability of candlestick charting on the Stockholm Stock Exchange

Filip Demitz-Helin* & Alexander Mahdi†

May 15, 2016

MSc Thesis in Finance
Stockholm School of Economics

Abstract

This study provides a systematic evaluation of the profitability of candlestick charting, the oldest known form of technical analysis, on a sample of 72 stocks listed on the Stockholm Stock Exchange over the period 2000-2015. In contrast to recent studies on Chinese, Taiwanese and US data, we find that the majority of candlesticks generate raw returns that are only moderately positive and not statistically significant after accounting for transaction costs of 0.10%. Performance is also poor on a risk-adjusted basis as most candlesticks produce negative four-factor alphas. The results are robust across two different trend definitions (three day simple moving average and ten day exponential moving average), two exit strategies (Caginalp-Laurent and Marshall-Young-Rose) and four holding periods (one, two, three and ten days). While a few candlesticks have both statistically and economically significant alphas that to some extent can be explained by successful market timing ability, their performance is not consistent across trends, holding periods nor over time. We additionally demonstrate that the profitability of candlestick charting has largely deteriorated in recent years, supporting the notion that the market has become more efficient in the weak form sense. We therefore conclude that candlestick investors are unlikely to make profits on the Stockholm Stock Exchange.

Keywords: Candlestick Charting, Technical Analysis, Trading Rules, Return Predictability, Market Timing, Market Efficiency, Bootstrapping

Thesis advisor: Paolo Sodini[1]

*22581@student.hhs.se
†22559@student.hhs.se
[1]We would like to thank Paolo Sodini for the help and support in writing this thesis.

Contents

List of Figures

List of Tables

1 Introduction

Technical analysis is a method for predicting price movements through the study of historical data on price and other trade statistics. It has a long history of extensive use by practitioners in financial markets and is by many regarded as the original form of investment analysis (Brock et al., 1992). In contrast, technical analysis has for decades been met with scepticism in academia due to its conflict with the widely accepted efficient market hypothesis (Jensen, 1978) and has even been described as an "anathema to the academic world" (Malkiel, 1981, p. 116). Scepticism is also supported by seminal papers by Fama and Blume (1966), Van Horne and Parker (1967), and Jensen and Benington (1970), showing that technical trading rules are not profitable, especially after accounting for transaction costs. More recently, however, a number of studies indicate that technical analysis consistently generates profits in a variety of markets. Park and Irwin (2007) review existing literature and show that among 95 modern studies on the profitability of technical analysis in the futures, foreign exchange and equity markets, 56 find positive results, 19 find mixed results and 20 find negative results.

In this study, we evaluate the profitability of candlestick charting, a technique designed to predict short-term price movements by utilising the relationship between open, high, low and close prices, on 72 stocks listed on the Stockholm Stock Exchange over the period 2000-2015. Originally developed in the 18^{th} century, candlestick charting is the oldest known form of technical analysis and while it has been the focus of several academic studies, there is no consensus on its effectiveness (see Marshall et al., 2006, Goo et al., 2007, Horton, 2009, Duvinage et al., 2013, Lu et al., 2015, Zhu et al., 2015, Lu and Shiu, 2016). Evidence from these studies suggests that profitability significantly varies between countries, which warrants a re-examination of candlestick charting on Swedish data. In addition, as candlestick returns at best have been benchmarked against a buy-and-hold strategy, the size of abnormal returns has been largely unaddressed in these studies. We aim to bridge this gap by examining whether candlestick patterns are able to deliver positive one-factor (CAPM) and four-factor (Fama-French-Carhart) alphas.

We test 264 unique combinations, made up of twenty-two different candlestick patterns, two different trend definitions and six different holding strategies. First, we examine whether raw returns are statistically greater than zero, taking into account relatively low two-way transaction costs of 0.10%. Second, we investigate if candlestick strategies generate positive alphas and whether any alphas can be explained by successful market timing ability by incorporating a quadratic market factor into the standard CAPM and Fama-French-Carhart model (Treynor and Mazuy, 1966). Third, we evaluate the economic significance of the most promising candlesticks by comparing their cumulative returns over the entire sample period to expected returns. Finally, we divide our sample into two sub-periods of equal length (2000-2007 and 2008-2015) in order to assess how profitability has evolved over time.

Our results suggest that while around one-third of the 264 combinations have raw gross returns that are positive and statistically significant, the mean return across the significant combinations is rather low (0.32%). After deducting transaction costs of 0.10%, the number of significant combinations is reduced by more than half. Overall, performance is inferior compared to recent studies on Chinese, Taiwanese and US data (Lu, 2014, Lu et al., 2015, Zhu et al., 2015). The results from the factor analysis show that candlesticks do not generate abnormal returns, as most combinations have negative four-factor alphas after transaction costs and only a few combinations have positive and statistically significant alphas. Moreover, while these positive alphas arguably also are economically significant and to some extent can be explained by successful market timing ability, they are not robust across trends nor holding periods.

Finally, the sub-period analysis indicates considerable profitability deterioration in recent years. In particular, while eight combinations have positive and statistically significant alphas in sub-period 1 and most bearish patterns perform well using a one-day holding period, not a single combination has a significant four-factor alpha in sub-period 2. This adds to the growing body of literature demonstrating that returns from technical analysis have been decreasing since the early 1990s as the market has become more efficient in the weak form sense. Based on the combined evidence that i) most combinations generate negative alphas even under low transaction costs, ii) the profitability of the few combinations with (barely) significant alphas is not robust across trends nor holding periods and iii) the alphas for the majority of combinations have eroded over time, we conclude that candlestick charting is not profitable on the Stockholm Stock Exchange.

The remainder of this study is structured as follows. In section 2, we provide a background on candlestick charting and describe its three key components. A literature review, covering both candlestick charting and technical analysis more broadly, is presented in section 3. We introduce the data in section 4 and our methodology in section 5. The empirical results are presented in section 6. In section 7, we discuss the results and highlight some limitations of this study. Finally, section 8 concludes and suggests directions for further research.

2 Background

Technical analysis is an umbrella term that encompasses a wide range of techniques. Martin Pring, a prominent technical analyst, defines it as follows (Pring, 2002, p. 2):

> "The technical approach to investment is essentially a reflection of the idea that

> prices move in trends that are determined by the changing attitudes of investors toward a variety of economic, monetary, political, and psychological forces. The art of technical analysis, for it is an art, is to identify a trend reversal at a relatively early stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed."

Candlestick charting is the oldest form of technical analysis. It was developed during the 18^{th} century by Munehisa Homma, often referred to as the "God of the markets" (Nison, 1991). Homma was born in 1724 in Sakata, Japan and started his trading career at the local rice exchange. He quickly became successful and following the passing of his father, Homma became responsible for managing his family's assets. He decided to go to Osaka and start trading rice futures on Japan's largest rice exchange, the Dojima Rice Exchange, where he subsequently made a fortune. His strategy was based on analysing both fundamental value (he often placed men on rooftops in order to monitor rice supplies) and the daily evolution of open, high, low and close prices. The idea was that these prices contain insight into the change in balance of supply and demand and hence could be used to predict price movements. Before his death in 1803, Homma wrote two books about the market and his trading principles evolved into the candlestick charting technique. While this technique has been in used in various financial markets in Japan for a long time and is deeply intertwined with Japanese culture (Marshall et al., 2008), it was only in 1991 that it was introduced to the West (Nison, 1991). Since then, candlestick charting has become "ubiquitous, available in almost every software and online charting package" (Nison, 2004, p. 22).

Candlestick charting requires four pieces of price data: open, high, low and close. The relationship between these prices can be visually represented as a "candlestick", as shown in Figure 1. The difference between the open and close price is called the "body" of the candlestick. The body is white if the close price is higher than the open price (bullish session) and black if the close price is lower than the open price (bearish session). A candlestick without a real body (i.e. open price equals close price) is referred to as a "doji". The vertical line above (below) the body is called the "upper shadow" ("lower shadow") and represents the session's high (low) price. Candlesticks are typically applied to daily charts, although they theoretically can be used on any time frame, such as hourly and five-minute charts. The argument against using intraday data, however, is that it fails to account for investor sentiment towards overnight information, which is an integral part in candlestick analysis (Morris, 1995).

The premise of candlestick charting is that certain patterns have predictive value. The most common patterns are based on a two- to three-day time frame. One-day candlesticks ("single lines") also exist, but are not used as frequently (Nison, 1991). Patterns are categorised as either bullish (buying signal) or bearish (selling signal) and further also as either a reversal (marking a shift in the price trend) or a continuation (marking persistence in the prevailing trend). In practice, most traders focus on reversal patterns (Nison, 1994) and academic studies have consequently also devoted most attention to reversals.

In addition to patterns, there are two key components to candlestick charting: trends and holding strategies (Caginalp and Laurent, 1998). The importance of trends stems from the idea that candlesticks are supposed to signal whether a trend will continue or reverse, implying that the actual underlying trend must first be identified. Indeed, Nison (1991) highlights that candlesticks are not effective unless a trend has been properly defined. Trends are classified as either "uptrend", "downtrend" or "no trend". Once classified, trends are combined with the patterns to form buy and sell signals. For instance, a downtrend combined with a bullish reversal pattern is a buy signal, as it suggests that the prevailing downtrend will reverse into an uptrend. Holding strategies do not have an impact on the trading signal, but rather determine how many days positions are held and how to exit the trade.

3 Literature Review

We divide the literature review into two sections. In the first section, we provide a broad overview of research on the profitability of technical analysis. The research is split into six categories depending on the applied methodology and the results of key studies within each category are subsequently summarised. In the second section, we focus on previous studies on candlestick charting.

3.1 Technical Analysis

Park and Irwin (2007) provide a comprehensive review of the empirical literature on the profitability of technical analysis and show that among 95 modern studies in the futures, foreign exchange and equity markets, 56 find positive results, 19 find mixed results and 20 find negative results.[2] Overall, these studies suggest that in the US, technical analysis consistently generate profits in equity markets, at least up until the early 1990s. In more recent samples, however, the evidence has to a larger extent been mixed and several studies demonstrate that markets appear to have become more efficient. In other regions, including China, France, Spain, Sweden and Taiwan, profits tend to be larger and to a greater extent also present in recent samples.

[2]Studies conducted after 1987 are considered "modern". The distinction is made because early studies tend to perform inadequate statistical testing and ignore key aspects such as transaction costs and risks.

Modern studies can be split into six different categories depending on the applied methodology: standard, model-based bootstrap, reality check, genetic programming, non-linear and chart patterns (Park and Irwin, 2007).

Standard studies typically determine trading rules by parameter optimisation based on specific performance criterion and then test these rules out-of-sample. Notable examples include Lukac et al. (1988), who find that four trading systems generate significant CAPM alphas on several highly traded US commodities. More recently, Wang et al. (2014) examine a performance based reward strategy that combines moving average (MA) and break out rules on Nasdaq data over the period 1994-2010. A time variant particle swarm optimisation algorithm is used to determine the parameter values that maximise net profit, and the optimised strategy is shown to generate significant excess net profits over a buy-and-hold (B&H) strategy out-of-sample.

Model-based bootstrap studies compare returns conditional on trading signals from original data series to returns from simulated return series generated by stock price models. In a seminal study on 90 years of Dow Jones Industrial Average (DJIA) data, Brock et al. (1992) apply this methodology and find that rules based on range breaks and MAs generate high and consistent returns. In particular, the market increases at an annual rate of 12% following buy signals and decreases 7% following sell signals. Day and Wang (2002), however, re-examine these findings by adjusting returns for dividends and interest earned from short sale proceeds with the rationale that the results in Brock et al. (1992) are biased by the presence of nonsynchronous prices in the closing index level. They show that returns based on accurate closing prices are not statistically different from a B&H strategy and that the best trading rules underperform a B&H strategy in the most recent ten-year period.

The reality check (White, 2000) is a statistical procedure meant to mitigate the issue of data snooping associated with in-sample tests of a large set of trading rules. Sullivan et al. (1999) apply this procedure to the same DJIA sample as Brock et al. (1992), testing about 8,000 trading rules based on five different trading systems. They find that while the best rules generate significant profits during 1897-1996, all rules perform poorly during 1987-1996, suggesting that the DJIA has become more efficient over time.

In a rare study on Swedish data, Metghalchi et al. (2008) use the reality check and show that MA rules are profitable on the OMX30 over the 1986-2004 period. Metghalchi et al. (2012) extend this study by using stock data from 16 European countries, finding that the rules are more profitable in small and medium size markets, including the Danish, Finnish, Norwegian and Swedish markets. Shynkevich (2012) test nearly 13,000 rules belonging to the most common types of technical trading rules (filter, MA, support and resistance, and channel breakout) on growth and small cap stocks on the US stock market. The results indicate that the rules outperform a B&H strategy for small to moderate transaction costs during the first sub-period (1995-2002), but not during the second sub-period (2003-2010).

Genetic programming is an optimisation methodology based on the principle of survival of the fittest, where potential solutions to predefined problems are randomly generated by a computer and then evolves over several generations under a specific performance criterion (Koza, 1992). This methodology can potentially mitigate data snooping issues and is used in Allen and Karjalainen (1999), who test 100 genetically programmed trading rules on the S&P 500. The results indicate that the rules do not outperform a B&H strategy after accounting for transaction costs. Korczak and Roger (2002) perform a similar analysis on 24 stocks listed on the Paris Stock Exchange and find, in contrast, that nine out of ten rules outperform a B&H strategy. Manahov et al. (2014) employ a special adaptive learning algorithm on several US indices, finding that the algorithm significantly outperforms random walk benchmark forecasts for all indices out-of-sample over the period 2007-2012.

Non-linear studies evolved in an attempt to explain the temporal dynamics of returns generated by technical trading rules. These studies try to directly evaluate the profitability of rules that have been derived from a non-linear model and usually incorporate lagged returns or past buy and sell signals from a rule into the model. Gencay (1998) evaluates trading signals generated by a non-linear feedforward network model on DJIA data, finding that net returns from the trading rules range from 7% to 35%, dominating the range of -20% to 17% from a B&H strategy. Fernandez-Rodriguez et al. (2000) use a similar feedforward model on data from the Madrid Stock Market, finding that while gross returns dominate B&H returns in the first two sub-periods, the opposite is true for the most recent sub-period.

Chart pattern studies test the performance of visual chart patterns used by technical analysts, including candlestick patterns. Lo et al. (2000) consider a sample of New York Stock Exchange and Nasdaq stocks and investigate ten common patterns used to predict price movements, including head-and-shoulders and double tops-and-bottoms. Using the Kolmogorov-Smirnov (KS) test for equality, they show that return distributions conditioned on trading rules based on these patterns are significantly different from unconditional distributions, indicating that the patterns provide incremental information. They emphasise, however, that this does not necessarily imply that it is possible to extract excess profits from these patterns. Dawson and Steeley (2003) replicate this study on 225 Financial Times Stock Exchange (FTSE) stocks and also explicitly consider whether the patterns are profitable. They find that while the results from the KS test are similar, average market adjusted returns from the trading rules are negative. This is also supported by Kuang et al. (2014), who test the same rules on several emerging foreign exchange markets and find that they are not profitable.

3.2 Candlestick Charting

Previous studies on candlestick charting largely focus on the US and Asian equity markets. The results from these studies have been mixed, especially with regard to the US market. Studies with supporting evidence of profitability are summarised in section 3.2.1 and studies that do not find evidence of candlestick profitability are described in section 3.2.2.

3.2.1 Evidence in Support of Candlestick Charting

Caginalp and Laurent (1998) test eight three-day reversal patterns on S&P 500 stocks over the period 1992-1996 and find that all strategies are profitable. Goo et al. (2007) reach a similar conclusion using a sample of 25 Taiwanese stocks over the period 1997-2006. They test 26 single lines and two-day candlestick patterns and find that most generate a mean return that is statistically greater than zero, albeit the returns are rather sensitive to the holding period. Their results also suggest that both bullish and bearish two-day patterns perform better than single lines. The profitability of candlesticks on the Taiwanese stock market is further supported by Lu (2014), who demonstrates that out of 12 tested single lines, one bullish and three bearish lines are profitable on the Taiwan Stock Exchange during 1992-2009. He also shows that the candlesticks perform significantly better during the financial crises in 1997-1999 and 2007-2009, possibly due to pessimistic overreaction by a large number of unsophisticated retail investors in the Taiwanese market.

Zhu et al. (2015) test five bullish and five bearish two-day candlesticks with holding periods of one, five and ten days on stocks listed on the Shanghai Stock Exchange and Shenzhen Stock Exchange during the period 1999-2009. Using a bootstrapped skewness-adjusted t-test and applying two-way transaction costs of 0.26%, they are able to reject the null hypothesis that returns are less than or equal to zero for most patterns. Bearish candlesticks appear to perform better than their bullish counterparts, although this might be the result of short selling restrictions in the Chinese stock markets. They also show that the results are robust to a variety of market conditions.

Lu et al. (2015) test eight three-day candlesticks on DJIA component data over the period 1992-2012, using three trend definitions and four holding strategies. One of the key findings is that candlestick profits appear to be highly dependent on the exit strategy but rather insensitive to the trend definition. In particular, they show that while all eight candlesticks have mean net returns that are statistically greater than zero regardless of trend definition with a Caginalp-Laurent exit strategy, they are not profitable using a Marshall-Young-Rose exit strategy. The results are not qualitatively changed when looking at sub-samples for three different time periods and market conditions. Finally, they show that mean returns are higher on Nasdaq, suggesting that candlesticks perform better in more volatile markets. Lu and Shiu (2016) extend the analysis in Lu et al. (2015) by also testing 12 single lines on DJIA stocks over the period 1974-2009. They find that bullish single lines are profitable and consistently outperform their bearish counterparts. Interestingly, they also show that the candlesticks perform better in more recent sub-periods, in particular after 1992.

3.2.2 Evidence against Candlestick Charting

Fock et al. (2005) test 19 single lines and two-day candlesticks on five-minute intraday futures data from the German futures exchange (Eurex) over the 2002-2003 period. They compare candlestick returns against a benchmark constructed by randomised buy signals in the underlying futures and find that candlesticks are not profitable, even without considering transaction costs. The results are qualitatively unchanged when benchmarking returns against a mean return of zero. Combining the candlesticks with a trend signal (MA) marginally improves performance, but returns are still not statistically greater than zero.

Marshall et al. (2006) examine whether candlesticks have predictive value on DJIA stocks over the period 1992-2002. They utilise a bootstrap methodology together with a GARCH-M model to simulate 500 sets of open, high, low and close prices. The candlestick strategies are then applied to both the original series and the bootstrapped series, with the idea that the proportion of times that a candlestick generates more profit on the bootstrapped series following a trade signal is a simulated p-value for the null hypothesis that the candlestick has no value. They are not able to reject the null for any candlesticks and therefore conclude that they are not profitable. This conclusion is also robust to different entry points following a signal and different holding periods (two, five and ten days). Marshall et al. (2008) apply a similar methodology, but test candlesticks on a sample of the 100 largest stocks on the Tokyo Stock Exchange from 1975 to 2004. They find no evidence of profitability, even prior to adjusting for transaction costs. The results are also robust to different sub-periods and market conditions.

Horton (2009) evaluates the same candlesticks as Caginalp and Laurent (1998) on a sample of 349 US stocks. He first defines a "good" candlestick signal as a bull (bear) signal that within three days is followed by an upturn (downturn) and vice versa for a "bad" signal. A period in which the market neither rose nor fell is counted as a "sideway" signal. Three different nonparametric tests are then applied to investigate whether the good, bad and sideway signals are drawn from the same statistical distribution. The results indicate that all signals are drawn from the same distribution, implying that the probability of choosing a correct result based on candlesticks is no different than choosing a correct result at random.

Finally, Duvinage et al. (2013) test the intraday predictive power of 83 candlesticks at the five-minute interval on DJIA stocks from 2010 to 2011, using a methodology similar to Marshall et al. (2006). Candlestick returns are compared to a B&H strategy, which is constructed using a bootstrap methodology that assumes different return generating models, including random walk, AR(1) and GARCH-M. They find that while around one-third of the candlesticks outperform the B&H strategy at the conservative Bonferroni level, only three remain significant after accounting for transaction costs. Moreover, these three candlesticks only appear a handful of times in their sample and are therefore not economically significant. The results are qualitatively similar regardless of chosen return generating model, entry point following a signal, trend definition and holding period.

4 Data

We source price data from the financial information provider SIX. The data include open, high, low and close prices for stocks listed on the Stockholm Stock Exchange (Nasdaq Stockholm). Based on the availability of open prices, our sample stretches from January 1, 2000 to December 31, 2015. The sample thus starts more than eight years after candlestick charting was introduced to the West by Nison (1991). All prices are adjusted for stock splits, rights issues and bonus issues. Dividends are assumed to be reinvested, which is in line with Day and Wang's (2002) recommendation that studies on technical analysis should include dividend data. We focus on stocks that are present throughout the entire sample period and since technical trading rules are considered to be most effective for actively traded stocks (Marshall et al., 2006), we also exclude stocks traded on First North. The final dataset contains 269,072 observations and 72 unique firms.

We do not expect survivorship bias to be an issue in this study. As pointed out by Marshall et al. (2008), the holding period in candlestick analysis is short (we test periods of one, two, three and ten days) and returns are thus determined by the day-to-day volatility in stock prices rather than any factors related to long-term persistence that might be present in stocks that survive over long time periods. The notion that performance is not affected by long-term persistence is further supported by the sub-sample analysis in Marshall et al. (2008), which shows that there is no difference in candlestick profitability across prolonged bull and bear markets.

We use US Fama-French-Carhart factors, which are sourced from Kenneth French's data library. Solnik and Roulet (2000) show that the historical correlation between the US stock market and the "world" market exceeds 80%, suggesting that US factors serve as a decent proxy for global factors. The choice of global factors over local factors is based on Karolyi and Stulz (2003), who show that a domestic capital asset pricing model can give rise to a systematic bias as it understates asset returns when the global market portfolio is positively correlated with the asset's domestic market residual. Moreover, they argue that it is reasonable to expect that returns of multinational companies are correlated with foreign markets, thereby making the returns of a domestic market portfolio unable to capture all their systematic risk. This is particularly relevant in our case, as we focus on large cap stocks that to a large extent have an international footprint.

5 Methodology

In this section, we introduce the methodology used in our empirical tests. First, we present the candlestick patterns and define them mathematically using a set of inequalities. Second, we describe the two trend definitions that combined with the patterns are used to form trading signals, as well as the six holdings strategies that are used to calculate returns from the candlestick trades. Third, we present the hypothesis and the bootstrap methodology used to test this hypothesis. Fourth, we describe the factor models used to evaluate the profitability and market timing ability of the candlesticks. Fifth, we introduce the methodology used to evaluate the economic significance of the best performing patterns. Finally, we provide a brief description of the sub-period analysis.

5.1 Candlestick Patterns

We test twenty-two candlestick patterns, of which eleven are bullish and eleven are bearish. Nine patterns consist of three candlesticks and thirteen patterns consists of two candlesticks. Nine of the bullish patterns have a bearish counterpart, twenty are reversal patterns and two are continuation patterns. We chose the patterns based on both prevalence in existing academic literature (see, for instance, Horton, 2009, Lu et al., 2015, Zhu et al., 2015) and evidence of profitability from practitioners (Bulkowski, 2012). The patterns are defined in section 5.1.1 though 5.1.13 and presented visually in Figure 2. We also show examples of various candlestick patterns based on the stock prices of SEB, SSAB and Nokia during December, 2015 in Figure 3.

5.1.1 Three White Soldiers and Three Black Crows

Three White Soldiers (TWS) is a three-day bullish reversal pattern and Three Black Crows (TBC) is its bearish counterpart. TWS consists of three white candles with open and close at progressively higher prices and all open prices are within the real body of the previous day. Formally, it is defined as:

$$
\begin{gathered}
P^c_{t-2} > P^o_{t-2}\,; P^c_{t-1} > P^o_{t-1}\,; P^c_t > P^o_t \\
P^c_{t-2} > P^o_{t-1} > P^o_{t-2}\,; P^c_{t-1} > P^o_t > P^o_{t-1} \\
P^c_t > P^c_{t-1} > P^c_{t-2}
\end{gathered} \tag{1}
$$

where P equals the stock price, superscripts o and c indicate open and close price, respectively, and subscript t denotes the day of the trading signal, i.e. the final day of the candlestick pattern. This notation is applied consistently throughout section 5.1. The definition of TBC is given by reversing all inequality signs in equation (1). The bearish counterparts of the bullish patterns defined in equations (2) through (9) are similarly defined by reversing all inequality signs.

5.1.2 Three Inside Up and Three Inside Down

Three Inside Up (TIU) is a three-day bullish reversal pattern and Three Inside Down (TID) is its bearish counterpart. It consists of a black candle followed by two white candles. The real body of the second candle is contained within the body of the first candle. The close price of the third candle exceeds the close of the preceding candles. The definition is shown below.

$$
\begin{gathered}
P^o_{t-2} \geq P^o_{t-1} > P^c_{t-2}\,; P^o_{t-2} > P^c_{t-1} \geq P^c_{t-2} \\
P^c_{t-1} > P^o_{t-1}\,; P^c_t > P^o_{t-2}\,; P^c_t > P^o_t
\end{gathered} \tag{2}
$$

5.1.3 Morning Star and Evening Star

Morning Star (MS) is a three-day bullish reversal pattern and Evening Star (ES) is its bearish counterpart. A black candle is followed by a white or a black candle with a body that gaps below the close of the previous day. The third candle is white, with a close price that exceeds the close of the preceding days. The definition is shown below.

$$
\begin{gathered}
P^o_{t-2} > P^c_{t-2}\,; P^c_{t-2} > P^c_{t-1}\,; P^c_{t-2} > P^o_{t-1}\,; P^c_t > P^o_t \\
\mid P^o_{t-1} - P^c_{t-1} \mid > 0 \\
P^c_t > (P^o_{t-2} + P^c_{t-2})/2
\end{gathered} \tag{3}
$$

5.1.4 Morning Doji and Evening Doji

Morning Doji (MD) is a three-day bullish reversal pattern and Evening Doji (ED) is its bearish counterpart. Both patterns are similarly defined as MS and ES, except that the second candle consists of a doji. The definition is shown below.

$$\begin{gathered} P^o_{t-2} > P^c_{t-2}\,; P^c_{t-2} > P^c_{t-1}\,; P^c_{t-2} > P^o_{t-1} \\ P^o_{t-1} = P^c_{t-1}\,; P^c_t > P^o_t \\ P^c_t > (P^o_{t-2} + P^c_{t-2})/2 \end{gathered} \tag{4}$$

5.1.5 Above the Stomach and Below the Stomach

Above the Stomach (ATS) is a two-day bullish reversal pattern and Below the Stomach (BTS) is its bearish counterpart. ATS consists of a black candle followed by a white candle with an open price above the midpoint of the black candle's body. The definition is shown below.

$$\begin{gathered} P^o_{t-1} > P^c_{t-1}\,; P^c_t > P^o_t \\ P^o_t > (P^o_{t-1} + P^c_{t-1})/2 \end{gathered} \tag{5}$$

5.1.6 Bullish Cross and Bearish Cross

Bullish Cross (BUC) is a two-day bullish reversal pattern and Bearish Cross (BEC) is its bearish counterpart. BUC consists of a black candle followed by a doji with an open/close price that gaps below the close of the black candle. The definition is shown below.

$$\begin{gathered} P^o_{t-1} > P^c_{t-1}\,; P^c_{t-1} > P^c_t \\ P^c_{t-1} > P^o_t\,; P^c_t = P^o_t \end{gathered} \tag{6}$$

5.1.7 Last Engulfing Bottom and Last Engulfing Top

Last Engulfing Bottom (LEB) is a two-day bullish reversal pattern and Last Engulfing Top (LET) is its bearish counterpart. LEB consists of a white candle followed by a black candle with a real body that encompasses the body of the white candle. The definition is shown below.

$$\begin{gathered} P^c_{t-1} > P^o_{t-1}\,; P^o_{t-1} > P^c_t \\ P^o_t > P^c_t\,; P^o_t > P^c_{t-1} \end{gathered} \tag{7}$$

5.1.8 Bullish Meeting Lines and Bearish Meeting Lines

Bullish Meeting Lines (BUML) is a two-day bullish reversal pattern and Bearish Meeting Lines (BEML) is its bearish counterpart. BUML consists of a black candle followed by a white candle with the same close price. The definition is shown below.

$$P_{t-1}^{o} > P_{t-1}^{c} \,; P_{t}^{c} > P_{t}^{o}$$
$$P_{t}^{c} = P_{t-1}^{c} \tag{8}$$

5.1.9 Bullish Separating Lines and Bearish Separating Lines

Bullish Separating Lines (BUSL) is a two-day bullish continuation pattern and Bearish Separating Lines (BESL) is its bearish counterpart. BUSL consists of a black candle followed by a white candle with the same open price. The definition is shown below.

$$P_{t-1}^{o} > P_{t-1}^{c} \,; P_{t}^{c} > P_{t}^{o}$$
$$P_{t}^{o} = P_{t-1}^{o} \tag{9}$$

5.1.10 Homing Pigeon

Homing Pigeon (HP) is a two-day bullish reversal pattern. It consists of a black candle followed by another black candle with a real body that is contained within the body of the first candle. The definition is shown below.

$$P_{t-1}^{o} > P_{t-1}^{c} \,; P_{t-1}^{o} > P_{t}^{o}$$
$$P_{t}^{o} > P_{t}^{c} \,; P_{t}^{c} > P_{t-1}^{c} \tag{10}$$

5.1.11 Matching Low

Matching Low (ML) is a two-day bullish reversal pattern. It consists of two consecutive black candles with the same close price. The open price of the first candle is higher than the open price of the second candle. The definition is shown below.

$$P_{t-1}^{o} > P_{t-1}^{c} \,; P_{t-1}^{o} > P_{t}^{o}$$
$$P_{t-1}^{c} = P_{t}^{c} \tag{11}$$
$$P_{t}^{o} > P_{t}^{c}$$

5.1.12 Shooting Star

Shooting Star (SS) is a two-day bearish reversal pattern. It consists of a white candle followed by a white or a black candle with a real body that gaps above the close price of the first candle. The second candle also has a long upper shadow and short lower shadow. It is defined as:

$$
\begin{gathered}
P^c_{t-1} > P^o_{t-1} \\
P^h_t - \max(P^o_t, P^c_t) > \frac{3}{2} \mid P^o_t - P^c_t \mid \\
\min(P^o_t, P^c_t) > P^c_{t-1} \\
\frac{1}{3} \mid P^o_t - P^c_t \mid > \min(P^o_t, P^c_t) - P^l_t
\end{gathered} \tag{12}
$$

where superscripts h and l indicate high and low price, respectively.

5.1.13 Upside Gap Two Crows

Upside Gap Two Crows (UGTC) is a three-day bearish reversal pattern. It consists of a white candle followed by a black candle with a body that gaps above the close price of the white candle. The third candle is also black, with a body that gaps above the close price of the first candle and encompasses the body of the second candle. The definition is shown below.

$$
\begin{gathered}
P^c_{t-2} > P^o_{t-2}\,;P^o_{t-1} > P^c_{t-1} \\
P^c_{t-1} > P^c_t\,;P^c_{t-1} > P^c_{t-2} \\
P^o_t > P^c_t\,;P^o_t > P^o_{t-1}\,;P^c_t > P^c_{t-2}
\end{gathered} \tag{13}
$$

5.2 Trends

While Nison (1991) emphasises the importance of trends within the candlestick charting framework, he does not provide much guidance in how to define and incorporate them. Considering also that most practitioners apply parametric trend identification methods that are subject to interpretation (Caginalp and Laurent, 1998), it is not clear how a trend should be defined. In this study, we use the two most common trend definitions from existing literature. The first is based on a three day simple moving average (MA3) and the second is based on a ten day exponential moving average (EMA10). The trends are described below.

5.2.1 Three Day Simple Moving Average

The MA3 definition was proposed by Caginalp and Laurent (1998) and is utilised in e.g. Goo et al. (2007), Horton (2009), and Lu et al. (2015). This trend is defined as:

$$
MA^f_{3,t} = \frac{1}{3} \sum_{n=-2}^{0} P^{f,c}_{t+n} \tag{14}
$$

where $P^{f,c}_{t+n}$ denotes the close price for firm f at time $t+n$. A firm f is then considered to experience an uptrend at time t if:

$$MA^{f}_{3,t} > MA^{f}_{3,t-1} > ... > MA^{f}_{3,t-6} > MA^{f}_{3,t-7} \tag{15}$$

with at most one inequality violation. A downtrend is analogously defined as:

$$MA^{f}_{3,t} < MA^{f}_{3,t-1} < ... < MA^{f}_{3,t-6} < MA^{f}_{3,t-7} \tag{16}$$

with at most one inequality violation. The uptrend and downtrend definitions are supposed to capture the general idea that prices are trending while also allowing for the possibility of fluctuations.

5.2.2 Ten Day Exponential Moving Average

The EMA10 definition was proposed by Morris (1995) and is used in e.g. Marshall et al. (2006), Marshall et al. (2008), Duvinage et al. (2013) and Lu et al. (2015). This trend is defined as:

$$EMA^{f}_{10,t} = \alpha P^{f,c}_{t} + (1-\alpha) EMA^{f}_{10,t-1} \tag{17}$$

where α=2/(10+1) and $P^{f,c}_{t}$ denotes the close price for firm f at time t. A firm f is then considered to experience an uptrend at time t if:

$$P^{f,c}_{t} > EMA^{f}_{10,t} \tag{18}$$

and a downtrend if:

$$P^{f,c}_{t} < EMA^{f}_{10,t} \tag{19}$$

EMA10 assigns progressively larger weights to more recent observations, with the weight being determined by the α. Also notice that uptrends and downtrends under EMA10 allow for greater fluctuations and are thus not as strictly defined as under MA3. We therefore expect EMA10 to generate more buying and selling signals when combined with candlestick patterns compared to MA3.

Having defined trends, we generate buy and sell signals by combining them with the candlestick patterns in accordance with the methodology used in e.g. Caginalp and Laurent (1998), Horton (2009) and Lu et al. (2015). Specifically, a buy (sell) signal is generated if a bullish (bearish) reversal pattern emerges on day t for stock f and the price of stock f is in a downtrend (an uptrend) on the day preceding the first candlestick in the emerged pattern, i.e. on day $t-3$ for three-day patterns and on day $t-2$ for two-day patterns. For instance, if the three-day bullish reversal pattern TWS is formed during day $t-2$, $t-1$ and t for Volvo, a buy signal is generated if the stock price of Volvo is in a downtrend on day $t-3$.

5.3 Holding Strategy

The holding strategy is of particular importance in candlestick charting as the technique is short-term focused (Morris, 1995), but a consensus on the optimal strategy following a trading signal does currently not exist. A holding strategy is made up of two parts: the holding period and the exit strategy. Holding periods in existing literature range from one to ten days, which is in line with Morris' (1995) suggestion of a maximum holding period of ten days. The exit strategy determines how to exit trades and two different strategies have been prevalent in previous studies: Marshall-Young-Rose (MYR) and Caginalp-Laurent (CL). In this study, we consider a MYR strategy with four different holding periods (one, two, three and ten days) and a CL strategy with two different holding periods (three and ten days). The strategies are described below.

5.3.1 Marshall-Young-Rose

The MYR strategy was proposed by Marshall et al. (2006) and is used in e.g. Marshall et al. (2008), Lu et al. (2015) and Zhu et al. (2015). Returns under a MYR strategy are calculated as:

$$R_{MYR1} = \ln\left(\frac{P^c_{t+1}}{P^o_{t+1}}\right) \tag{20}$$

$$R_{MYR2} = \ln\left(\frac{P^c_{t+2}}{P^o_{t+1}}\right) \tag{21}$$

$$R_{MYR3} = \ln\left(\frac{P^c_{t+3}}{P^o_{t+1}}\right) \tag{22}$$

and

$$R_{MYR10} = \ln\left(\frac{P^c_{t+10}}{P^o_{t+1}}\right) \tag{23}$$

for holding periods of one, two, three and ten days, respectively. The MYR strategy thus consists of buying one unit at the open price on day $t+1$ following a bullish trade signal on day t and selling at the close price on day $t+d$, where d is the number of days as determined by the holding period. Opposite trades are taken for bearish trading signals, i.e. shorting one unit at the open price on day $t+1$ and closing out the position on day $t+d$.

5.3.2 Caginalp-Laurent

The CL strategy was proposed by Caginalp and Laurent (1998) and is used in Lu et al. (2015). Returns under a CL strategy are calculated as:

$$R_{CL3} = \frac{\frac{1}{3}\sum_{n=t+1}^{t+3} P_n^c - P_{t+1}^o}{P_{t+1}^o} \tag{24}$$

and

$$R_{CL10} = \frac{\frac{1}{10}\sum_{n=t+1}^{t+10} P_n^c - P_{t+1}^o}{P_{t+1}^o} \tag{25}$$

for a holding period of three and ten days, respectively. The CL strategy is less dependent on the close price at the final day of the holding period than MYR, as it consists of buying one unit at the open price on day $t+1$ following a bullish trade signal on day t and selling at an average close price over the holding period. The selling process can more intuitively be thought of as selling an equally weighted proportion of the unit each day at the close price throughout the holding period.

5.4 Raw Returns Analysis

As a first step in our profitability evaluation, we follow the methodology in e.g. Goo et al. (2007), Lu et al. (2015), Zhu et al. (2015) and Lu and Shiu (2016), hypothesising that gross returns from candlestick strategies are greater than zero. Hence, we formulate the null hypothesis as:

$$H_0: \ \mu_{i,j,k} \leq 0 \tag{26}$$

and test it against the alternative:

$$H_1: \ \mu_{i,j,k} > 0 \tag{27}$$

where i denotes candlestick pattern i, j denotes underlying trend j and k denotes holding strategy k. The hypothesis is evaluated using a one tailed t-test, where we apply a non-parametric bootstrap approach to calculate critical values as candlestick returns do not follow a standard t-distribution (Zhu et al., 2015). Specifically, for each combination of i, j and k, we assume that the return distribution $\delta_{i,j,k} = \overline{x}_{i,j,k} - \mu_{i,j,k}$ can be approximated by $\delta^*_{i,j,k} = \bar{x}^*_{i,j,k} - \bar{x}_{i,j,k}$, where $\overline{x}_{i,j,k}$ and $\mu_{i,j,k}$ refer to sample and population means, respectively, and $\bar{x}^*_{i,j,k}$ is the mean of the bootstrapped returns for candlestick pattern i, with underlying trend j and holding strategy k. We perform $1,000$ bootstrap replications and calculate $\delta^*_{i,j,k} = \bar{x}^*_{i,j,k} - \bar{x}_{i,j,k}$ for each bootstrap sample. For a test at the 10% level, the resulting 1,000 values of δ^* are sorted in ascending order and the 100^{th} and 900^{th} values (i.e. the 10^{th} and 90^{th} percentiles) are subsequently selected to approximate $\delta_{0.1}$ and $\delta_{0.9}$, respectively. The bootstrapped 80% confidence interval is then calculated as:

$$[\bar{x}_{i,j,k} - \delta^*_{0.1,i,j,k},\ \bar{x}_{i,j,k} + \delta^*_{0.9,i,j,k}] \tag{28}$$

From the bootstrapped lower bound we solve for the critical value to be compared to the t-statistic at the 10% level and get that:

$$CV_{0.1,i,j,k} = \frac{\bar{x}_{i,j,k} - (\bar{x}_{i,j,k} - \delta^*_{0.1,i,j,k})}{s_{i,j,k}} = \frac{\delta^*_{0.1,i,j,k}}{s_{i,j,k}} \tag{29}$$

where $s_{i,j,k}$ is the estimated standard deviation of returns for candlestick pattern i, with underlying trend j and holding strategy k. Given the critical values, we calculate t-statistics conventionally as:

$$ts_{i,j,k} = \frac{\bar{x}_{i,j,k} - 0}{s_{i,j,k}/\sqrt{n_{i,j,k}}} \tag{30}$$

and reject the null if $ts_{i,j,k} > CV_{0.1,i,j,k}$. Tests at the 5% and 1% levels are performed using a corresponding approach. Since we evaluate twenty-two different candlestick patterns using two different trend definitions and six different holding strategies, the tests are applied to 264 unique combinations.

As emphasised in Park and Irwin (2007), a profitability evaluation of technical trading rules is incomplete without a consideration of transaction costs, as investors will not be able to achieve gross returns in practice. We therefore proceed by evaluating net returns using the same methodology. Transaction costs are considered in most candlestick studies and range from 0.10% (Duvinage et al., 2013) to 1.00% (Lu et al., 2012), partly depending on whether institutional or retail investors are considered. We find it more sensible to focus on institutional investors as candlesticks are short-term strategies that are unlikely to be profitable for unsophisticated retail investors with high transaction costs and therefore assume two-way costs of 0.10%. As a point of reference, McSheery (2011) estimates that two-way brokerage commissions in the US average about 0.15% for institutional equity investors, implying that our assumed costs can be considered as relatively low.

In addition to testing the hypothesis, we evaluate the winning percentage, defined as the number of trading signals with positive returns divided by the total number of trading signals, for all combinations. The winning percentage shows how consistent the combinations are in generating positive returns and serves as a complementary measure in our profitability evaluation. Finally, we investigate tail risk by calculating the common risk measure value-at-risk at the 5% and 1% levels. We express value-at-risk as a percentage and thus report 5^{th} and 1^{th} percentile returns for all combinations.

5.5 Abnormal Returns Analysis

While raw returns provide indicative results of performance, we argue that abnormal returns are more relevant from a profitability evaluation perspective. In contrast to previous studies on candlestick charting, we therefore also consider abnormal returns by incorporating the CAPM and the Fama-French-Carhart (FFC) model into the analysis (Fama and French, 1993, Carhart, 1997). Here, we draw from Han et al. (2013), who use both these models to evaluate the profitability of volatility sorted portfolios consisting of returns from MA rules.

For both factor models, we regress daily net excess strategy returns onto daily CAPM and FFC factors. For the CAPM, the regression specification is given by:

$$r_t^{i,j,k} - r_t^f = \alpha_t^{i,j,k} + \beta_{Mkt}^{i,j,k}(r_t^{Mkt} - r_t^f) + \epsilon_t^{i,j,k} \tag{31}$$

and the FFC model specification is given by:

$$r_t^{i,j,k} - r_t^f = \alpha_t^{i,j,k} + \beta_{Mkt}^{i,j,k}(r_t^{Mkt} - r_t^f) + \beta_{SMB}^{i,j,k} SMB_t + \beta_{HML}^{i,j,k} HML_t + \beta_{UMD}^{i,j,k} UMD_t + \epsilon_t^{i,j,k} \tag{32}$$

where $r_t^{i,j,k}$ denotes daily returns at time t for candlestick i in combination with underlying trend j for holding strategy k. The risk free rate and market return for the corresponding time periods are denoted r_t^f and r_t^{Mkt}, respectively, and the FFC factors are denoted SMB_t (small minus big), HML_t (high minus low) and UMD_t (up minus down). Note that since MYR returns are defined as log returns and CL returns are defined as simple returns, we use log factor returns for $k =$MYR1, $k =$MYR2, $k =$MYR3, and $k =$MYR10, and simple factor returns for $k =$CL3 and $k =$CL10. Robust standard errors are applied in both specifications in order to correct for heteroscedasticity.

As returns for MYR2, MYR3, MYR10, CL3 and CL10 correspond to two, three and ten day returns, we first transform them into daily returns such that each daily return corresponds to the change in market value of the position, and distribute transaction costs evenly over the number of days for each holding period. Specifically, daily returns based on MYR are calculated as:

$$r_{t+l}^{i,j,MYR} = \begin{cases} ln(P_{t+l}^c / P_{t+l}^o) * 100 - 0.1/d & \text{for } l = 0 \\ ln(P_{t+l}^c / P_{t+l-1}^c) * 100 - 0.1/d & \text{for } l \neq 0 \end{cases} \tag{33}$$

where d denotes the number of days for each holding period, and $l = 0$ for MYR1, $l = 0, 1$ for MYR2, $l = 0, 1, 2$ for MYR3 and $l = 0, 1, 2, ..., 9$ for MYR10. Similarly, daily returns based on CL are calculated as:

$$r_{t+l}^{i,j,CL3} = \begin{cases} (P_{t+l}^{c}/P_{t+l}^{o} - 1) * 100 - 0.1/3 & \text{for } l = 0 \\ \left[\left(\frac{2}{3}P_{t+l}^{c} + \frac{1}{3}P_{t+l-1}^{c}\right)/P_{t+l-1}^{c} - 1\right] * 100 - 0.1/3 & \text{for } l = 1 \\ \left[\dfrac{\frac{1}{3}P_{t+l}^{c} + \frac{1}{3}P_{t+l-1}^{c} + \frac{1}{3}P_{t+l-2}^{c}}{\frac{1}{3}P_{t+l-2}^{c} + \frac{2}{3}P_{t+l-1}^{c}} - 1\right] * 100 - 0.1/3 & \text{for } l = 2 \end{cases} \tag{34}$$

and

$$r_{t+l}^{i,j,CL10} = \begin{cases} (P_{t+l}^{c}/P_{t+l}^{o} - 1) * 100 - 0.1/10 & \text{for } l = 0 \\ \left[\left(\frac{9}{10}P_{t+l}^{c} + \frac{1}{10}P_{t+l-1}^{c}\right)/P_{t+l-1}^{c} - 1\right] * 100 - 0.1/10 & \text{for } l = 1 \\ \left[\dfrac{\frac{10-l}{10}P_{t+l}^{c} + \sum_{m=1}^{9}\frac{1}{10}P_{t+l-m}^{c}}{\frac{10-l+1}{10}P_{t+l-1}^{c} + \sum_{n=2}^{9}\frac{1}{10}P_{t+l-n}^{c}} - 1\right] * 100 - 0.1/10 & \text{for } l \geq 2 \end{cases} \tag{35}$$

for CL3 and CL10, respectively, where $l = 0, 1, 2$ for CL3 and $l = 0, 1, 2, ..., 9$ for CL10. For days in which there are overlapping return observations for any combination of i, j and k, the daily average return is used.[3]

5.6 Market Timing

The quote by Pring (2002) in section 2 highlights that the key to technical analysis is to time the market through identifying trend reversals, and Horton (2009) further emphasises that candlestick charting is all about market timing. As a next step in our empirical analysis, we assess this claim by investigating whether market timing ability can explain the returns for any candlestick patterns that generate positive FFC alphas. Similarly to Han et al. (2013), we do so by applying a methodology originally developed by Treynor and Mazuy (1966), which incorporates a quadratic market factor into the standard CAPM model. As in section 5.5, we regress daily net excess strategy returns onto daily model factors and our quadratic regression specification is hence given by:

$$r_t^{i,j,k} - r_t^f = \alpha_t^{i,j,k} + \beta_{Mkt}^{i,j,k}(r_t^{Mkt} - r_t^f) + \beta_{Mkt^2}^{i,j,k}(r_t^{Mkt} - r_t^f)^2 + \epsilon_t^{i,j,k} \tag{36}$$

[3] As an example of overlapping observations, consider two signals over two consecutive days for MYR2, where the second day return for the first signal occurs on the same day as the first day return for the second signal.

where $(r_t^{Mkt} - r_t^f)^2$ denotes the quadratic market factor. We also test a second specification, where the quadratic factor is added to the FFC model. This specification is given by:

$$\begin{aligned} r_t^{i,j,k} - r_t^f = \alpha_t^{i,j,k} + \beta_{Mkt}^{i,j,k}(r_t^{Mkt} - r_t^f) + \beta_{Mkt^2}^{i,j,k}(r_t^{Mkt} - r_t^f)^2 \\ + \beta_{SMB}^{i,j,k} SMB_t + \beta_{HML}^{i,j,k} HML_t + \beta_{UMD}^{i,j,k} UMD_t + \epsilon_t^{i,j,k} \end{aligned} \tag{37}$$

with remaining variables defined as in (32). Notice that the inclusion of a quadratic factor implies a relationship between excess strategy returns and market returns that is no longer linear. A positive coefficient estimate on the quadratic factor suggests successful market timing ability. As demonstrated in Treynor and Mazuy (1966), the idea is that in rising markets, funds with good market timing ability will tilt their portfolios to more volatile securities and vice versa in falling markets, leading to a non-linear relationship between fund returns and market returns that is captured by the quadratic factor.

5.7 Economic Significance

Next, we assess whether any statistically significant FFC alphas from the analysis in section 5.5 also can be considered to be of economic significance for investors. The distinction between statistical and economic significance is of particular importance in candlestick charting for two reasons. First, compared to technical trading rules that are based on e.g. MAs, the number of trading signals is more limited, implying that it is not necessarily possible to make a meaningful profit from alpha generating candlestick strategies. For example, the top performing candlesticks in Duvinage et al. (2013) only appear a handful of times throughout the entire sample period, rendering them virtually useless from a profitability perspective. Second, since the strategies are short-term focused, with holding periods of one to ten days, any alphas will likely be relatively small, especially after transaction costs. Hence, even if the number of trading signals is large, this does not necessarily imply meaningful profits.

We assess economic significance by investigating the performance of individual trading strategies that invest in all signals generated by any candlestick combination with a positive and statistically significant FFC alpha. The strategies have a starting value of 100 units on January 1, 2000, and returns are calculated net of transaction costs, so that two-way costs of 0.10% are applied to each trade. The performance is benchmarked against expected returns determined by FFC factor exposures. Specifically, using the factor estimates obtained in section 5.5, we compute expected daily returns for each alpha generating strategy as:

$$\hat{ER}_t^{i,j,k} = r_t^f + \beta_{Mkt}^{i,j,k}(r_t^{Mkt} - r_t^f) + \beta_{SMB}^{i,j,k} SMB_t + \beta_{HML}^{i,j,k} HML_t + \beta_{UMD}^{i,j,k} UMD_t \tag{38}$$

for days following a trade signal and with remaining variables defined as in (32). As before, we compute average daily returns for days on which there are multiple positions for any given combination of i, j and k as well as for simultaneous positions in different stocks, implying equally weighted positions in each active trade. On days following a trade signal, we assume a 100% loading on the equally weighted positions, and on days with no active positions, we assume that the portfolio is invested at the risk free rate. Both expected and actual returns are subsequently compounded over the sixteen year period and compared in order to assess whether the alpha strategies have generated excess profits that are economically significant.

5.8 Sub-periods

As a final step in our profitability evaluation, we split our dataset into two sub-periods of equal length, 2000-2007 and 2008-2015, and perform the same analysis as described in section 5.5 on both periods. The rationale for this analysis is threefold. First, in light of the growing body of literature describing the decrease in profitability of technical trading rules over time (see e.g. Day and Wang, 2002, Park and Irwin, 2007, Shynkevich, 2012), it is of interest to investigate whether this tendency also is evident for candlestick strategies on the Swedish stock market. Second, sub-periods have not been investigated thoroughly in existing literature on candlestick charting. While Lu et al. (2015) split their sample into three sub-periods, with the most recent period being 2006-2012, they restrict the analysis to only include the EMA10 trend combined with the CL3 holding strategy. Finally, this analysis serves as a robustness test.

6 Empirical Results

6.1 Descriptive Statistics

Return statistics and number of trading signals are presented in Table 1. For the purpose of brevity, statistics for bullish and bearish candlestick patterns, trends and holding strategies are shown as averages. Throughout the subsequent parts of the analysis, however, we present statistics for all 264 unique combinations. Panel A in Table 1 reports equally weighted averages for each candlestick pattern across trends and holding strategies. Panel B in Table 1 reports equally weighted averages for each trend across candlestick patterns and holding strategies. Finally, Panel C in Table 1 reports equally weighted averages for each holding strategy across candlestick patterns and trends.

In Panel A, we observe that thirteen out of the twenty-two patterns generate positive mean returns. The contrast between bullish and bearish patterns is rather large, as all bullish patterns except TWS and MS have positive mean returns but only ES, BEC, SS and UGTC have positive mean returns among bearish patterns. The bullish HP, BUC and ML have the highest mean returns and the bearish TBC, BEML and BESL have the lowest mean returns. Volatility, as measured by standard deviation, averages 4.21% among the patterns and ranges from a low of 3.28% for TBC to a high of 5.37% for ML. Returns for bullish patters are slightly more volatile than bearish patterns. In terms of skewness, all but three bullish patterns have returns that are positively skewed and the average bullish skewness is 0.37. The returns of bearish patterns are negatively skewed, with an average skewness of -0.35. All patterns have a kurtosis above three and thus have fat tails compared to a normal distribution. Finally, the average number of trading signals is 1,131 for bullish patterns and 1,014 for bearish patterns. The number of trading signals varies considerably between patterns, ranging from an average of 38 for UGTC to 3,432 for ATS.

In terms of trends, Panel B shows that the average return for MA3 is considerably higher than EMA10 for bullish patterns (0.26% versus 0.15%) but not for bearish patterns (-0.04% versus -0.01%). Also, volatility is nearly identical between the two trends, but returns under MA3 have lower skewness and thinner tails. The EMA10 trend generates 1,668 trading signals per pattern on average, which is roughly 3.5x the amount of signals generated by MA3. As highlighted in section 5.2.2, this is expected considering that EMA10 is a less strict trend definition, allowing for larger fluctuations.

With regard to holding strategies, Panel C shows that bullish patterns have positive average returns for all six holding strategies. Average returns are the highest for a holding period of ten days (0.38% under CL10 and 0.34% under MYR10) and the lowest for a period of one day (0.01% under MYR1). Bearish patterns show contrasting results, having positive average returns for holding periods of three days or less but considerable negative returns for a holding period of ten days (-0.14% under CL10 and -0.18% under MYR10). MYR1 generates the highest average return (0.11%), followed by MYR2 (0.04%). The exit strategy only has a minor impact on returns for both bullish and bearish patterns. We also observe that volatility increases monotonically with the holding period and is lower under a CL exit strategy. MYR1 has the lowest average volatility (2.34%) and MYR10 has by far the highest volatility (7.46%). CL returns are more positively skewed than MYR returns across bullish patterns and more negatively skewed across bearish patterns. The return distributions under CL also have slightly fatter tails.

6.2 Raw Returns Analysis

The results of the hypothesis tests are presented in Table 2, Table 3 and Table 4. We note that 87 out of the 264 combinations generate positive mean gross returns that are statistically significant at the 10% level. The mean return across these significant combinations is 0.32%. At the 5% and 1% levels, the number of significant combinations fall to 61 and 26, respectively. Second, after accounting for two-way transaction costs of 0.10%, only 38, 25 and 6 combinations are significant at the 10%, 5% and 1% levels, respectively. The patterns with the highest (lowest) mean returns perform well (poorly) across most holding periods. For instance, HP combined with the MA3 trend has significant positive mean net returns across all holding periods (0.71%, 0.66%, 0.54%, 0.51%, 0.41%, 0.23% under MYR10, CL10, MYR3, CL3, MYR2 and MYR1, respectively) and BESL combined with the EMA10 trend generates negative mean net returns across all periods (-0.12%, -0.19%, -0.30%, -0.39%, -0.80%, -0.98% under MYR1, MYR2, CL3, MYR3, CL10 and MYR10, respectively).

We also observe that bullish patterns are clearly dominant, accounting for 23/25 of the significant combinations at the 5% level and 6/6 at the 1% level. The two significant bearish combinations at the 5% level are both SS (MA3 MYR1 and EMA10 MYR1). Moreover, we do not find that a one trend strictly dominates the other. While there are more MA3 combinations than EMA10 at the 5% level (14 versus 11), there are less at the 1% level (2 versus 6). In terms of holding periods, the results overall suggest that ten days is the dominant period, accounting for 15/25 of the combinations at the 5% level and 4/6 at the 1% level. As indicated in section 6.1, however, the distinction between bullish and bearish patterns is important in this context as long holding periods work well for bullish patterns but poorly for bearish patterns. In particular, while 41/44 of the bullish CL10 and MYR10 combinations generate positive average net returns, the corresponding number for bearish patterns is only 7/41. Finally, we note that the exit strategy has an insignificant impact on returns compared to the holding period. For instance, CL accounts for half (19/38) of the net return combinations that are significant at the 10% level.

Table 2, Table 3 and Table 4 also show winning percentage (WP) and value-at-risk (VaR) statistics. We notice that while the majority (161/264) of combinations have a gross WP above 50%, only 91 remain above 50% after deducting transaction costs. Bullish patterns account for 71 of these combinations and produce an average net WP of 50.2% across all combinations, which is not very convincing. For a holding period of ten days, however, the average net WP increases to 53.2% and 40/44 combinations have a net WP above 50%. For bearish patterns, the net WP is below 50% for all holding periods, averaging 47.2%. While 16/22 of the MYR1 combinations produce at gross WP above 50%, only 4/22 combinations have a net WP above 50%. With regard to tail risk, we observe that the average 5% VaR and 1% VaR is -6.3% and -12.1%, respectively, across all combinations. The VaR statistics are relatively similar across patterns and trends. Both the holding period and exit strategy, however, have a rather large impact as the VaR increases monotonically with the holding period and is significantly lower under CL.

6.3 Abnormal Returns Analysis

The results of the abnormal returns analysis are presented in Table 5 through Table 8. Overall, the results indicate that the candlestick strategies are not able to generate neither one-factor nor four-factor alphas after transaction costs of 0.10%. In particular, only five combinations have CAPM and FFC alphas that are statistically significant at the 10% level and not a single combination is significant at the 1% level. Out of the 264 combinations, 164 (167) generate negative CAPM (FFC) alphas. The majority of FFC alphas are in the -0.10% to 0.05% range. Bullish patterns are not as dominant as in section 6.2, accounting for 58/97 of the combinations with positive FFC alphas and 3/5 of the significant combinations. The reason behind the more balanced performance is mainly related to market factor exposure, as bullish patters have an average CAPM beta loading of 0.45, whereas bearish patterns have an average loading of -0.43. We also observe that average exposures to the SMB, HML and UMD factors in the FFC model are rather small for both bullish and bearish patterns, resulting in an estimated R^2 that is relatively similar between the CAPM and FFC regressions for most combinations. The largest FFC factor exposure for bullish (bearish) patterns is towards the HML (UMD) factor, with an average exposure of 0.082 (0.080). The CL exit strategy has slightly lower factor exposures on average.

We also find additional support for that short holding periods are superior for bearish patterns. In particular, holding periods of three days or less account for 35/39 of the bearish combinations with positive average FFC alphas. The best performing holding strategy is MYR1, as it accounts for both of the significant bearish combinations and has positive FFC alphas across 14/22 combinations. The other holding periods generate negative FFC alphas for the majority of bearish combinations. For bullish patterns, the holding period has a less significant impact on returns, as the combinations with positive FFC alphas are rather equally distributed across all holding periods except for the one-day period, which performs slightly worse. With regard to exit strategy, we find that performance is rather equal for CL and MYR. Similarly, there does not appear to be a clear performance difference between MA3 and EMA10 on an aggregate level, as they generate roughly equal alphas on average. We observe, however, that alphas for individual patterns can vary considerably depending on the applied trend definition.

The daily alphas for the five significant combinations are 0.34% (SS MA3 MYR1), 0.16% (HP MA3 MYR3), 0.14% (HP MA3 CL3), 0.13% (TBC EMA10 MYR1) and 0.02% (BUSL EMA10 CL10). While the performance of BUSL is rather consistent, with positive (albeit small) alphas for most trends and holding strategies, the overall performance of SS, HP and TBC is not convincing. TBC generates average alphas that are negative after transaction costs for all combinations except those involving MYR1. Similarly, the profitability of SS deteriorates significantly outside of MYR1. HP performs well under MA3, but produces negative or only marginally positive alphas under EMA10. Thus, as opposed to the evidence in section 6.2, we do not find that the best patterns perform consistently well across holding periods and trends.

6.4 Market Timing

The results from the market timing regressions for the five significant combinations are presented in Table 9. While we find support for successful market timing abilities, the evidence is somewhat mixed. TBC MA3 MYR1 is the only combination with a statistically significant loading on the quadratic market factor. The daily alpha consequently decreases from 0.13% to 0.04% and is no longer statistically significant. The SS based combination, which is also bearish and based on MA3 and MYR1, on the other hand, has a negative (albeit not significant) loading on the quadratic factor. The two HP based strategies both have positive loadings on the quadratic factor that are not significant. However, the alpha for HP MA3 MYR3 decreases from 0.16% to 0.12% and is no longer significant as a result of this positive loading. The alpha for HP MA3 CL3 decreases from 0.14% to 0.12% but remains significant at the 10% level (albeit no longer at the 5% level). Finally, the inclusion of the quadratic factor has a negligible impact on the BUSL based strategy as its loading on this factor is close to zero.

6.5 Economic Significance

While the results in section 6.2 and section 6.3 suggest that candlestick charting is not profitable on the Stockholm Stock Exchange, we note that the five statistically significant combinations generate enough trading signals to potentially also be economically significant. Specifically, BUSL EMA10 CL10, TBC EMA10 MYR1, HP MA3 MYR1, HP MA3 MYR3 and SS MA3 MYR1 produce 2,050, 803, 378, 387 and 196 trading signals, respectively, throughout the entire sample period (see Panel A in Table 1 for average number of signals across trends and holding strategies). We investigate this by constructing trading strategies that start with 100 units and invest in all signals generated by the five significant combinations, as described in section 5.7. Cumulative expected returns and actual net returns from these trading strategies are plotted in Figure 4 and yearly returns are shown in Figure 5.

First, we note that at the final date (December 31, 2015), the actual values of the five strategies exceed expected values by 70.1% on average. The HP MA3 CL3 strategy has the highest value (321), exceeding the expected value by 108.0%, and the SS MA3 MYR1 strategy has the lowest value (162), exceeding the expected value by 34.5%. The BUSL based strategy is by far the most volatile, rallying from a value of 129 in March, 2003 to 365 in May, 2007 and thereafter tumbling down to 214 in December, 2008. We also observe that expected returns for the bearish strategies are rather low, which is due to their negative factor exposures, in particular with regard to the market factor. For instance, the estimated loadings for TBC EMA10 MYR1 on the market, SMB, HML and UMD factors are -0.63, -0.19, -0.17 and 0.15, respectively (Table 5), resulting in an expected final investment value of 105, i.e. merely a 5% return over a sixteen year period.

The strategies thus arguably generate a decent return over the entire sample period, suggesting that the statistically significant alphas also are of economic significance. We observe, however, that performance is not robust over time. In particular, while it is evident from Figure 4 that all five combinations generate rather large abnormal returns in the first half of the sample, performance in the most recent half is less impressive. To further illustrate this, Figure 6 plots cumulative expected returns and actual net returns from January 1, 2008 to December 31, 2015. While the HP based strategies perform relatively well, with final day values of 180 (40.7% above expected value) and 183 (49.7% above expected value), the SS and TBC based strategies generate returns that only marginally exceed expected values. The BUSL based strategy generates a final value of 118, which is 4.5% below expected value. We also note that the SS, TBC and BUSL based strategies have cumulative actual returns that are considerably below expected returns during a large part of the period.

In order to provide a more robust evaluation of how the profitability has developed over time, we turn to the next section, which provides the results of the sub-period analysis for all 264 combinations.

6.6 Sub-periods

The results from the sub-period analysis is presented in Table 10, Table 11 and Table 12. We find strong support for the notion that profitability of technical trading rules has been decreasing over time due to increasing market efficiency, as our results show that while profitability is decent in sub-period 1 (2000-2007), it largely deteriorates in sub-period 2 (2008-2015). Specifically, we find that in sub-period 1, eight combinations have statistically significant positive FFC alphas at the 10% level after transaction costs and six combinations remain significant at the 5% level. In sub-period 2, however, not a single combination has a significant FFC alpha.

The relatively strong performance in sub-period 1 is mainly driven by bearish patterns, producing an average alpha that is positive across all trends and holding strategies, as well as accounting for 7/8 of the significant combinations.[4] ES is the most consistent pattern, generating positive FFC alphas across all 12 combinations. For holding periods of three days or less, more than half of the bearish combinations (46/88) produce positive FFC alphas. Again, MYR1 is the dominant holding period, with an average daily FFC alpha of 0.16% and positive FFC alphas for 16/22 of the bearish combinations. The performance of bullish patterns is relatively poor, with only one significant combination at the 10% level (BUSL EMA10 CL10, which produces an average daily FFC alpha of 0.03%). The dominant holding strategy is CL10, generating positive FFC alphas for most patterns. The top performing pattern is MD, with positive FFC alphas across all 12 combinations.

Comparing performance across both sub-periods, we notice that the profitability deterioration in sub-period 2 is mostly accounted for by bearish patterns. In particular, only 43/132 of the bearish combinations generate positive FFC alphas in sub-period 2 and performance is poor across all holding strategies. While MYR1 is still dominant, only 9/22 of the MYR1 combinations generate positive FFC alphas and the average daily MYR1 alpha is negative (-0.01%). BESL produces negative average alphas across all 12 combinations and BTS, ES, and LET have negative alphas for all but 1 combination. The only consistently well performing bearish pattern is UGTC, with an average daily FFC alpha of 0.14% and positive FFC alphas across 11/12 combinations. The performance of bullish patterns only deteriorates marginally in sub-period 2, as 50/132 combinations generate positive FFC alphas, compared to 54/132 in sub-period 1. Among the holding strategies, only CL10 generates a (marginally) positive average alpha. HP is the top performing pattern, with statistically significant CAPM (but not FFC) alphas at the 5% level under MA3 MYR1 and MA3 CL3.

7 Discussion

Apart from our findings that candlestick strategies do not generate abnormal returns and that profitability has deteriorated over time, the empirical results point to a number of interesting insights with bearing on existing literature. The findings that bullish trading

[4]The significant bearish combinations are SS MA3 MYR1, TID MA3 MYR1, ES MA3 MYR2, ES MA3 MYR3, TBC EMA10 MYR1, ES MA3 CL3 and LET MA3 MYR3, generating average daily FFC alphas of 0.53%, 0.33%, 0.33%, 0.25%, 0.24%, 0.17% and 0.17%, respectively.

signals generate higher raw returns and WPs than bearish signals is in line with Lu et al. (2015), who demonstrate that TWC, TIU and MS consistently outperform TBC, TID and ES for holding periods of three and ten days. Lu and Shiu (2016) reach a similar conclusion for single line patterns using holding periods of one, five and ten days. The returns and WPs for both bullish and bearish patterns in these studies are, however, considerably higher compared to our results. In particular, about half of the patterns generate mean gross returns above 1.5% and gross WPs above 65% under CL3 and CL10 in Lu et al. (2015). They also show that MS generates a spectacular mean return of 2.36% and a WP of 91.5% under MA3 CL3. In contrast, we find that not a single combination produces neither a mean gross return above 1.5% nor a WP above 65%. MS under MA3 CL3 generates a negative mean gross return of -0.20% and has a WP of 50.1%.

While evidence in existing literature of profitability dispersion between geographical markets was a key motivation for using Swedish data in this study, we find these considerable differences surprising and difficult to reconcile. Considering that Lu et al. (2015) and Lu and Shiu (2016) use DJIA component data, one can hardly make the argument that this study is conducted on a more efficient market. Moreover, although a longer sample is utilised in Lu et al. (2015) and Lu and Shiu (2016), their sub-period analyses show that returns do not deteriorate significantly in the more recent sub-periods. For instance, the sub-period analysis in Lu et al. (2015), applied to the EMA10 trend and CL3 holding strategy, indicates mean gross returns of 1.64% across all patterns in the first sub-period (1992-1998) and 1.36% in the most recent period (2006-2012). Finally, the argument in Marshall et al. (2006) that technical trading rules perform better on actively traded stocks does not reconcile these differences, as our results are qualitatively unchanged when applied to only large cap stocks (not shown here).

In terms of trends, our findings that they do not appear to have a significant impact on profitability is in line with Lu et al. (2015). In contrast to our results, however, they find that the exit strategy has a large impact on profitability. In particular, while 46/48 of the bullish and bearish combinations under CL3 and CL10 have statistically significant mean net returns, the corresponding number under MYR3 and MYR10 is only 12/48. The performance of MYR3 is particularly poor, with negative mean returns for 21/24 combinations. Again, our results do not indicate any considerable differences between CL and MYR in terms of neither raw nor abnormal returns, although CL has lower volatility, VaR and factor exposure, which is consistent with the argument in Lu et al. (2015) that CL is superior from a risk sharing perspective.

Our results also shed light on the ambiguity surrounding the role of holding periods. We find strong support for that holding periods have a significant impact on profitability, especially with regard to bearish patterns, as they consistently perform relatively well using a short holding period of one day and poorly using a long holding period of ten days. Bullish patterns generate higher raw returns using ten days, but abnormal returns are rather unaffected by the holding period. This evidence is largely in line with Goo et al. (2007), who show that while bullish patterns generate the highest mean return for holding periods of nine and ten days, bearish patterns are more profitable using holding periods of one, two and three days.

However, our holding period results do not support Caginalp and Laurent's (1998) findings that gross WPs for both bullish and bearish patterns range from about 63% to 68% under multiple holding periods, suggesting that the period only has a minor impact on profitability. Similarly, Lu et al. (2015) show that raw returns are rather equal across three-day and ten-day holding periods for both bullish and bearish patterns. Moreover, while Zhu et al. (2015) demonstrate that holding periods have a significant impact on returns, their results run opposite of ours, as bullish patterns only have significant raw returns using a one-day holding period and bearish patterns have higher returns using a ten-day holding period. It should finally be noted that most candlestick studies only test a rather small number of patterns, which could at least partly explain the significant variation in results. In particular, Zhu et al. (2015) test ten patterns (five bullish and five bearish) and Caginalp and Laurent (1998) and Lu et al. (2015) test eight patterns (four bullish and four bearish).

Finally, we want to highlight two limitations of this study. First, data snooping is a widely recognised issue in studies of technical trading rules (see e.g. White, 2000). Here, data snooping refers to the bias that one is likely to find profitable rules by chance alone when testing a large number of rules on a single data set, even if the rules do not have any real predictive value. As pointed out in Marshall et al. (2008), however, candlestick charting is less susceptible to data snooping biases compared to e.g. filter and break out rules, as it was originally developed for a different market (the Japanese rice market). Evaluating the performance of candlesticks on the Swedish stock market can therefore rather be considered an out-of-sample test in its own right. In support of this argument, the test statistics in Lu et al. (2015) are unchanged for the vast majority of combinations after accounting for data snooping bias through the inclusion of the Stepwise Superior Predictive Ability (Step-SPA) test developed by Hsu et al. (2010).[5] In addition, since our results indicate that candlestick strategies do not generate significant alphas, any potential upward biases in this study should not be major points of concern as they would not change our conclusions qualitatively.

[5] In particular, without the Step-SPA test, 46/48 of the combinations under CL3 and CL10 generate positive and statistically significant raw net returns at the 5% level. Using the Step-SPA test, 45/48 of the combinations remain significant at the 5% asymptotic familywise error rate.

Second, since we restrict our tests to a subset of candlestick patterns, our conclusions are not necessarily robust across all available patterns. However, it should be noted that many patterns excluded from this study occur rather infrequently and therefore are unlikely to have alphas that are economically significant. For a comprehensive review of 103 candlestick patterns, including number of observations in a sample of 500 stocks over a ten-year period, we suggest the interested reader to consult Bulkowski (2012).

8 Conclusion

This study sets out to provide a systematic evaluation of the profitability of candlestick charting on the Stockholm Stock Exchange. Drawing on previous studies conducted on stocks in other geographical markets, we first examine whether raw return are larger than zero. We test 264 unique combinations, made up of twenty-two different candlestick patterns, two different trend definitions and six different holding strategies, and find that about one-third of the combinations produce statistically significant positive gross returns. However, mean returns are low and only about one-seventh of the combinations remain significant after accounting for two-way transaction costs of 0.10%.

By extending the analysis to incorporate abnormal returns, we also provide novel evidence that the majority of candlestick strategies generate negative alphas. Only five combinations produce statistically significant four-factor (Fama-French-Carhart) alphas at the 10% level after transaction costs and not a single combination is significant at the 1% level. The significant combinations are based on the patterns Bullish Separating Lines, Homing Pigeon, Shooting Star and Three Black Crows, with alphas that to some extent can be explained by successful market timing ability. While the alphas also are at least moderately economically significant, they are not robust across trends nor holding periods.

We additionally evaluate how the profitability of candlestick strategies has evolved over time by dividing our sample into two sub-periods of equal length. In doing so, we find that abnormal returns are considerably higher in sub-period 1 (2000-2007) than sub-period 2 (2008-2015), which is in line with the growing body of literature suggesting that the profitability of technical trading rules has been decreasing over time as a result of increasing market efficiency. The deterioration in profitably is particularly evident among bearish patterns, as the average daily alpha after transaction costs under the optimal holding strategy (MYR1) falls from 0.16% in sub-period 1 to -0.01% in sub-period 2. Based on the combined evidence that i) most combinations generate negative alphas even under low transaction costs, ii) the profitability of the few combinations with (barely) significant alphas is not robust across trends nor holding periods and iii) the alphas for the majority of combinations have eroded over time, we conclude that candlestick charting is not profitable on the Stockholm Stock Exchange.

To the best of our knowledge, this is the first study on candlestick charting that utilises European stock data. Further research is therefore needed to shed more light on the cross-country variation in candlestick returns and reconcile our evidence with the results obtained on Chinese, Taiwanese and US data in previous studies. We urge future research to focus efforts on abnormal returns rather than raw returns in order to more appropriately capture the potential investment value of candlesticks. Finally, it would be of interest to investigate whether the profitability of candlestick charting can be enhanced by incorporating other strategies and statistics. A few studies have already acknowledged this potential and presented some promising results. For instance, Goo et al. (2007) find that the performance of most candlestick strategies can be improved by incorporating a stop loss strategy and Zhu et al. (2015) show that certain candlesticks perform better when applied to stocks that are small and highly liquid.

References

Franklin Allen and Risto Karjalainen. Using genetic algorithms to find technical trading rules. *Journal of Financial Economics*, 51(2):245–271, 1999.

William Brock, Josef Lakonishok, and Blake LeBaron. Simple technical trading rules and the stochastic properties of stock returns. *The Journal of Finance*, 47(5):1731–1764, 1992.

Thomas N Bulkowski. *Encyclopedia of Candlestick Charts*, volume 332. John Wiley & Sons, 2012.

Gunduz Caginalp and Henry Laurent. The predictive power of price patterns. *Applied Mathematical Finance*, 5(3-4):181–205, 1998.

Mark M Carhart. On persistence in mutual fund performance. *The Journal of Finance*, 52 (1):57–82, 1997.

Edward R Dawson and James M Steeley. On the existence of visual technical patterns in the uk stock market. *Journal of Business Finance & Accounting*, 30(1-2):263–293, 2003.

Theodore E Day and Pingying Wang. Dividends, nonsynchronous prices, and the returns from trading the dow jones industrial average. *Journal of Empirical Finance*, 9(4):431–454, 2002.

Matthieu Duvinage, Paolo Mazza, and Mikael Petitjean. The intra-day performance of market timing strategies and trading systems based on japanese candlesticks. *Quantitative Finance*, 13(7):1059–1070, 2013.

Eugene F Fama and Marshall E Blume. Filter rules and stock-market trading. *The Journal of Business*, 39(1):226–241, 1966.

Eugene F Fama and Kenneth R French. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56, 1993.

Fernando Fernandez-Rodriguez, Christian Gonzalez-Martel, and Simon Sosvilla-Rivero. On the profitability of technical trading rules based on artificial neural networks: Evidence from the madrid stock market. *Economics Letters*, 69(1):89–94, 2000.

J Henning Fock, Christian Klein, and Bernhard Zwergel. Performance of candlestick analysis on intraday futures data. *The Journal of Derivatives*, 13(1):28–40, 2005.

Ramazan Gencay. Optimization of technical trading strategies and the profitability in security markets. *Economics Letters*, 59(2):249–254, 1998.

Yeong-Jia Goo, Dar-Hsin Chen, and Yi-Wei Chang. The application of japanese candlestick trading strategies in taiwan. *Investment Management & Financial Innovations*, 4(4):49, 2007.

Yufeng Han, Ke Yang, and Guofu Zhou. A new anomaly: The cross-sectional profitability of technical analysis. *Journal of Financial and Quantitative Analysis*, 48(05):1433–1461, 2013.

Marshall J Horton. Stars, crows, and doji: The use of candlesticks in stock selection. *The Quarterly Review of Economics and Finance*, 49(2):283–294, 2009.

Po-Hsuan Hsu, Yu-Chin Hsu, and Chung-Ming Kuan. Testing the predictive ability of technical analysis using a new stepwise test without data snooping bias. *Journal of Empirical Finance*, 17(3):471–484, 2010.

Michael C Jensen. Some anomalous evidence regarding market efficiency. *Journal of Financial Economics*, 6(2/3):95–101, 1978.

Michael C Jensen and George A Benington. Random walks and technical theories: Some additional evidence. *The Journal of Finance*, 25(2):469–482, 1970.

G Andrew Karolyi and René M Stulz. Are financial assets priced locally or globally? *Handbook of the Economics of Finance*, 1:975–1020, 2003.

Jerzy Korczak and Patrick Roger. Stock timing using genetic algorithms. *Applied Stochastic Models in Business and Industry*, 18(2):121–134, 2002.

John R Koza. *Genetic programming: on the programming of computers by means of natural selection*, volume 1. MIT press, 1992.

Pei Kuang, M Schröder, and Qingwei Wang. Illusory profitability of technical analysis in emerging foreign exchange markets. *International Journal of Forecasting*, 30(2):192–205, 2014.

Andrew W Lo, Harry Mamaysky, and Jiang Wang. Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *The Journal of Finance*, 55(4):1705–1770, 2000.

Tsung-Hsun Lu. The profitability of candlestick charting in the taiwan stock market. *Pacific-Basin Finance Journal*, 26:65–78, 2014.

Tsung-Hsun Lu and Yung-Ming Shiu. Can 1-day candlestick patterns be profitable on the 30 component stocks of the djia? *Applied Economics*, pages 1–10, 2016.

Tsung-Hsun Lu, Yung-Ming Shiu, and Tsung-Chi Liu. Profitable candlestick trading strategiesthe evidence from a new perspective. *Review of Financial Economics*, 21(2):63–68, 2012.

Tsung-Hsun Lu, Yi-Chi Chen, and Yu-Chin Hsu. Trend definition or holding strategy: What determines the profitability of candlestick charting? *Journal of Banking & Finance*, 61: 172 – 183, 2015.

Louis P Lukac, B Wade Brorsen, and Scott H Irwin. A test of futures market disequilibrium using twelve different technical trading systems. *Applied Economics*, 20(5):623–639, 1988.

Burton Gordon Malkiel. *A random walk down Wall Street, second ed.* Norton, New York, 1981.

Viktor Manahov, Robert Hudson, and Bartosz Gebka. Does high frequency trading affect technical analysis and market efficiency? And if so, how? *Journal of International Financial Markets, Institutions and Money*, 28:131–157, 2014.

Ben R Marshall, Martin R Young, and Lawrence C Rose. Candlestick technical trading strategies: can they create value for investors? *Journal of Banking & Finance*, 30(8): 2303–2323, 2006.

Ben R Marshall, Martin R Young, and Rochester Cahan. Are candlestick technical trading strategies profitable in the japanese equity market? *Review of Quantitative Finance and Accounting*, 31(2):191–207, 2008.

E McSheery. High frequency trading volumes continue to increase throughout the world. *Newsletter*, 8(3):5, 2011.

Massoud Metghalchi, Yung-Ho Chang, and Juri Marcucci. Is the swedish stock market efficient? evidence from some simple trading rules. *International Review of Financial Analysis*, 17(3):475–490, 2008.

Massoud Metghalchi, Juri Marcucci, and Yung-Ho Chang. Are moving average trading rules profitable? evidence from the european stock markets. *Applied Economics*, 44(12): 1539–1559, 2012.

GL Morris. *Candlestick Charting Explained: Time Techniques for Trading Stocks and Futures, second ed.* MeGraw-Hill Trade, New York., 1995.

Steve Nison. *Japanese candlestick charting techniques: A Contemporary Guide to the Ancient Investment Technique of the Far East.* New York Institute of Finance, New York, 1991.

Steve Nison. *Beyond candlesticks: New Japanese charting techniques revealed*, volume 56. John Wiley & Sons, 1994.

Steve Nison. Candlestick trading principles. *Technical Analysis of Stocks and Commodities November*, pages 22–27, 2004.

Cheol-Ho Park and Scott H Irwin. What do we know about the profitability of technical analysis? *Journal of Economic Surveys*, 21(4):786–826, 2007.

Martin J Pring. *Technical analysis explained: The successful investor's guide to spotting investment trends and turning points.* McGraw-Hill Professional, 2002.

Andrei Shynkevich. Performance of technical analysis in growth and small cap segments of the us equity market. *Journal of Banking & Finance*, 36(1):193–208, 2012.

Bruno Solnik and Jacques Roulet. Dispersion as cross-sectional correlation. *Financial Analysts Journal*, 56(1):54–61, 2000.

Ryan Sullivan, Allan Timmermann, and Halbert White. Data-snooping, technical trading rule performance, and the bootstrap. *The Journal of Finance*, 54(5):1647–1691, 1999.

Jack Treynor and Kay Mazuy. Can mutual funds outguess the market. *Harvard Business Review*, 44(4):131–136, 1966.

James C Van Horne and George GC Parker. The random-walk theory: an empirical test. *Financial Analysts Journal*, 23(6):87–92, 1967.

Fei Wang, LH Philip, and David W Cheung. Combining technical trading rules using particle swarm optimization. *Expert Systems with Applications*, 41(6):3016–3026, 2014.

Halbert White. A reality check for data snooping. *Econometrica*, 68(5):1097–1126, 2000.

Min Zhu, Said Atri, and Eyub Yegen. Are candlestick trading strategies effective in certain stocks with distinct features? *Pacific-Basin Finance Journal*, 2015.

A Appendix

Figure 1: Daily Open, High, Low and Close Prices Depicted as Candlesticks

This figure shows the components of a candlestick. The white candle represents a bullish session and the black candle represents a bearish session.

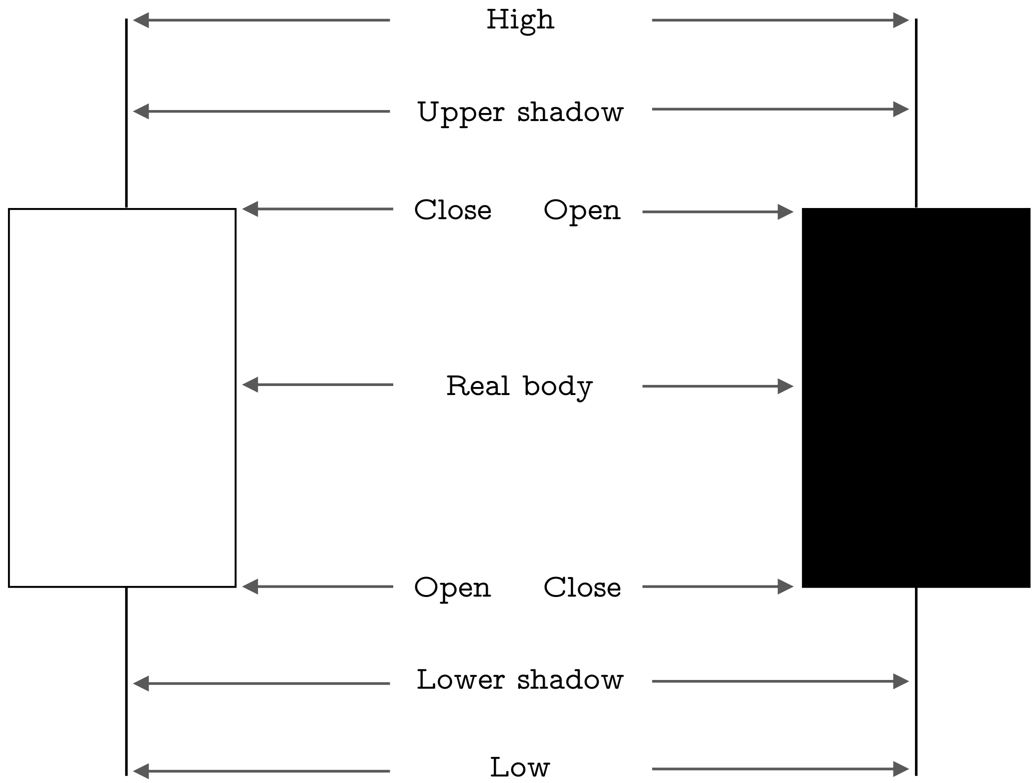

Figure 2: Candlestick Patterns

This figure presents the twenty-two candlestick patterns evaluated in this study. Eleven patterns are bullish and eleven patterns are bearish. Nine of the bullish patterns have a bearish counterpart. Nine patterns are three-day patterns and thirteen patterns are two-day patterns. Twenty patterns are reversal patterns and two patterns (BUSL and BESL) are continuation patterns. The arrows show the preceding trend, with upward sloping arrows representing uptrends and downward sloping arrows representing downtrends. The white and black candles are defined in accordance with Figure 1. Real bodies coloured grey represent bodies that can be either black or white and real bodies in the form of horizontal lines represent dojis (days when open price equals close price).

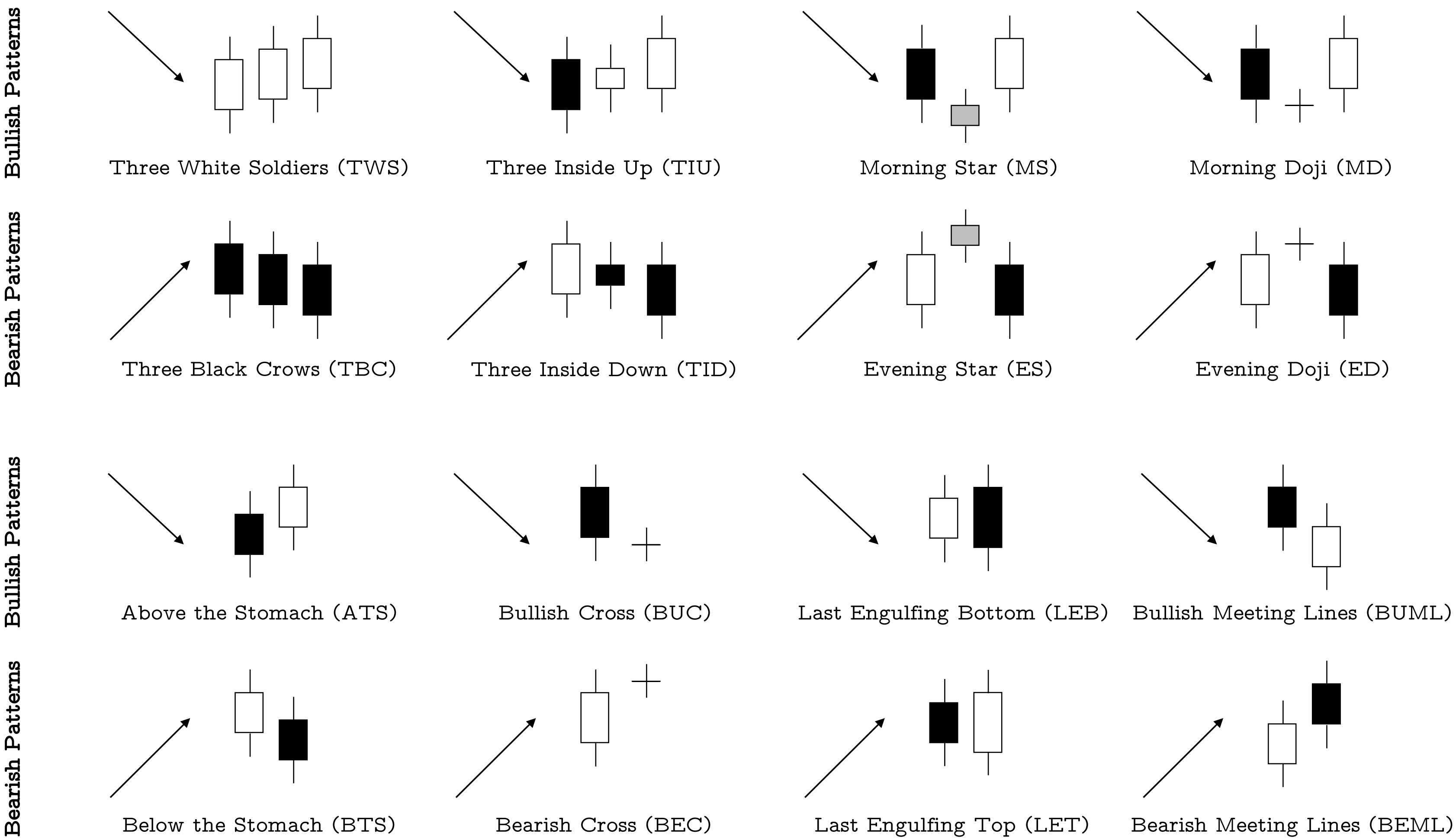

Figure 2 (Cont.): Candlestick Patterns

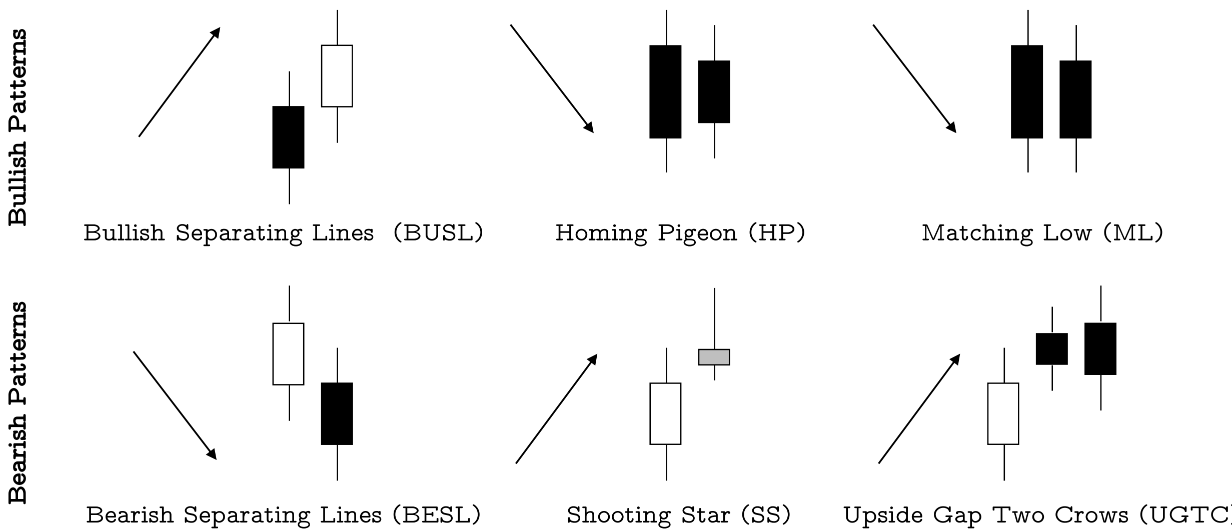

Figure 3: Examples of Candlestick Patterns

This figure shows examples of candlestick patterns for SEB, Nokia and SSAB during December, 2015

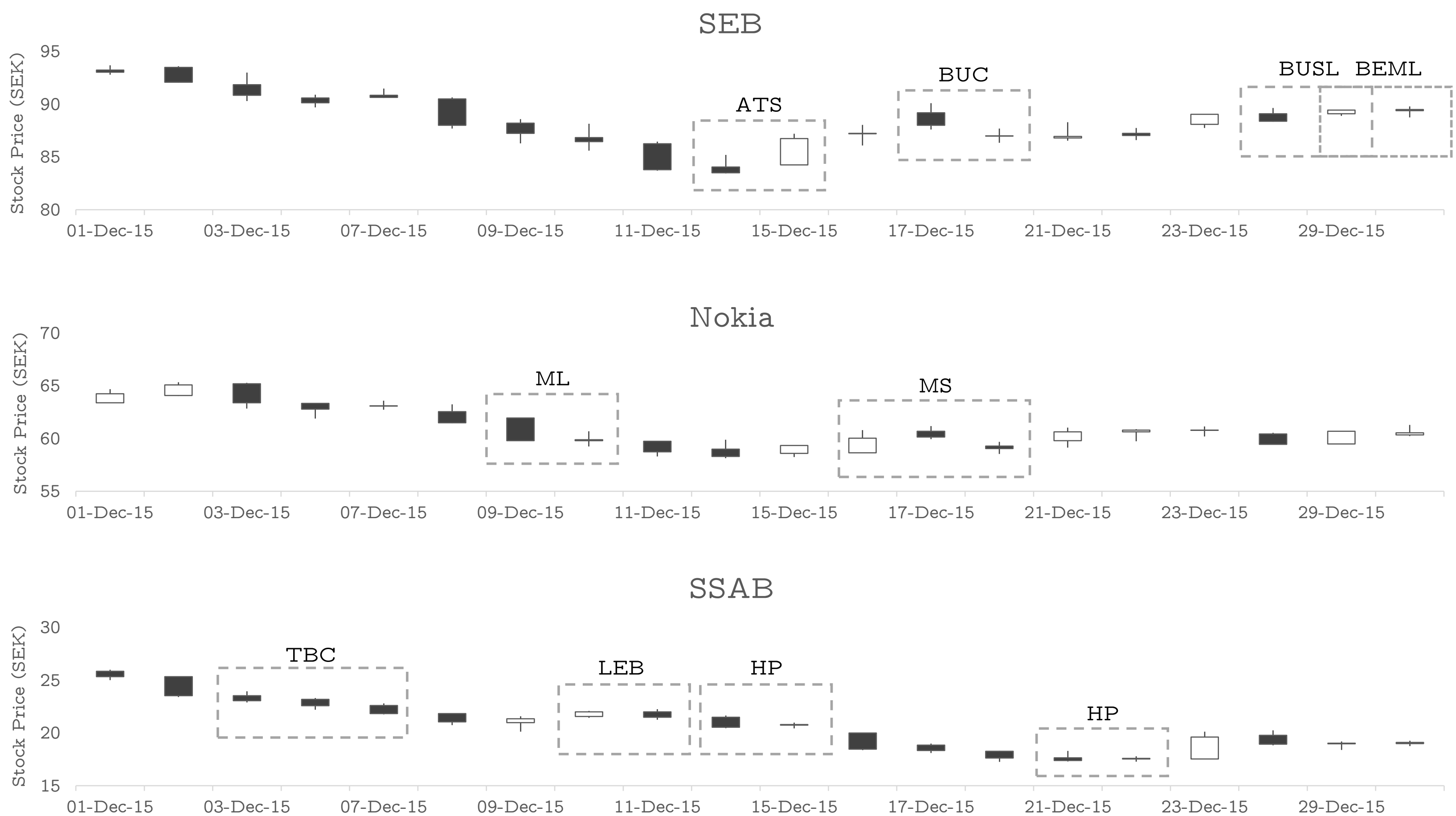

Table 1: Descriptive Statistics

This table presents descriptive statistics for the twenty-two candlestick patterns, two trend defintions and six holding strategies evaluated in this study. The sample consists of 72 stocks listed on the Stockholm Stock Exchange over the period January 2000-December 2015. Panel A reports equally weighted averages for each candlestick pattern across trends and holding strategies. Panel B reports equally weighted averages for each trend across candlestick patterns and holding strategies. Panel C reports equally weighted averages for each holding strategy across candlestick patterns and trends. Mean and standard deviation statistics are in percent.

Panel A: Candlestick Patterns

	N	Mean	Std. Dev.	Skewness	Kurtosis
Bull Patterns					
TWS	269	-.02	3.41	-.46	5.59
TIU	911	.24	4.69	.38	10.36
MS	940	-.08	4.51	-.64	8.41
MD	188	.27	4.4	.48	8.97
BUC	725	.37	4.85	.17	9.58
ATS	3,432	.06	4.51	.91	19.71
BUML	1,057	.19	5.06	1.01	26.52
HP	886	.41	5.01	.80	10.48
LEB	1,819	.22	4.27	-.19	6.94
ML	879	.31	5.37	.26	18.33
BUSL	1,337	.28	4.16	1.32	21.14
Bull Average	1,131	.20	4.57	.37	13.28
Bear Patterns					
TBC	542	-.11	3.28	-.19	5.69
TID	843	-.07	3.50	.18	7.35
ES	953	.02	3.78	.07	9.44
ED	257	-.09	4.15	-.33	8.57
UGTC	38	.29	3.58	-.17	4.97
BEC	1,111	.07	3.54	.18	10.12
BTS	2,894	-.04	3.73	.07	9.42
BEML	1,370	-.16	4.18	-1.54	18.34
SS	394	.17	4.62	-1.99	22.59
LET	1,752	-.03	3.46	.04	10.57
BESL	994	-.32	4.62	-.20	11.03
Bear Average	1,014	-.03	3.86	-.35	10.73
Total Average	1,072	.09	4.21	.01	12.00

Panel B: Trend Definitions

	N	Mean	Std. Dev.	Skewness	Kurtosis
Bull Patterns					
MA-3	495	.26	4.66	.23	10.33
EMA-10	1,767	.15	4.48	.50	16.22
Bull Average	1,131	.20	4.57	.37	13.28
Bear Patterns					
MA-3	458	-.04	3.79	-.45	10.57
EMA-10	1,569	-.01	3.92	-.25	10.90
Bear Average	1,014	-.03	3.86	-.35	10.73
Total Average	1,072	.09	4.21	.01	12.00

Panel C: Holding Strategies

	N	Mean	Std. Dev.	Skewness	Kurtosis
Bull Patterns					
MYR-1	1,139	.01	2.54	.14	11.22
MYR-2	1,136	.15	3.73	.32	11.48
MYR-3	1,136	.16	4.65	.34	12.12
MYR-10	1,129	.34	8.09	-.51	11.10
CL-3	1,134	.18	3.28	.82	12.30
CL-10	1,114	.38	5.11	1.08	21.43
Bull Average	1,131	.20	4.57	.37	12.38
Bear Patterns					
MYR-1	1,020	.11	2.13	-.04	9.15
MYR-2	1,017	.04	3.22	-.42	11.50
MYR-3	1,017	.01	3.89	-.40	11.18
MYR-10	1,015	-.18	6.84	.15	9.50
CL-3	1,014	.01	2.77	-.72	11.54
CL-10	998	-.14	4.30	-.69	11.55
Bear Average	1,014	-.03	3.86	-.35	10.73
Total Average	1,072	.09	4.21	.01	12.00

Table 2: Hypothesis Testing - MYR1 & MYR2 Holding Strategies

This table presents results from the hypothesis testing for MYR1 and MYR2 holding strategies. The null that mean returns (pre and post transaction costs of 0.10%) are less than or equal to zero is tested against the one sided alternative of positive mean returns. Critical values are bootstrapped as returns do not follow a standard t-distribution. This table also shows winning percent (WP) and value-at-risk (VaR) at the 5% and 1% levels. Mean returns and VaR are in percent, and WP is a fraction.

	MA3 Trend								EMA10 Trend							
	Pre Transaction Costs					Post Transaction Costs			Pre Transaction Costs					Post Transaction Costs		
	Mean	t-stat	WP	VaR 5	VaR 1	Mean	t-stat	WP	Mean	t-stat	WP	VaR 5	VaR 1	Mean	t-stat	WP
								MYR1 Holding Strategy								
Bull Patterns																
TWS	.00	.01	.52	-3.77	-6.34	-.10	-.54	.47	.09	.92	.52	-3.08	-5.65	-.01	-.07	.48
TIU	.18*	1.28	.54	-3.95	-7.03	.08	.56	.50	.21***	3.23	.52	-3.28	-5.63	.11**	1.68	.48
MS	-.37	-3.41	.46	-4.64	-8.49	-.47	-4.32	.43	-.17	-2.81	.48	-3.97	-7.06	-.27	-4.46	.44
MD	-.18	-.65	.42	-4.35	-7.65	-.28	-1.01	.38	-.04	-.27	.47	-3.64	-6.45	-.14	-1	.42
BUC	.16	.94	.55	-4.45	-9.05	.06	.34	.49	.06	.80	.52	-3.92	-6.56	-.04	-.55	.45
ATS	-.03	-.46	.48	-3.43	-6.32	-.13	-2.09	.44	-.03	-.86	.48	-3.42	-6.06	-.13	-4.03	.44
BUML	.19*	1.28	.51	-4.49	-8.70	.09	.60	.46	-.06	-.84	.49	-4.49	-8.70	-.16	-2.30	.42
HP	.33**	2.25	.55	-4	-6.20	.23*	1.57	.53	-.04	-.56	.49	-3.90	-6.83	-.14	-2.06	.46
LEB	.04	.47	.51	-3.43	-6.83	-.06	-.75	.48	-.07	-1.68	.49	-3.68	-6.53	-.17	-4.01	.45
ML	.00	.01	.52	-4.76	-9.35	-.10	-.52	.48	-.04	-.58	.49	-4.09	-7.80	-.14	-1.86	.43
BUSL	.14*	1.50	.49	-2.90	-5.28	.04	.40	.44	-.04	-.70	.49	-3.35	-7.41	-.14	-2.68	.43
Average Bull	.04	.29	.51	-4.01	-7.38	-.06	-.52	.46	-.01	-.30	.49	-3.71	-6.79	-.11	-1.94	.44
Bear Patterns																
TBC	.06	.58	.56	-2.84	-5.77	-.04	-.35	.50	.17***	2.39	.53	-3.08	-5.53	.07	1.01	.48
TID	.15*	1.58	.48	-2.36	-3.79	.05	.51	.44	.05	.96	.50	-2.82	-5.20	-.05	-.89	.46
ES	.16*	1.59	.50	-2.94	-6.20	.06	.62	.47	.17***	3.07	.52	-2.81	-5.19	.07*	1.25	.48
ED	.20	.90	.50	-2.42	-5.91	.10	.45	.46	.22**	2	.56	-3.33	-5.20	.12	1.08	.49
UGTC	-.49	-1.03	.44	-8	-8	-.59	-1.23	.37	.37*	1.39	.56	-2.12	-8	.27	1.01	.50
BEC	.21**	2.37	.58	-2.74	-4.17	.11	1.22	.51	.06	1.24	.52	-3.05	-4.91	-.04	-.91	.45
BTS	.10**	1.74	.49	-2.68	-5.73	.00	.01	.46	.11***	3.51	.51	-2.85	-5.56	.01	.27	.46
BEML	.16**	1.93	.54	-2.70	-5.82	.06	.73	.48	.04	.78	.53	-3.34	-7.21	-.06	-1.23	.46
SS	.45***	2.61	.60	-2.87	-6.36	.35**	2.04	.56	.27***	2.80	.57	-3.19	-6.64	.17**	1.78	.51
LET	-.04	-.68	.49	-2.91	-4.54	-.14	-2.27	.46	-.01	-.23	.50	-2.94	-4.65	-.11	-3.04	.46
BESL	.05	.37	.52	-3.97	-9.10	-.05	-.39	.46	-.02	-.36	.49	-4.45	-8	-.12	-1.81	.43
Average Bear	.09	1.09	.52	-3.31	-5.94	-.01	.12	.47	.13	1.59	.53	-3.09	-6.01	.03	-.13	.47
Average MYR1	.07	.69	.51	-3.66	-6.66	-.03	-.20	.47	.06	.65	.51	-3.40	-6.40	-.04	-1.04	.46
								MYR2 Holding Strategy								
Bull Patterns																
TWS	-.19	-.77	.59	-5.88	-7.26	-.29	-1.16	.56	.13	.99	.56	-4.30	-7.26	.03	.24	.53
TIU	.41**	2.01	.55	-5.64	-11.39	.31*	1.52	.52	.23***	2.46	.52	-4.96	-7.98	.13*	1.41	.49
MS	-.22	-1.22	.51	-6.94	-14.96	-.32	-1.78	.49	-.08	-.87	.52	-5.48	-11.67	-.18	-1.91	.50
MD	.43	1	.51	-4.46	-7.75	.33	.76	.48	.36**	1.65	.52	-4.63	-7.74	.26	1.19	.48
BUC	.32*	1.40	.55	-5.93	-10.44	.22	.96	.50	.09	.79	.53	-6.19	-10.54	-.01	-.12	.49
ATS	.04	.39	.50	-5.30	-9.91	-.06	-.61	.47	.00	-.05	.50	-5.29	-9.83	-.10	-2.08	.48
BUML	.14	.76	.51	-5.55	-11.44	.04	.23	.48	-.08	-.88	.48	-5.68	-11.95	-.18	-1.95	.44
HP	.51**	2.11	.57	-6.11	-13.35	.41**	1.70	.55	.11	1.05	.50	-5.75	-10.54	.01	.08	.48
LEB	.34***	2.81	.53	-5.16	-8.93	.24**	1.99	.51	.11**	1.68	.52	-5.46	-9.32	.01	.14	.50
ML	.19	.82	.55	-5.97	-12.63	.09	.40	.51	.18*	1.53	.53	-5.83	-10.21	.08	.67	.48
BUSL	.26**	2	.48	-4.08	-7.65	.16	1.24	.44	.12**	1.64	.49	-4.76	-9.21	.02	.28	.45
Average Bull	.20	1.03	.53	-5.55	-10.52	.10	.48	.50	.11	.91	.52	-5.30	-9.66	.01	-.19	.48
Bear Patterns																
TBC	-.09	-.55	.52	-4.94	-7.70	-.19	-1.18	.50	.00	-.04	.48	-4.45	-7.48	-.10	-.99	.46
TID	-.10	-.72	.48	-4.18	-7.17	-.20	-1.46	.46	-.08	-1.04	.47	-4.27	-8.24	-.18	-2.28	.45
ES	.12	.87	.51	-4.35	-8.88	.02	.16	.47	.18**	2.23	.52	-4.34	-8.88	.08	1.02	.49
ED	-.40	-1.15	.44	-7.83	-10.59	-.50	-1.44	.40	.02	.09	.52	-5.08	-10.96	-.08	-.46	.47
UGTC	.38	.48	.47	-5.35	-5.35	.28	.35	.47	.37	.90	.57	-5.35	-6.12	.27	.66	.57
BEC	.23**	1.69	.55	-4.12	-9.21	.13	.95	.50	.06	.88	.51	-4.12	-7.95	-.04	-.59	.47
BTS	-.03	-.35	.49	-4.23	-8.95	-.13	-1.57	.46	.10**	2.07	.50	-4.49	-8.20	.00	-.07	.47
BEML	.24**	1.83	.54	-4.08	-6.71	.14	1.06	.50	.00	.01	.52	-4.90	-9.81	-.10	-1.36	.47
SS	.01	.02	.51	-4.52	-18.94	-.09	-.30	.47	.10	.71	.53	-4.53	-11.12	.00	.03	.50
LET	-.06	-.61	.49	-4.05	-8.15	-.16	-1.65	.46	.05	.92	.50	-4.07	-7.38	-.05	-.95	.47
BESL	-.11	-.56	.52	-6.80	-12.92	-.21	-1.09	.49	-.09	-.96	.49	-5.56	-11.33	-.19	-2.04	.45
Average Bear	.02	.09	.50	-4.95	-9.51	-.08	-.56	.47	.06	.52	.51	-4.65	-8.86	-.04	-.64	.48
Average MYR2	.11	.56	.52	-5.25	-10.01	.01	-.04	.49	.09	.72	.51	-4.98	-9.26	-.01	-.41	.48

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Hypothesis Testing - MYR3 & MYR10 Holding Strategies

This table presents results from the hypothesis testing for MYR3 and MYR10 holding strategies. The null that mean returns (pre and post transaction costs of 0.10%) are less than or equal to zero is tested against the one sided alternative of positive mean returns. Critical values are bootstrapped as returns do not follow a standard t-distribution. This table also shows winning percent (WP) and value-at-risk (VaR) at the 5% and 1% levels. Mean returns and VaR are in percent, and WP is a fraction.

	MA3 Trend								EMA10 Trend							
	Pre Transaction Costs					Post Transaction Costs			Pre Transaction Costs					Post Transaction Costs		
	Mean	t-stat	WP	VaR 5	VaR 1	Mean	t-stat	WP	Mean	t-stat	WP	VaR 5	VaR 1	Mean	t-stat	WP
MYR3 Holding Strategy																
Bull Patterns																
TWS	-.44	-1.49	.48	-7.37	-11.35	-.54	-1.82	.48	-.15	-.86	.52	-6.32	-12.07	-.25	-1.42	.51
TIU	.33*	1.28	.54	-6.34	-15.89	.23	.89	.53	.16*	1.34	.52	-6.10	-13.13	.06	.53	.50
MS	-.23	-1.02	.53	-7.87	-21.89	-.33	-1.46	.52	-.08	-.67	.52	-6.92	-15.36	-.18	-1.51	.50
MD	.26	.51	.52	-7.95	-15.05	.16	.31	.50	.37*	1.60	.56	-5.16	-12.45	.27	1.17	.52
BUC	.47*	1.51	.54	-8.52	-14.05	.37*	1.19	.53	.20*	1.45	.53	-7.34	-14.17	.10	.72	.50
ATS	.04	.33	.51	-6.54	-11.81	-.06	-.48	.49	.04	.62	.51	-6.42	-12.12	-.06	-1	.48
BUML	.21	.86	.52	-7.28	-13.78	.11	.46	.50	-.11	-1	.49	-7.28	-13.79	-.21	-1.89	.45
HP	.64**	2.12	.56	-7.23	-15.74	.54**	1.79	.54	.11	.82	.52	-8.15	-15.24	.01	.07	.49
LEB	.47***	3.25	.53	-6.31	-10.62	.37***	2.55	.51	.14**	1.63	.53	-7.43	-13.23	.04	.42	.51
ML	.41*	1.28	.54	-7.50	-14.57	.31	.97	.52	.30**	2.20	.53	-6.67	-13.12	.20*	1.47	.50
BUSL	.22*	1.42	.49	-5.29	-8.43	.12	.78	.46	.20**	2.16	.51	-5.91	-10.29	.10	1.09	.48
Average Bull	.22	.91	.53	-7.11	-13.93	.12	.47	.51	.11	.84	.52	-6.70	-13.18	.01	-.03	.50
Bear Patterns																
TBC	-.15	-.79	.50	-5.60	-9.99	-.25	-1.31	.47	-.10	-.85	.48	-5.51	-9.53	-.20	-1.68	.46
TID	.12	.70	.51	-5.27	-9.13	.02	.14	.47	.02	.20	.49	-5.32	-9.53	-.08	-.77	.47
ES	.07	.46	.48	-4.65	-8.88	-.03	-.20	.46	.14*	1.46	.51	-5.13	-9.93	.04	.42	.48
ED	.03	.08	.46	-7.37	-9.35	-.07	-.20	.44	.20	.94	.51	-5.88	-13.10	.10	.46	.46
UGTC	.13	.16	.50	-9.35	-9.35	.03	.04	.47	-.18	-.37	.49	-8.44	-9.35	-.28	-.57	.48
BEC	.15	.88	.53	-5.30	-9.97	.05	.28	.51	.03	.40	.51	-5.39	-10.22	-.07	-.75	.48
BTS	-.05	-.49	.48	-5.27	-10.90	-.15	-1.47	.46	.10**	1.66	.50	-5.56	-9.92	.00	-.08	.47
BEML	-.06	-.33	.50	-6.14	-12.84	-.16	-.92	.47	-.07	-.75	.50	-6.23	-13.95	-.17	-1.87	.46
SS	.13	.34	.51	-4.81	-34.54	.03	.08	.49	.11	.58	.51	-6.16	-16.84	.01	.05	.49
LET	.02	.18	.47	-4.91	-9.82	-.08	-.60	.44	.15**	2.18	.50	-5.01	-9.38	.05	.74	.48
BESL	-.20	-.91	.46	-6.62	-12.55	-.30	-1.35	.43	-.29	-2.51	.46	-7.52	-14	-.39	-3.37	.43
Average Bear	.02	.03	.49	-5.94	-12.49	-.08	-.50	.46	.01	.27	.50	-6.01	-11.43	-.09	-.67	.47
Average MYR3	.12	.47	.51	-6.52	-13.21	.02	-.02	.49	.06	.56	.51	-6.36	-12.31	-.04	-.35	.48
MYR10 Holding Strategy																
Bull Patterns																
TWS	.23	.40	.57	-10.19	-22.18	.13	.23	.55	.11	.35	.56	-10.33	-16.90	.01	.02	.54
TIU	.16	.41	.53	-14.06	-23.76	.06	.16	.52	.13	.63	.54	-12.77	-21.19	.03	.15	.53
MS	.20	.49	.61	-13.16	-34.35	.10	.24	.59	-.06	-.30	.56	-13.16	-25.36	-.16	-.77	.55
MD	.34	.39	.61	-12.95	-33.21	.24	.28	.60	.20	.46	.56	-13.43	-23.87	.10	.23	.54
BUC	1.21***	2.37	.61	-13.75	-21.13	1.11**	2.18	.60	.15	.57	.56	-13.79	-27.49	.05	.19	.54
ATS	-.03	-.15	.54	-13.06	-26.71	-.13	-.63	.53	.12	1.18	.54	-11.83	-22.95	.02	.22	.52
BUML	.68*	1.51	.53	-13.06	-23.92	.58	1.29	.52	.20	.90	.52	-13.69	-26.38	.10	.46	.50
HP	.81**	1.88	.55	-11.92	-25.23	.71*	1.65	.54	.53***	2.43	.53	-11.93	-22.80	.43**	1.97	.52
LEB	.20	.69	.55	-12.20	-24.39	.10	.34	.54	.29**	2	.54	-11.21	-23.36	.19*	1.32	.53
ML	.51	.99	.54	-15.67	-29.85	.41	.79	.54	.40*	1.63	.55	-13.31	-27.49	.30	1.23	.53
BUSL	.51**	1.78	.55	-9.12	-21.84	.41*	1.43	.54	.56***	3.21	.55	-10.84	-18.57	.46***	2.63	.53
Average Bull	.44	.98	.56	-12.65	-26.05	.34	.72	.55	.24	1.19	.55	-12.39	-23.30	.14	.70	.53
Bear Patterns																
TBC	-.33	-1.02	.47	-8.49	-14.27	-.43	-1.33	.46	-.33	-1.60	.47	-10.54	-14.27	-.43	-2.07	.46
TID	-.23	-.75	.47	-9.56	-15.87	-.33	-1.08	.46	-.31	-1.70	.47	-9.99	-18.81	-.41	-2.25	.46
ES	-.62	-2.03	.44	-11.33	-23.73	-.72	-2.35	.43	-.06	-.28	.47	-10.32	-20.97	-.16	-.78	.46
ED	-.83	-1.28	.42	-13.68	-24.43	-.93	-1.44	.40	-.12	-.31	.48	-11.64	-27.31	-.22	-.57	.46
UGTC	1.10	.90	.47	-6.64	-6.64	1	.82	.47	.95	1.07	.54	-8.07	-19.12	.85	.95	.53
BEC	.05	.20	.47	-8.98	-15.29	-.05	-.17	.46	-.17	-1.04	.46	-9.84	-16.79	-.27	-1.66	.45
BTS	-.23	-1.27	.47	-9.92	-18.23	-.33	-1.83	.46	-.22	-2.19	.47	-10.26	-17.93	-.32	-3.17	.46
BEML	-.90	-2.86	.45	-11.55	-23.83	-1	-3.18	.43	-.52	-3.11	.47	-11.81	-25.89	-.62	-3.71	.46
SS	.62	1.23	.57	-10.21	-22.53	.52	1.03	.57	.03	.10	.49	-10.45	-22.53	-.07	-.22	.48
LET	-.15	-.69	.46	-8.58	-15.47	-.25	-1.17	.45	-.06	-.50	.47	-8.91	-15.75	-.16	-1.31	.46
BESL	-.76	-1.73	.47	-14.34	-21.28	-.86	-1.96	.45	-.88	-4.19	.45	-13.98	-25.57	-.98	-4.66	.43
Average Bear	-.21	-.85	.47	-10.30	-18.32	-.31	-1.15	.46	-.15	-1.25	.48	-10.53	-20.45	-.25	-1.77	.46
Average MYR10	.11	.07	.52	-11.47	-22.19	.01	-.21	.50	.04	-.03	.51	-11.46	-21.88	-.06	-.54	.50

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Hypothesis Testing - CL3 & CL10 Holding Strategies

This table presents results from the hypothesis testing for CL3 and CL10 holding strategies. The null that mean returns (pre and post transaction costs of 0.10%) are less than or equal to zero is tested against the one sided alternative of positive mean returns. Critical values are bootstrapped as returns do not follow a standard t-distribution. This table also shows winning percent (WP) and value-at-risk (VaR) at the 5% and 1% levels. Mean returns and VaR are in percent, and WP is a fraction.

	MA3 Trend								EMA10 Trend							
	Pre Transaction Costs					Post Transaction Costs			Pre Transaction Costs					Post Transaction Costs		
	Mean	t-stat	WP	VaR 5	VaR 1	Mean	t-stat	WP	Mean	t-stat	WP	VaR 5	VaR 1	Mean	t-stat	WP
								CL3 Holding Strategy								
Bull Patterns																
TWS	-.18	-.83	.54	-4.88	-6.60	-.28	-1.30	.51	.07	.54	.54	-4.45	-7.25	-.03	-.29	.52
TIU	.39**	2.14	.55	-4.84	-9.74	.29*	1.60	.53	.27***	3.12	.52	-4.30	-7.56	.17**	1.97	.50
MS	-.20	-1.31	.50	-5.20	-13.62	-.30	-1.96	.48	-.05	-.58	.50	-4.80	-9.71	-.15	-1.80	.48
MD	.22	.57	.52	-4.34	-9.42	.12	.31	.52	.29*	1.61	.54	-3.68	-7.82	.19	1.06	.53
BUC	.39**	1.80	.55	-5.24	-9.84	.29*	1.34	.53	.18**	1.89	.53	-5.26	-8.37	.08	.86	.50
ATS	.09	1.05	.49	-4.36	-7.91	-.01	-.09	.48	.07*	1.56	.50	-4.39	-8.09	-.03	-.75	.48
BUML	.26*	1.55	.50	-4.77	-8.92	.16	.96	.48	-.02	-.28	.48	-5.11	-8.92	-.12	-1.53	.46
HP	.61***	2.83	.58	-4.82	-11.56	.51***	2.37	.56	.14*	1.51	.52	-5.08	-9.11	.04	.42	.50
LEB	.34***	3.25	.53	-4.74	-7.31	.24	2.30	.51	.12**	2.07	.52	-4.93	-8.19	.02	.31	.50
ML	.26*	1.24	.52	-5.02	-11.86	.16*	.76	.52	.22**	2.23	.52	-4.80	-8.65	.12	1.22	.50
BUSL	.26***	2.15	.48	-3.44	-6.43	.16	1.32	.46	.16***	2.41	.49	-4.09	-7.73	.06	.88	.47
Average Bull	.22	1.31	.52	-4.70	-9.39	.12	.69	.51	.13	1.46	.51	-4.63	-8.31	.03	.21	.49
Bear Patterns																
TBC	-.09	-.68	.51	-4.20	-7.33	-.19	-1.40	.50	-.02	-.21	.50	-3.90	-7.18	-.12	-1.33	.48
TID	.02	.17	.49	-3.50	-6.60	-.08	-.67	.47	-.05	-.67	.48	-3.64	-7.58	-.15	-2.09	.46
ES	.08	.65	.49	-3.46	-8.08	-.02	-.19	.47	.12**	1.72	.52	-3.76	-6.99	.02	.28	.50
ED	-.12	-.42	.47	-5.41	-8.80	-.22	-.77	.45	.09	.60	.51	-4.72	-9.60	-.01	-.05	.49
UGTC	-.04	-.06	.42	-7.35	-7.35	-.14	-.23	.42	.14	.40	.52	-5.45	-7.35	.04	.12	.52
BEC	.16*	1.35	.55	-3.60	-7.16	.06	.48	.54	.02	.31	.51	-3.75	-7.11	-.08	-1.34	.49
BTS	-.04	-.52	.49	-3.53	-8.45	-.14	-1.90	.47	.05	1.25	.50	-3.83	-7.56	-.05	-1.23	.48
BEML	.06	.51	.54	-3.87	-7.53	-.04	-.35	.51	-.07	-1.05	.52	-4.41	-9.52	-.17	-2.61	.49
SS	.10	.37	.52	-3.92	-26.29	.00	.01	.51	.09	.64	.53	-3.97	-9.88	-.01	-.11	.51
LET	-.07	-.77	.50	-3.56	-6.95	-.17	-1.95	.48	.03	.55	.50	-3.63	-6.45	-.07	-1.56	.48
BESL	-.13	-.83	.51	-4.92	-10.36	-.23	-1.46	.49	-.20	-2.46	.47	-5.08	-10.85	-.30	-3.69	.45
Average Bear	-.01	-.02	.50	-4.30	-9.54	-.11	-.77	.48	.02	.10	.51	-4.20	-8.19	-.08	-1.24	.49
Average CL3	.11	.65	.51	-4.50	-9.46	.01	-.04	.49	.07	.78	.51	-4.41	-8.25	-.03	-.51	.49
								CL10 Holding Strategy								
Bull Patterns																
TWS	-.07	-.22	.54	-7.42	-10.87	-.17	-.52	.51	.11	.63	.54	-5.87	-10.46	.01	.08	.52
TIU	.22	.77	.52	-8.49	-16.19	.12	.42	.50	.21*	1.54	.51	-7.29	-13.65	.11	.80	.50
MS	.23	.98	.58	-7.89	-18.27	.13	.55	.56	.14	1.15	.54	-7.72	-14.24	.04	.35	.53
MD	.46	.79	.56	-8.30	-14.66	.36	.62	.56	.49**	1.83	.55	-5.65	-13.40	.39*	1.46	.53
BUC	.82***	2.61	.58	-6.46	-13.15	.72**	2.29	.57	.40***	2.54	.54	-7.82	-13.71	.30**	1.90	.53
ATS	.23**	1.68	.52	-7.44	-13.75	.13	.94	.51	.21***	3.16	.52	-7.04	-12.79	.11**	1.67	.51
BUML	.59***	2.14	.53	-6.73	-10.75	.49**	1.78	.53	.24*	1.52	.50	-7.86	-13.81	.14	.89	.49
HP	.76***	2.55	.53	-6.74	-13.15	.66**	2.21	.52	.42***	2.90	.52	-7.86	-13.15	.32**	2.21	.51
LEB	.38**	2.38	.54	-7.55	-10.63	.28**	1.75	.53	.30***	3.33	.53	-7.20	-13.11	.20***	2.22	.52
ML	.68**	2	.56	-9.48	-16.68	.58**	1.71	.56	.61***	4.16	.55	-6.67	-14.15	.51***	3.48	.54
BUSL	.43**	2.27	.52	-5.50	-12.14	.33**	1.74	.51	.49***	4.08	.52	-6.23	-11.03	.39***	3.25	.51
Average Bull	.43	1.63	.54	-7.45	-13.66	.33	1.23	.53	.33	2.44	.53	-7.02	-13.05	.23	1.67	.52
Bear Patterns																
TBC	-.16	-.81	.49	-6.08	-9.63	-.26	-1.31	.48	-.24	-1.88	.48	-6.22	-10.67	-.34	-2.66	.46
TID	-.19	-1.01	.49	-5.80	-10.37	-.29	-1.53	.48	-.22	-1.94	.48	-6.03	-12.03	-.32	-2.81	.47
ES	-.18	-.91	.48	-6.89	-15.14	-.28	-1.43	.46	.01	.09	.49	-6.62	-13.41	-.09	-.78	.48
ED	-.44	-1.11	.41	-7.59	-10.39	-.54	-1.36	.40	.06	.24	.49	-7.12	-12.48	-.04	-.19	.48
UGTC	.27	.32	.53	-8.63	-8.63	.17	.20	.53	.47	.93	.53	-5.53	-10.18	.37	.73	.53
BEC	.10	.61	.52	-5.80	-9.13	.00	.01	.51	-.11	-1.13	.49	-6.22	-10.94	-.21	-2.16	.47
BTS	-.18	-1.63	.49	-6.31	-12.97	-.28	-2.52	.47	-.17	-2.66	.49	-6.68	-11.72	-.27	-4.22	.48
BEML	-.48	-2.39	.48	-7.01	-17.18	-.58	-2.90	.45	-.39	-3.70	.48	-7.41	-15.74	-.49	-4.66	.46
SS	.21	.49	.55	-5.63	-15.80	.11	.26	.51	-.09	-.43	.50	-6.10	-15.80	-.19	-.90	.48
LET	-.14	-1.03	.45	-5.41	-11.74	-.24	-1.76	.44	-.10	-1.30	.48	-5.86	-10.68	-.20	-2.60	.46
BESL	-.44	-1.57	.49	-9.17	-13.92	-.54	-1.93	.48	-.70	-5.31	.46	-9.52	-18.97	-.80	-6.07	.45
Average Bear	-.15	-.82	.49	-6.76	-12.26	-.25	-1.30	.47	-.14	-1.55	.49	-6.66	-12.96	-.24	-2.39	.47
Average CL10	.14	.41	.52	-7.11	-12.96	.04	-.04	.50	.10	.44	.51	-6.84	-13.01	.00	-.36	.50

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Factor Analysis - MYR1 & MYR2 Holding Strategies

This table shows the results from the one-factor (CAPM) and four-factor (Fama-French-Carhart) analyses for MYR1 and MYR2 holding strategies. Daily strategy excess returns are regressed on corresponding daily factors using a pooled OLS approach. The excess returns are net of transaction costs of 0.10%. The sample stretches over the period January 2000-December 2015. Averages for bull and bear patterns and for each holding strategy are equally weighted. The alphas are daily and in percent.

	MA3 Trend									EMA10 Trend								
	CAPM			FFC 4 Factors						CAPM			FFC 4 Factors					
	α	β_{Mkt}	R^2	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}	R^2	α	β_{Mkt}	R^2	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}	R^2
MYR1 Holding Strategy																		
Bull Patterns																		
TWS	-.20	.57***	.12	-.21	.53***	-.05	.09	-.07	.12	-.05	.37***	.06	-.06	.32***	-.25*	-.07	-.20*	.08
TIU	-.12	.60***	.09	-.14	.61***	.07	.27	.01	.10	.03	.59***	.11	.02	.56***	.25**	.22*	-.08	.12
MS	-.53	.37***	.04	-.51	.49***	-.20	-.14	.46***	.09	-.30	.42***	.05	-.30	.47***	-.01	-.05	.21**	.06
MD	-.23	.77***	.09	-.15	.42	1.34*	.18	-.13	.15	-.10	.28**	.02	-.10	.31**	.20	.14	.09	.03
BUC	-.06	.48***	.08	-.03	.48***	.32	.24	-.23	.10	-.12	.46***	.08	-.13	.48***	.28**	.27**	-.03	.09
ATS	-.16	.42***	.05	-.18	.42***	.07	.06	.08	.05	-.12	.44***	.06	-.13	.42***	.15**	.16***	.02	.06
BUML	.04	.48***	.07	.06	.40***	.41	-.07	-.26	.08	-.18	.39***	.04	-.18	.34***	.22	-.19	-.16	.05
HP	.20	.57***	.08	.17	.61***	.10	.18	.18	.09	-.13	.41***	.06	-.13	.42***	.09	-.09	.05	.06
LEB	-.10	.40***	.07	-.12	.36***	.18	.28*	.02	.08	-.21	.46***	.08	-.21	.46***	.00	.11	.04	.08
ML	.04	.47***	.05	.04	.45**	.03	.67**	.25	.07	-.13	.35***	.03	-.14	.34***	.15	.25	.06	.03
BUSL	.02	.51***	.05	.01	.47***	.07	.37**	-.10	.06	-.12	.41***	.03	-.12	.38***	.03	.16	-.07	.04
Average Bull	-.10	.51	.07	-.10	.48	.21	.19	.02	.09	-.13	.42	.06	-.13	.41	.10	.08	-.01	.06
Bear Patterns																		
TBC	.02	-.66***	.15	.01	-.68***	.07	-.58***	-.09	.18	.12*	-.69	.15	.13*	-.63	-.19	-.17	.15	.16
TID	.08	-.48***	.06	.08	-.47***	-.19	-.19	-.13	.07	.01	-.47***	.07	.01	-.47***	-.19*	-.10	-.08	.08
ES	-.04	-.57***	.12	-.04	-.55***	.00	.11	.06	.12	.02	-.51***	.10	.02	-.47***	-.11	.06	.09	.10
ED	.07	-.34	.03	.01	-.24	.12	.12	.24	.04	.11	-.45***	.07	.08	-.42***	.13	-.20	.10	.07
UGTC	-.63	-1.04**	.12	-.82	-.79	-.26	.70	.93	.21	.28	-.13	.01	.27	-.23	-.44	-.53	.01	.06
BEC	.05	-.29**	.02	.06	-.18	-.02	.04	.27*	.03	-.06	-.31***	.03	-.06	-.24***	-.03	-.11	.14**	.03
BTS	.00	-.51***	.08	.00	-.50***	-.14	-.16	-.08	.08	.02	-.49***	.10	.02	-.49***	-.09	-.13**	-.04	.10
BEML	.06	-.15	.00	.06	-.12	-.22	-.03	-.03	.01	-.06	-.30***	.02	-.06	-.32***	.05	-.10	-.05	.02
SS	.30*	-.62**	.08	.34*	-.69	.10	.72*	.08	.11	.14	-.44***	.04	.14	-.47***	.02	.29*	.04	.04
LET	-.14	-.53***	.10	-.12	-.50***	-.03	-.28	.10	.12	-.11	-.44***	.08	-.10	-.43***	-.04	-.16**	.04	.08
BESL	-.02	-.22*	.01	-.02	-.21*	-.14	-.35*	.02	.02	-.11	-.27***	.02	-.11	-.26***	.03	-.11	.04	.02
Average Bear	-.02	-.49	.07	-.04	-.45	-.06	.01	.13	.09	.03	-.41	.06	.03	-.40	-.08	-.12	.04	.07
Average MYR1	-.06	.01	.07	-.07	.01	.07	.10	.07	.09	-.05	.00	.06	-.05	.00	.01	-.02	.02	.07
MYR2 Holding Strategy																		
Bull Patterns																		
TWS	-.21	.53***	.10	-.25	.52***	-.05	.28	.00	.11	-.02	.47***	.08	-.04	.42***	-.36***	-.05	-.26***	.11
TIU	.03	.66***	.12	.01	.60***	.14	.20	-.12	.12	.03	.66***	.13	.03	.59***	.14*	.05	-.18***	.13
MS	-.19	.65***	.16	-.16	.71***	-.26	-.19	.20	.17	-.10	.64***	.16	-.10	.68***	-.09	-.04	.12	.16
MD	.20	.65**	.10	.21	.60**	.18	-.34	-.04	.11	.11	.44***	.05	.12	.45***	-.05	-.01	.03	.05
BUC	.03	.53***	.10	.03	.55***	.20	.35*	.00	.12	-.05	.51***	.08	-.06	.50***	.24**	.24**	-.07	.08
ATS	-.06	.56***	.08	-.07	.58***	.01	-.01	.08	.08	-.05	.54***	.09	-.06	.53***	.06	.07	.02	.09
BUML	-.06	.43***	.05	-.06	.40***	-.12	.04	-.15	.06	-.12	.34***	.03	-.12	.32***	.11	-.03	-.05	.03
HP	.14	.71***	.13	.13	.72***	-.09	-.02	.07	.14	.01	.56***	.11	.01	.57***	.02	-.03	.01	.11
LEB	.06	.50***	.10	.05	.49***	-.12	.33***	.03	.11	-.05	.56***	.11	-.06	.57***	-.07	.14**	.04	.11
ML	-.02	.54***	.06	-.03	.58***	-.08	.26	.22	.06	-.01	.44***	.03	-.02	.43***	.23*	.11	.05	.04
BUSL	.06	.44***	.04	.05	.37***	.14	.12	-.11	.04	.00	.37***	.03	-.01	.33***	.14**	.12	-.08*	.03
Average Bull	.00	.56	.10	-.01	.56	-.01	.09	.01	.10	-.02	.50	.08	-.03	.49	.03	.05	-.03	.09
Bear Patterns																		
TBC	-.07	-.55***	.09	-.08	-.53***	.08	-.30*	.10	.11	-.01	-.62***	.12	-.01	-.57***	.00	.03	.24***	.13
TID	-.10	-.58***	.09	-.10	-.51***	-.27	-.27*	-.01	.10	-.04	-.52***	.08	-.04	-.49***	-.19**	-.21***	.01	.09
ES	.03	-.44***	.08	.03	-.36***	-.17	.07	.16*	.08	.03	-.50***	.08	.03	-.46***	-.16*	.06	.09	.09
ED	-.13	-.50***	.06	-.14	-.53***	.18	.07	-.02	.06	.00	-.50***	.05	-.01	-.40***	-.09	-.01	.25	.06
UGTC	.15	-1.85***	.22	.15	-1.95***	1	-.32	.21	.25	.14	-.38	.03	.10	-.52***	-.07	-.61	-.04	.06
BEC	.03	-.32***	.02	.03	-.25***	-.07	.13	.16	.03	-.03	-.35***	.03	-.03	-.31***	-.04	-.06	.09*	.03
BTS	-.06	-.48***	.06	-.06	-.46***	-.09	-.13	-.01	.07	.01	-.47***	.08	.01	-.44***	-.10*	-.07	.05*	.08
BEML	.06	-.29***	.02	.07	-.19**	-.36**	.02	.11	.02	-.05	-.37***	.03	-.05	-.38***	-.05	-.10	-.06	.03
SS	-.13	-.57***	.06	-.11	-.72***	.09	.44	-.12	.07	-.03	-.56***	.06	-.03	-.61***	.11	.18	-.02	.06
LET	-.07	-.44***	.05	-.07	-.40***	-.02	-.10	.10	.06	-.03	-.43***	.07	-.03	-.42***	-.03	-.12**	.03	.07
BESL	-.08	-.47***	.06	-.08	-.44***	-.09	.01	.10	.06	-.09	-.31***	.02	-.09	-.28***	-.11	.04	.09	.02
Average Bear	-.03	-.59	.07	-.03	-.58	.03	-.04	.07	.08	-.01	-.46	.06	-.01	-.44	-.06	-.08	.07	.07
Average MYR2	-.02	-.01	.08	-.02	-.01	.01	.03	.04	.09	-.02	.02	.07	-.02	.02	-.02	-.01	.02	.08

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Factor Analysis - MYR3 & MYR10 Holding Strategies

This table shows the results from the one-factor (CAPM) and four-factor (Fama-French-Carhart) analyses for MYR3 and MYR10 holding strategies. Daily strategy excess returns are regressed on corresponding daily factors using a pooled OLS approach. The excess returns are net of transaction costs of 0.10%. The sample stretches over the period January 2000-December 2015. Averages for bull and bear patterns and for each holding strategy are equally weighted. The alphas are daily and in percent.

	MA3 Trend									EMA10 Trend								
	CAPM			FFC 4 Factors						CAPM			FFC 4 Factors					
	α	β_{Mkt}	R^2	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}	R^2	α	β_{Mkt}	R^2	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}	R^2
MYR3 Holding Strategy																		
Bull Patterns																		
TWS	-.17	.48***	.14	-.19	.42***	.09	.29	.01	.14	-.09	.50***	.11	-.11	.43***	-.27**	.05	-.25***	.13
TIU	.01	.65***	.11	-.01	.61***	.06	.26*	-.09	.11	.00	.63***	.11	.00	.59***	.02	.09	-.15***	.12
MS	-.17	.54***	.10	-.18	.59***	-.34**	.04	.13	.11	-.08	.57***	.12	-.09	.60***	-.18***	.07	.06	.12
MD	.05	.54**	.07	.07	.50**	.10	-.06	-.31	.08	.07	.52***	.06	.07	.51***	-.18	-.09	-.08	.06
BUC	.06	.55***	.11	.06	.54***	.06	.20	-.06	.11	-.01	.53***	.08	-.01	.53***	.12	.17*	-.02	.08
ATS	-.07	.57***	.09	-.07	.58***	-.01	.06	.06	.09	-.03	.55***	.09	-.03	.54***	.07*	.12***	-.02	.09
BUML	-.01	.34***	.03	-.01	.33***	-.11	.15	-.05	.03	-.09	.36***	.03	-.09	.34***	.12	.02	-.03	.03
HP	.17*	.68***	.11	.16*	.68***	-.06	-.01	.00	.11	.00	.59***	.11	.00	.58***	.00	-.02	-.04	.11
LEB	.07	.52***	.11	.06	.52***	-.08	.40***	.05	.13	-.03	.58***	.12	-.04	.60***	-.02	.22***	.08**	.12
ML	.04	.54***	.06	.03	.57***	-.13	.18	.12	.07	.02	.41***	.03	.01	.41***	.23**	.16	.04	.04
BUSL	.02	.44***	.04	.01	.37***	.21*	.09	-.13*	.05	.03	.36***	.02	.03	.32***	.13**	.11*	-.08*	.02
Average Bull	.00	.53	.09	-.01	.52	-.02	.15	-.02	.09	-.02	.51	.08	-.02	.49	.00	.08	-.04	.08
Bear Patterns																		
TBC	-.06	-.63***	.13	-.06	-.60***	-.04	-.32**	.04	.14	-.04	-.57***	.11	-.04	-.53***	-.03	-.02	.17***	.12
TID	.00	-.57***	.09	.01	-.50***	-.30*	-.23**	.05	.10	.01	-.54***	.09	.01	-.52***	-.15*	-.19***	.03	.10
ES	.00	-.42***	.07	.00	-.37***	-.06	-.05	.12	.07	.01	-.53***	.08	.01	-.50***	-.08	.07	.08	.09
ED	.01	-.42***	.05	.02	-.52***	.31	-.06	-.15	.05	.04	-.47***	.05	.03	-.39***	-.04	.13	.23*	.05
UGTC	.13	-1.63***	.18	-.21	-1.46***	.34	.88	1.08*	.31	-.05	-.47**	.05	-.07	-.54**	-.04	-.52	.09	.07
BEC	.01	-.35***	.03	.01	-.30***	-.04	.20	.13	.03	-.02	-.37***	.03	-.02	-.31***	-.07	.01	.16***	.04
BTS	-.04	-.57***	.09	-.04	-.51***	-.12	-.10	.11**	.09	.00	-.51***	.09	.00	-.47***	-.11***	-.09*	.11***	.09
BEML	-.05	-.27***	.01	-.05	-.18***	-.37***	.05	.09	.02	-.06	-.37***	.02	-.05	-.36***	-.10	-.09	-.03	.03
SS	.03	-.40***	.04	.05	-.44***	-.16	.24	-.06	.04	.01	-.54***	.06	.01	-.52***	-.12	.08	.02	.06
LET	-.01	-.48***	.05	-.01	-.44***	.00	-.04	.16**	.06	.01	-.43***	.06	.01	-.43***	.11*	-.09*	.06**	.06
BESL	-.09	-.54***	.07	-.08	-.54***	.15	.09	.10	.07	-.12	-.37***	.03	-.12	-.36***	-.08	.00	.05	.03
Average Bear	-.01	-.57	.07	-.03	-.53	-.03	.06	.15	.09	-.02	-.47	.06	-.02	-.45	-.07	-.06	.09	.07
Average MYR3	.00	-.02	.08	-.02	-.01	-.02	.10	.06	.09	-.02	.02	.07	-.02	.02	-.03	.01	.02	.08
MYR10 Holding Strategy																		
Bull Patterns																		
TWS	.02	.51***	.11	.01	.48***	.03	.24**	-.03	.12	-.03	.47***	.09	-.03	.43***	-.03	.12**	-.09**	.09
TIU	-.01	.62***	.11	-.01	.61***	-.02	.01	-.08	.11	-.01	.59***	.09	.00	.56***	-.01	.00	-.10***	.10
MS	-.03	.55***	.10	-.03	.55***	-.07	.01	-.03	.10	-.03	.56***	.10	-.03	.55***	-.06	.01	-.05*	.10
MD	.00	.57***	.07	.01	.56***	.08	.17	-.19	.08	.00	.49***	.06	.00	.48***	.13	.13	-.02	.06
BUC	.07	.51***	.08	.07	.49***	.06	.27***	-.10	.09	-.01	.49***	.06	-.01	.50***	.05	.20***	-.01	.06
ATS	-.04	.60***	.10	-.03	.59***	.00	-.03	-.05*	.10	-.01	.55***	.09	-.01	.53***	.06**	.02	-.07***	.09
BUML	.02	.41***	.04	.02	.40***	-.06	-.08	-.05	.04	.01	.45***	.04	.01	.44***	.03	.05	-.04	.04
HP	.02	.62***	.10	.03	.59***	-.01	-.22**	-.14**	.10	.01	.56***	.10	.01	.53***	.06	-.06	-.10***	.10
LEB	-.02	.62***	.12	-.02	.60***	-.05	.15**	-.07	.12	-.02	.61***	.12	-.02	.61***	-.05	.11***	.01	.12
ML	-.02	.53***	.07	-.02	.52***	-.03	-.02	-.04	.07	-.01	.43***	.04	-.01	.42***	.16***	.12**	.00	.04
BUSL	.02	.40***	.03	.01	.36***	.13**	.11*	-.06	.04	.03	.45***	.03	.03	.42***	.13***	.14***	-.03	.03
Average Bull	.00	.54	.09	.00	.52	.00	.06	-.08	.09	-.01	.51	.07	-.01	.50	.04	.08	-.04	.08
Bear Patterns																		
TBC	-.02	-.60***	.12	-.02	-.56***	-.05	-.14*	.15***	.13	-.02	-.56***	.10	-.03	-.52***	-.06	-.01	.19***	.11
TID	-.03	-.54***	.08	-.03	-.52***	-.29***	.03	.01	.09	-.03	-.51***	.08	-.03	-.50***	-.10**	-.08*	.00	.08
ES	-.05	-.54***	.10	-.05	-.43***	-.31***	-.34***	.14**	.12	-.01	-.56***	.08	-.01	-.51***	-.15***	-.06	.09***	.08
ED	-.08	-.46***	.06	-.09	-.40***	-.11	-.08	.13	.06	-.04	-.47***	.05	-.04	-.41***	-.17**	.03	.14**	.06
UGTC	.10	-.59***	.06	.05	-.45***	.15	.27	.37	.09	.07	-.36***	.04	.08	-.42***	.10	-.10	-.16	.05
BEC	-.02	-.39***	.04	-.02	-.34***	-.13*	-.04	.12***	.04	-.03	-.42***	.04	-.03	-.37***	-.19***	-.08**	.11***	.04
BTS	-.01	-.56***	.09	-.02	-.52***	-.11**	-.13**	.09**	.09	-.02	-.54***	.09	-.02	-.51***	-.05*	-.12***	.07***	.09
BEML	-.09	-.42***	.03	-.08	-.40***	-.15**	-.18***	.04	.04	-.06	-.42***	.03	-.05	-.40***	-.10***	-.15***	-.01	.03
SS	.02	-.55***	.08	.02	-.47***	-.24*	-.25*	.08	.08	-.01	-.54***	.06	-.01	-.52***	-.13*	-.04	.02	.06
LET	-.01	-.54***	.07	-.01	-.51***	-.04	-.01	.10***	.07	-.01	-.52***	.08	-.01	-.49***	-.08**	-.07**	.06***	.08
BESL	-.05	-.61***	.08	-.06	-.57***	.08	.17*	.15***	.08	-.08	-.46***	.04	-.09	-.44***	-.07	-.01	.06**	.04
Average Bear	-.02	-.53	.07	-.03	-.47	-.11	-.06	.13	.08	-.02	-.49	.06	-.02	-.46	-.09	-.06	.05	.07
Average MYR10	-.01	.01	.08	-.01	.03	-.05	.00	.02	.08	-.01	.01	.07	-.01	.02	-.02	.01	.00	.07

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Factor Analysis - CL3 & CL10 Holding Strategies

This table shows the results from the one-factor (CAPM) and four-factor (Fama-French-Carhart) analyses for CL3 and CL10 holding strategies. Daily strategy excess returns are regressed on corresponding daily factors using a pooled OLS approach. The excess returns are net of transaction costs of 0.10%. The sample stretches over the period January 2000-December 2015. Averages for bull and bear patterns and for each holding strategy are equally weighted. The alphas are daily and in percent.

	MA3 Trend									EMA10 Trend								
	CAPM			FFC 4 Factors						CAPM			FFC 4 Factors					
	α	β_{Mkt}	R^2	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}	R^2	α	β_{Mkt}	R^2	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}	R^2
							CL3 Holding Strategy											
Bull Patterns																		
TWS	-.11	.26***	.08	-.11	.23***	.02	.07	-.04	.09	-.02	.29***	.08	-.03	.24***	-.18**	-.04	-.18***	.10
TIU	.05	.45***	.10	.04	.42***	.04	.13	-.06	.10	.04	.44***	.10	.04	.40***	.06	.06	-.11***	.11
MS	-.14	.36***	.09	-.15	.40***	-.19*	-.04	.13	.10	-.07	.38***	.10	-.07	.40***	-.08	.02	.06	.10
MD	.04	.42***	.08	.05	.38**	.13	-.07	-.12	.08	.05	.31***	.05	.05	.31***	-.06	-.02	-.02	.05
BUC	.05	.36***	.09	.06	.36***	.07	.15	-.03	.09	-.01	.34***	.07	-.01	.34***	.12*	.13**	-.03	.07
ATS	-.03	.36***	.07	-.04	.37***	.00	.03	.05*	.07	-.02	.35***	.07	-.02	.35***	.05**	.08***	.00	.07
BUML	.01	.27***	.04	.02	.25***	.02	.10	-.07	.04	-.06	.24***	.03	-.05	.23***	.10	-.01	-.04	.03
HP	.15**	.46***	.10	.14**	.47***	-.04	-.01	.04	.11	.00	.38***	.09	.00	.37***	.01	-.03	-.01	.09
LEB	.04	.33***	.09	.03	.33***	-.04	.25***	.04	.10	-.03	.36***	.09	-.03	.37***	-.03	.12***	.04*	.10
ML	.02	.36***	.06	.01	.37***	-.04	.16	.10	.07	.01	.28***	.03	.00	.27***	.17**	.10	.03	.03
BUSL	.03	.31***	.03	.03	.26***	.11	.08	-.08*	.04	.01	.25***	.02	.01	.22***	.08**	.08*	-.06**	.02
Average Bull	.01	.36	.08	.01	.35	.01	.08	.00	.08	-.01	.33	.07	-.01	.32	.02	.04	-.03	.07
Bear Patterns																		
TBC	-.05	-.40***	.10	-.05	-.38***	-.03	-.24**	.03	.11	-.02	-.39***	.10	-.02	-.36***	-.06	-.01	.13***	.11
TID	-.04	-.35***	.07	-.03	-.31***	-.19**	-.15*	.00	.08	-.03	-.34***	.07	-.03	-.32***	-.13**	-.12**	.01	.08
ES	.00	-.31***	.07	-.01	-.26***	-.03	-.01	.12**	.07	.00	-.35***	.08	.00	-.32***	-.07	.04	.06	.08
ED	-.03	-.28***	.04	-.04	-.30***	.16	.02	.01	.04	.01	-.34***	.05	-.01	-.27***	.01	.05	.18*	.05
UGTC	.02	-1.00***	.15	-.13	-.95***	.30	.43	.47	.22	.04	-.25	.03	.03	-.31***	-.11	-.40	.02	.05
BEC	.01	-.21***	.02	.01	-.16***	-.04	.11	.11*	.02	-.03	-.23***	.03	-.03	-.20***	-.03	-.02	.09***	.03
BTS	-.05	-.35***	.07	-.05	-.32***	-.09	-.09	.04	.07	-.02	-.33***	.08	-.02	-.31***	-.06*	-.06**	.05***	.08
BEML	-.01	-.17***	.01	-.01	-.12**	-.23***	.01	.06	.02	-.06	-.24***	.02	-.05	-.24***	-.04	-.06	-.02	.02
SS	.01	-.29***	.03	.02	-.33***	.02	.21	-.03	.04	-.01	-.36***	.05	-.01	-.36***	-.01	.08	.00	.05
LET	-.04	-.33***	.06	-.04	-.31***	.01	-.07	.10**	.06	-.03	-.29***	.06	-.03	-.28***	.03	-.07*	.04*	.06
BESL	-.07	-.31***	.05	-.07	-.29***	.00	.01	.07	.05	-.10	-.23***	.02	-.10	-.21***	-.05	.00	.05	.02
Average Bear	-.02	-.36	.06	-.04	-.34	-.01	.02	.09	.07	-.02	-.30	.05	-.02	-.29	-.05	-.05	.06	.06
Average CL3	-.01	.00	.07	-.01	.01	.00	.05	.04	.08	-.02	.01	.06	-.02	.01	-.01	.00	.01	.06
							CL10 Holding Strategy											
Bull Patterns																		
TWS	-.02	.30***	.11	-.03	.28***	.04	.17***	.00	.12	-.02	.28***	.08	-.02	.25***	-.04	.06	-.07**	.09
TIU	-.01	.37***	.09	-.01	.36***	.00	.05	-.04	.09	.00	.34***	.08	.00	.32***	.01	.02	-.07***	.09
MS	-.01	.32***	.08	-.02	.33***	-.14***	-.05	.03	.09	-.01	.32***	.09	-.01	.32***	-.08***	-.02	.00	.09
MD	.01	.34***	.07	.02	.34***	.04	.07	-.14	.07	.03	.28***	.05	.03	.28***	.03	.04	-.02	.05
BUC	.04	.30***	.07	.05	.29***	.00	.18***	-.06	.08	.02	.29***	.05	.02	.29***	.03	.10***	-.02	.06
ATS	-.01	.32***	.08	-.01	.32***	-.01	.02	.00	.08	-.01	.30***	.07	-.01	.29***	.03**	.04**	-.02*	.07
BUML	.02	.22***	.03	.02	.22***	-.03	-.01	-.02	.03	.01	.24***	.03	.01	.23***	.05	.03	-.02	.03
HP	.04	.38***	.09	.04	.38***	-.08	-.09	-.04	.09	.01	.32***	.09	.01	.32***	.00	-.03	-.03*	.09
LEB	.01	.32***	.09	.01	.31***	-.01	.14***	-.02	.10	.00	.33***	.09	-.01	.33***	-.02	.08***	.01	.10
ML	.02	.31***	.06	.02	.31***	-.08	.01	.00	.06	.03	.24***	.03	.02	.24***	.09**	.08**	.02	.03
BUSL	.01	.22***	.03	.01	.19***	.11***	.07	-.06**	.03	.03**	.23***	.02	.02**	.22***	.06***	.07***	-.02	.02
Average Bull	.01	.31	.07	.01	.30	-.01	.05	-.03	.08	.01	.29	.06	.01	.28	.02	.04	-.02	.06
Bear Patterns																		
TBC	-.01	-.33***	.09	-.01	-.31***	-.01	-.09*	.07*	.10	-.02	-.31***	.08	-.03	-.29***	-.03	.00	.11***	.09
TID	-.03	-.29***	.07	-.03	-.27***	-.16***	-.02	.00	.07	-.03	-.27***	.06	-.02	-.26***	-.10***	-.06**	.00	.07
ES	-.02	-.27***	.07	-.02	-.22***	-.17***	-.10**	.06**	.08	-.01	-.30***	.07	-.01	-.28***	-.08***	-.01	.04**	.07
ED	-.04	-.24***	.04	-.04	-.23***	-.03	.00	.01	.04	-.01	-.24***	.04	-.01	-.21***	-.09**	.00	.06*	.04
UGTC	.01	-.43***	.06	-.03	-.34***	.07	.09	.28	.08	.03	-.20***	.03	.04	-.23***	.01	-.06	-.11	.04
BEC	-.01	-.22***	.03	-.01	-.19***	-.07*	.01	.07**	.03	-.02	-.22***	.03	-.02	-.20***	-.08***	-.02	.06***	.03
BTS	-.02	-.31***	.07	-.02	-.28***	-.08***	-.06**	.04**	.07	-.02	-.29***	.07	-.02	-.27***	-.05***	-.06***	.04***	.08
BEML	-.05	-.20***	.02	-.04	-.17***	-.13***	-.06	.05*	.02	-.05	-.21***	.02	-.05	-.21***	-.06***	-.07***	.00	.02
SS	.00	-.23***	.03	.00	-.24***	-.10	-.01	-.03	.03	-.02	-.29***	.04	-.02	-.27***	-.08*	.01	.03	.04
LET	-.02	-.29***	.05	-.02	-.27***	-.02	-.02	.08***	.05	-.02	-.27***	.06	-.02	-.25***	-.04*	-.04*	.05***	.06
BESL	-.04	-.32***	.06	-.05	-.29***	.00	.08	.09**	.06	-.08	-.24***	.03	-.08	-.23***	-.07**	-.01	.04**	.03
Average Bear	-.02	-.29	.05	-.02	-.26	-.06	-.02	.07	.06	-.02	-.26	.05	-.02	-.24	-.06	-.03	.03	.05
Average CL10	-.01	.01	.06	-.01	.02	-.04	.02	.02	.07	-.01	.01	.06	-.01	.02	-.02	.01	.00	.06

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Factor Analysis Summary - Candlestick Pattern Averages

This table summarises the results of the one-factor (CAPM) and four-factor (Fama-French-Carhart) analyses in Table 5, Table 6 and Table 7 by showing equally weighted averages for each candlestick pattern across both trend definitions and all six holding strategies. Averages for bull and bear patterns are equally weighted as well. Alphas are daily and in percent. The sample consists of 72 stocks listed on the Stockholm Stock Exchange over the period January 2000-December 2015.

	CAPM			FFC 4 Factors					
	α	β_{Mkt}	R^2	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}	R^2
Bull Patterns									
TWS	-.08	.42	.10	-.09	.38	-.09	.10	-.10	.11
TIU	.00	.55	.10	.00	.52	.06	.11	-.09	.11
MS	-.14	.47	.10	-.14	.51	-.14	-.03	.11	.11
MD	.02	.47	.06	.03	.43	.16	.01	-.08	.07
BUC	.00	.45	.08	.00	.44	.13	.21	-.05	.09
ATS	-.05	.46	.08	-.05	.46	.04	.05	.01	.08
BUML	-.04	.35	.04	-.03	.33	.06	.00	-.08	.04
HP	.05	.52	.10	.05	.52	.00	-.04	.00	.10
LEB	-.02	.47	.10	-.03	.46	-.02	.20	.02	.10
ML	.00	.41	.05	-.01	.41	.06	.17	.07	.05
BUSL	.01	.37	.03	.01	.33	.11	.13	-.07	.03
Average Bull	-.02	.45	.08	-.02	.43	.03	.08	-.02	.08
Bear Patterns									
TBC	-.02	-.53	.11	-.02	-.50	-.03	-.15	.11	.12
TID	-.02	-.46	.08	-.02	-.43	-.19	-.13	-.01	.08
ES	.00	-.44	.08	.00	-.39	-.12	-.01	.09	.09
ED	-.01	-.39	.05	-.02	-.36	.03	.01	.10	.05
UGTC	.03	-.70	.08	-.05	-.68	.09	-.01	.26	.13
BEC	-.01	-.31	.03	-.01	-.25	-.07	.02	.12	.03
BTS	-.02	-.45	.08	-.02	-.42	-.09	-.10	.04	.08
BEML	-.03	-.28	.02	-.03	-.26	-.15	-.06	.01	.02
SS	.03	-.45	.05	.03	-.47	-.04	.16	.00	.06
LET	-.04	-.42	.06	-.04	-.39	-.01	-.09	.08	.07
BESL	-.08	-.36	.04	-.08	-.34	-.03	-.01	.07	.04
Average Bear	-.02	-.43	.06	-.02	-.41	-.05	-.04	.08	.07

Table 9: Market Timing Factor Analysis

This table presents regression estimates from the market timing factor analysis for the five combinations that generate positive and statistically significant alphas at the 10% level in Table 5, Table 6 and Table 7. The quadratic market factor is based on Treynor and Mazuy (1966), where a positive and statistically significant quadratic coefficient is interpreted as evidence of successful market timing ability. This factor is added to both the one-factor (CAPM) and four-factor (Fama-French-Carhart) models. Alphas are daily and in percent.

	Candlestick Strategy				
	HP^{MA3}_{MYR3}	HP^{MA3}_{CL3}	$BUSL^{EMA10}_{CL10}$	SS^{MA3}_{MYR1}	TBC^{EMA10}_{MYR1}
CAPM					
α_{Mkt}	.12	.12*	.03**	.43**	.06
β_{Mkt}	.68***	.45***	.23***	-.71***	-.73***
β^2_{Mkt}	.02	.01	.00	-.11	.05*
R^2	.12	.11	.02	.09	.15
Fama-French-Carhart					
α_{FFC}	.12	.12*	.03**	.45**	.04
β_{Mkt}	.68***	.46***	.22***	-.78***	-.68***
β^2_{Mkt}	.02	.01	.00	-.10	.08***
β_{SMB}	-.03	-.02	.06***	.10	-.18*
β_{HML}	.02	.01	.07***	.68*	-.23
β_{UMD}	-.01	.04	-.02	.06	.21**
R^2	.12	.11	.02	.11	.17

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 4: Economic Significance - Cumulative Returns over Full Sample

This figure shows the economic significance of the five combinations that generate positive and statistically significant alphas at the 10% level in Table 5, Table 6 and Table 7, by plotting the cumulative value of strategies that invest in all trading signals generated by these combinations between January 1, 2000 and December 31, 2015. The strategies have a starting value of 100 units and returns are calculated net of transaction costs, so that two-way costs of 0.10% are applied to each trade. The number of trades is 2,050, 803, 378, 387 and 196 for BUSL EMA10 CL10, TBC EMA10 MYR1, HP MA3 MYR1, HP MA3 MYR3 and SS MA3 MYR1, respectively. Performance is benchmarked against expected returns based on four-factor (Fama-French-Carhart) exposures from Table 5, Table 6 and Table 7. The strategies take equally weighted positions on days with multiple active trades and the values are invested at the risk free rate on days with no active trades.

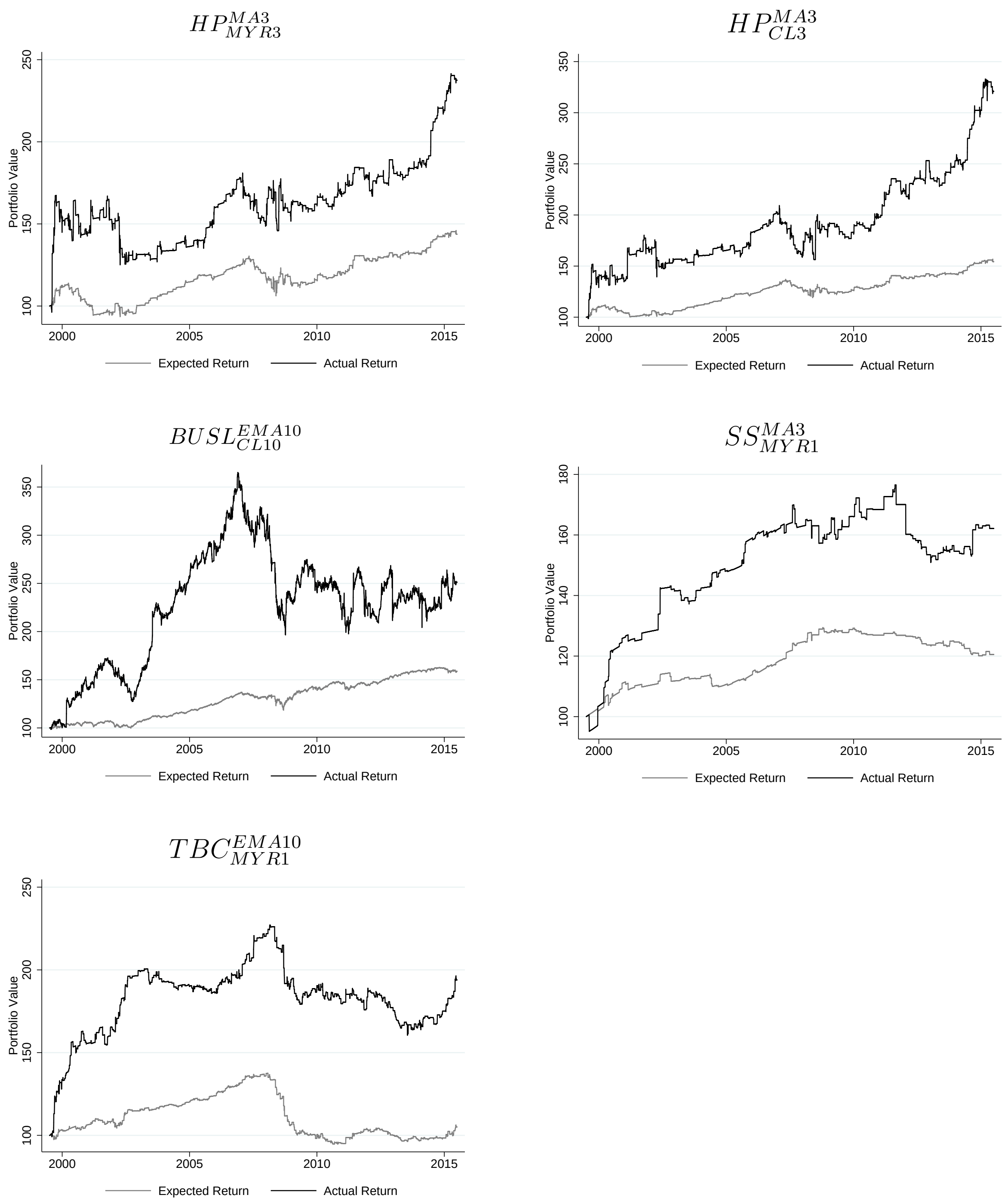

Figure 5: Economic Significance - Yearly Returns over Full Sample

This figure shows the economic significance of the five combinations that generate positive and statistically significant alphas at the 10% level in Table 5, Table 6 and Table 7, by plotting the yearly returns of strategies that invest in all trading signals generated by these combinations between January 1, 2000 and December 31, 2015. Returns are calculated net of transaction costs, so that two-way costs of 0.10% are applied to each trade. The number of trades is 2,050, 803, 378, 387 and 196 for BUSL EMA10 CL10, TBC EMA10 MYR1, HP MA3 MYR1, HP MA3 MYR3 and SS MA3 MYR1, respectively. Performance is benchmarked against expected returns based on four-factor (Fama-French-Carhart) exposures from Table 5, Table 6 and Table 7. The strategies take equally weighted positions on days with multiple active trades and the values are invested at the risk free rate on days with no active trades.

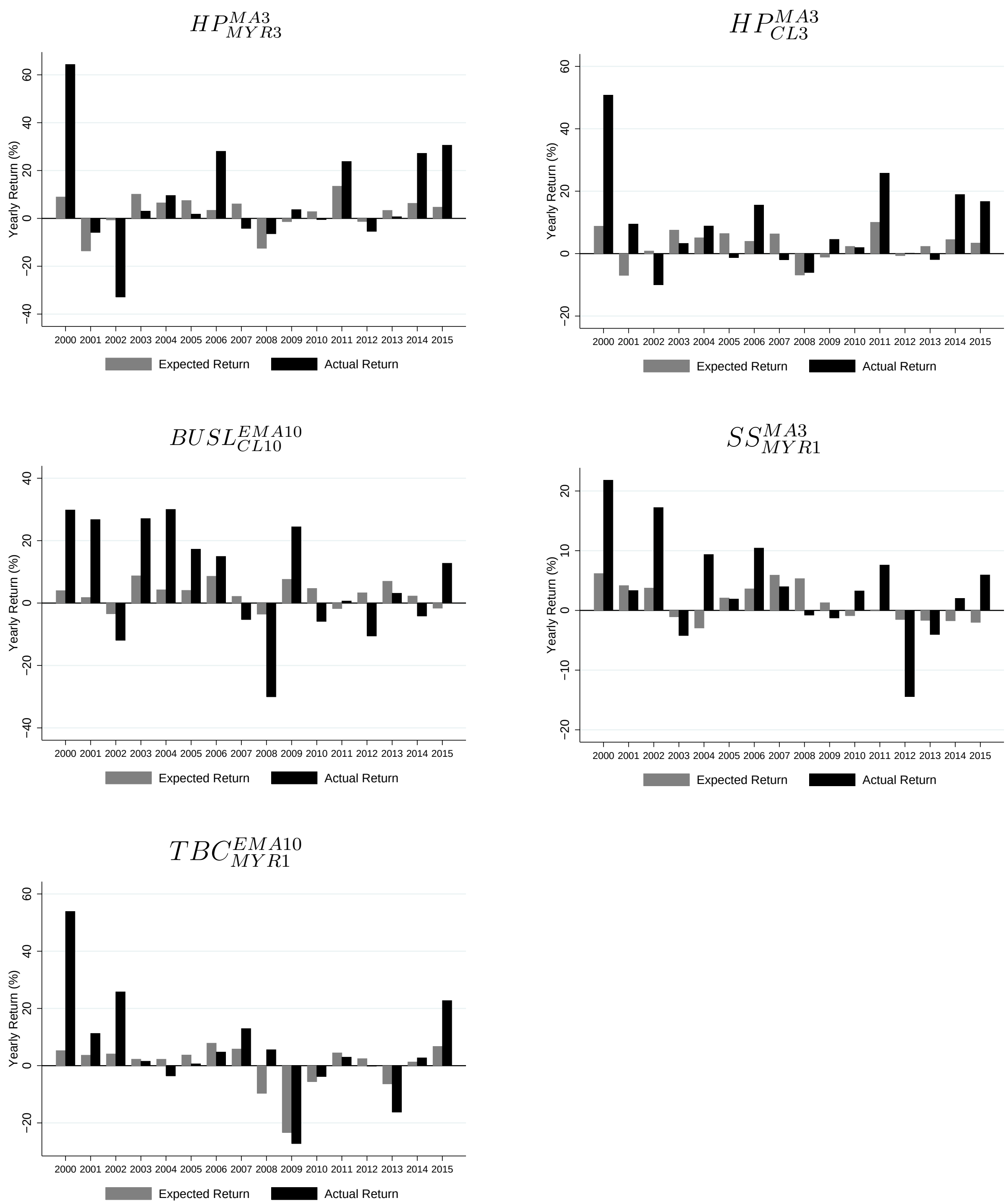

Figure 6: Economic Significance - Cumulative Returns 2008-2015

This figure shows the economic significance of the five combinations that generate positive and statistically significant alphas at the 10% level in Table 5, Table 6 and Table 7, by plotting the cumulative value of strategies that invest in all trading signals generated by these combinations between January 1, 2008 and December 31, 2015. The strategies have a starting value of 100 units and returns are calculated net of transaction costs, so that two-way costs of 0.10% are applied to each trade. Performance is benchmarked against expected returns based on four-factor (Fama-French-Carhart) exposures from Table 5, Table 6 and Table 7. The strategies take equally weighted positions on days with multiple active trades and the values are invested at the risk free rate on days with no active trades.

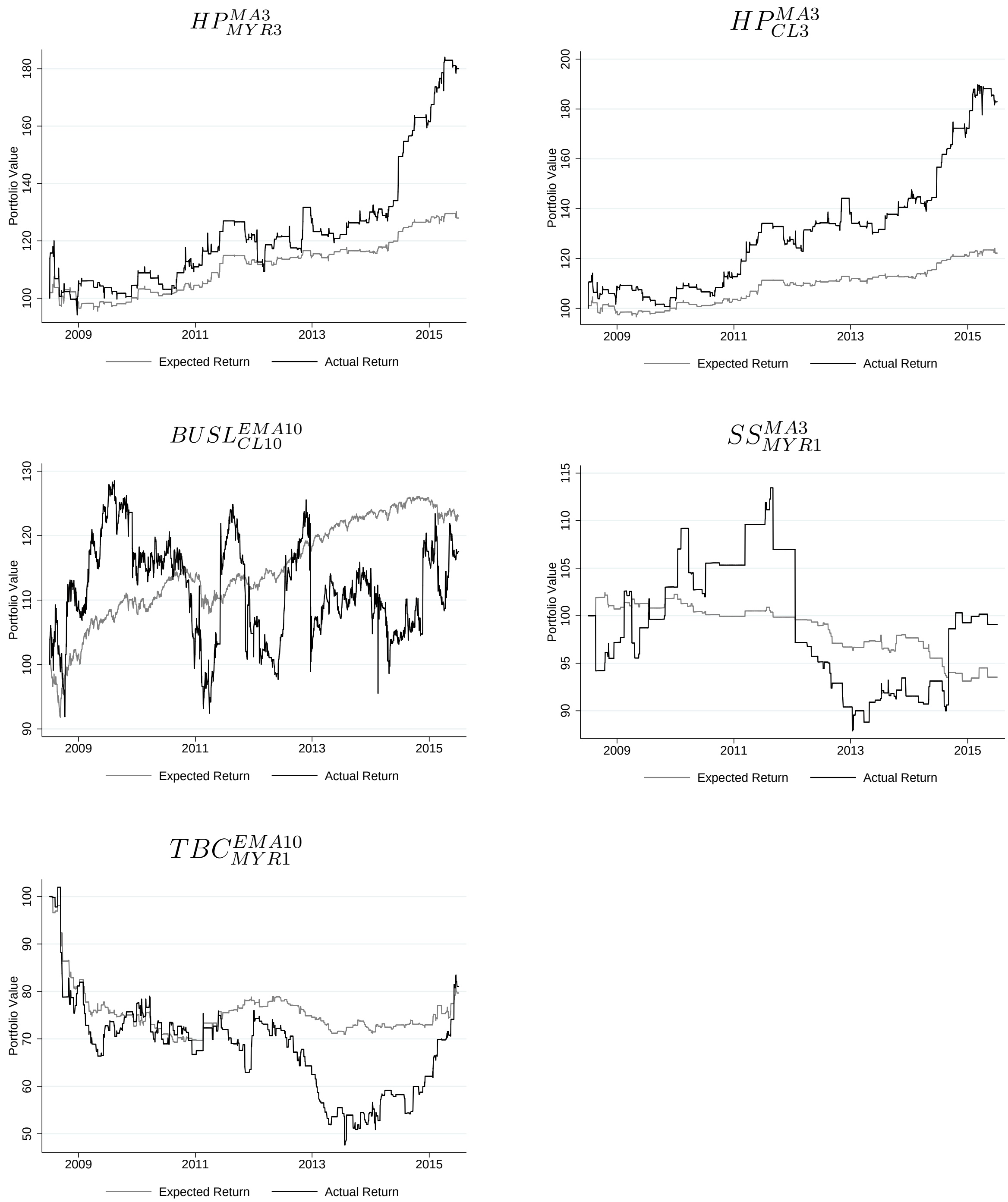

Table 10: Sub-period Factor Analysis - MYR1 & MYR2 Holding Strategies

This table shows the results from the sub-period one-factor (CAPM) and four-factor (Fama-French-Carhart) analyses for MYR1 and MYR2 holding strategies. Daily strategy excess returns are regressed on corresponding daily factors using a pooled OLS approach. Excess returns are net of transaction costs of 0.10%. The sample stretches over the period January 2000-December 2015. Averages for bull and bear patterns and for each holding strategy are equally weighted. The daily alphas are in percent.

	2000-2007				2008-2015			
	MA3		EMA10		MA3		EMA10	
	α_{CAPM}	$\alpha_{4Factor}$	α_{CAPM}	$\alpha_{4Factor}$	α_{CAPM}	$\alpha_{4Factor}$	α_{CAPM}	$\alpha_{4Factor}$
				MYR1 Holding Strategy				
Bull Patterns								
TWS	-.27	-.38	-.15	-.15	-.15	-.13	-.03	-.04
TIU	-.02	-.03	.12	.12	-.30	-.31	-.10	-.10
MS	-.63	-.49	-.37	-.34	-.53	-.50	-.30	-.29
MD	-.21	.04	.05	.01	-.19	-.28	-.36	-.35
BUC	-.10	-.06	-.23	-.24	-.04	-.15	.12	.12
ATS	-.10	-.11	-.09	-.10	-.25	-.25	-.18	-.17
BUML	.03	.06	-.13	-.12	.06	.06	-.26	-.27
HP	.08	-.02	-.14	-.15	.32*	.22	-.14	-.15
LEB	-.10	-.12	-.24	-.25	-.11	-.13	-.18	-.19
ML	.00	.01	-.23	-.25	.00	.00	-.05	-.06
BUSL	-.05	-.08	-.08	-.09	.09	.12	-.21	-.22
Average Bull	-.12	-.12	-.14	-.14	-.10	-.12	-.15	-.16
Bear Patterns								
TBC	.02	.04	.24**	.24**	.03	.01	.03	.04
TID	.33**	.33**	.04	.03	-.13	-.17	-.01	-.01
ES	.25	.27	.14	.15	-.21	-.21	-.06	-.06
ED	-.09	-.11	.04	.00	.40	.35	.29	.26
UGTC	-1.06	1.30	.39	.39	-.41	-.10	.25	.21
BEC	.10	.11	-.01	.00	-.02	.02	-.16	-.14
ATS	.11	.13	.06	.06	-.10	-.09	-.02	-.01
BEML	.11	.15	.01	.02	-.01	.01	-.15	-.15
SS	.53**	.53*	.16	.15	.05	.00	.11	.14
LET	-.14	-.12	-.16	-.15	-.14	-.12	-.07	-.07
BESL	.03	.04	-.14	-.13	-.12	-.13	-.07	-.06
Average Bear	.02	.02	.07	.07	-.06	-.04	.01	.01
Average MYR1	-.05	-.05	-.03	-.04	-.08	-.08	-.07	-.07
				MYR2 Holding Strategy				
Bull Patterns								
TWS	-.43	-.55	-.10	-.13	-.07	-.09	.00	-.02
TIU	.11	.10	.04	.05	-.14	-.17	-.01	-.02
MS	-.17	-.10	-.15	-.14	-.24	-.21	-.07	-.06
MD	.25	.31	.20	.19	.01	.17	-.02	-.02
BUC	-.04	-.04	-.12	-.13	.15	.15	.08	.08
ATS	-.06	-.05	-.07	-.07	-.09	-.07	-.05	-.04
BUML	-.06	-.08	-.11	-.11	-.05	-.08	-.14	-.14
HP	.12	.10	.01	.00	.12	.07	-.01	-.02
LEB	.05	.04	-.09	-.09	.07	.06	-.03	-.04
ML	.01	-.04	.00	-.01	-.08	-.07	-.06	-.06
BUSL	.05	.03	.02	.00	.06	.06	-.04	-.05
Average Bull	-.02	-.02	-.03	-.04	-.02	-.02	-.03	-.03
Bear Patterns								
TBC	-.19	-.20	.00	-.01	.02	.02	.00	.01
TID	-.10	-.04	-.09	-.08	-.09	-.12	.01	.01
ES	.32**	.33**	.07	.07	-.16	-.14	.00	.00
ED	-.11	-.08	-.10	-.11	-.17	-.06	.21	.20
UGTC	-.03	.23	.27	.11	.12	.32	.09	.22
BEC	.05	.05	-.01	.00	-.01	.00	-.07	-.05
BTS	-.01	.02	.04	.04	-.11	-.09	-.01	.00
BEML	.01	.02	-.03	-.01	.14	.15	-.07	-.07
SS	-.10	-.09	.02	.01	-.19	-.26	-.08	-.07
LET	.01	.02	-.05	-.04	-.12	-.11	-.02	-.02
BESL	.01	.01	-.08	-.08	-.19	-.20	-.09	-.09
Average Bear	-.01	-.01	.00	-.01	-.07	-.04	.00	.01
Average MYR2	-.01	-.01	-.02	-.02	-.05	-.03	-.02	-.01

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Sub-period Factor Analysis - MYR3 & MYR10 Holding Strategies

This table shows the results from the sub-period one-factor (CAPM) and four-factor (Fama-French-Carhart) analyses for MYR3 and MYR10 holding strategies. Daily strategy excess returns are regressed on corresponding daily factors using a pooled OLS approach. Excess returns are net of transaction costs of 0.10%. The sample stretches over the period January 2000-December 2015. Averages for bull and bear patterns and for each holding strategy are equally weighted. The daily alphas are in percent.

	2000-2007				2008-2015			
	MA3		EMA10		MA3		EMA10	
	α_{CAPM}	$\alpha_{4Factor}$	α_{CAPM}	$\alpha_{4Factor}$	α_{CAPM}	$\alpha_{4Factor}$	α_{CAPM}	$\alpha_{4Factor}$
Bull Patterns				**MYR3 Holding Strategy**				
TWS	-.33	-.45	-.16	-.19	-.05	-.06	-.05	-.07
TIU	.07	.04	-.01	-.01	-.09	-.13	-.01	-.01
MS	-.25	-.24	-.18	-.19	-.15	-.14	-.03	-.03
MD	.04	.12	.05	.05	.07	.17	.07	.06
BUC	-.04	-.04	-.05	-.06	.21	.23	.06	.06
ATS	-.10	-.10	-.05	-.05	-.05	-.05	-.03	-.02
BUML	.05	.03	-.04	-.04	-.09	-.09	-.16	-.16
HP	.15	.15	.00	.00	.14	.12	-.02	-.02
LEB	.09	.09	-.07	-.07	.03	.03	-.02	-.02
ML	-.01	-.03	.03	.03	.09	.08	-.02	-.03
BUSL	-.01	-.03	.05	.03	.05	.04	.00	-.01
Average Bull	-.03	-.03	-.04	-.04	.01	.02	-.02	-.02
Bear Patterns TBC	-.04	-.05	-.01	-.02	-.05	-.05	-.06	-.05
TID	.01	.04	-.04	-.03	-.01	-.02	.06	.06
ES	.24**	.25**	.05	.05	-.14	-.13	-.03	-.02
ED	-.02	.00	.00	-.01	.09	.13	.12	.12
UGTC	-.31	-.89	-.16	-.19	.24	.37	.04	.11
BEC	.08	.07	.00	.01	-.10	-.08	-.06	-.05
BTS	-.02	-.02	.01	.01	-.06	-.05	.01	.01
BEML	-.08	-.07	-.01	.00	-.01	.01	-.11	-.11
SS	.14	.13	.05	.05	-.08	-.15	-.03	-.04
LET	.16**	.17**	.02	.02	-.10	-.10	.01	.01
BESL	-.09	-.09	-.15	-.15	-.07	-.06	-.05	-.05
Average Bear	.01	.01	-.02	-.02	-.03	-.01	-.01	.00
Average MYR3	-.01	-.01	-.03	-.03	-.01	.00	-.01	-.01
Bull Patterns				**MYR10 Holding Strategy**				
TWS	.06	.04	.00	-.01	-.04	-.03	-.05	-.05
TIU	.02	.02	.00	.00	-.08	-.09	-.03	-.03
MS	-.12	-.12	-.08	-.07	.04	.04	-.01	-.01
MD	.00	.01	.02	.02	-.01	.03	-.03	-.03
BUC	.04	.04	-.02	-.02	.11	.11	-.02	-.02
ATS	-.07	-.06	-.04	-.04	-.02	-.02	.01	.01
BUML	-.02	-.02	-.01	-.01	.03	.03	.02	.01
HP	.02	.03	-.01	-.01	.01	.00	.02	.02
LEB	-.07	-.07	-.07	-.08	.01	.01	.02	.02
ML	-.03	-.02	.00	-.01	-.02	-.02	-.04	-.04
BUSL	.04	.03	.05*	.03	-.02	-.02	.00	.00
Average Bull	-.01	-.01	-.02	-.02	.00	.00	-.01	-.01
Bear Patterns								
TBC	-.10	-.09	-.06	-.06	.03	.03	.01	.00
TID	-.05	-.03	-.04	-.04	-.02	-.02	.00	.00
ES	.00	.02	.00	.00	-.07	-.07	-.01	-.01
ED	-.15	-.15	-.04	-.04	.06	.07	-.04	-.04
UGTC	.06	-.07	.19	.18	.11	.15	.00	.02
BEC	-.01	-.01	-.02	-.01	-.04	-.04	-.06	-.05
BTS	.00	.01	-.02	-.02	-.02	-.02	-.01	-.01
BEML	-.11	-.09	-.06	-.04	-.04	-.03	-.05	-.05
SS	.08	.06	.00	.00	-.03	-.06	-.02	-.03
LET	.05	.05	.01	.02	-.05	-.05	-.03	-.02
BESL	-.06	-.07	-.12	-.12	-.03	-.02	-.01	-.01
Average Bear	-.03	-.03	-.01	-.01	-.01	-.01	-.02	-.02
Average MYR10	-.02	-.02	-.01	-.01	.00	.00	-.02	-.01

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Sub-period Factor Analysis - CL3 & CL10 Holding Strategies

This table shows the results from the sub-period one-factor (CAPM) and four-factor (Fama-French-Carhart) analyses for CL3 and CL10 holding strategies. Daily strategy excess returns are regressed on corresponding daily factors using a pooled OLS approach. Excess returns are net of transaction costs of 0.10%. The sample stretches over the period January 2000-December 2015. Averages for bull and bear patterns and for each holding strategy are equally weighted. The daily alphas are in percent.

	2000-2007				2008-2015			
	MA3		EMA10		MA3		EMA10	
	α_{CAPM}	$\alpha_{4Factor}$	α_{CAPM}	$\alpha_{4Factor}$	α_{CAPM}	$\alpha_{4Factor}$	α_{CAPM}	$\alpha_{4Factor}$
Bull Patterns				**CL3 Holding Strategy**				
TWS	-.23	-.26	-.08	-.09	-.03	-.04	.01	-.01
TIU	.08	.07	.04	.04	-.03	-.06	.02	.02
MS	-.19	-.17	-.13	-.14	-.14	-.14	-.03	-.03
MD	.07	.11	.08	.08	-.05	.01	-.01	-.01
BUC	.01	.01	-.05	-.05	.11	.11	.08	.08
ATS	-.05	-.05	-.03	-.04	-.02	-.02	-.02	-.01
BUML	.04	.03	-.03	-.03	-.02	-.03	-.09	-.09
HP	.13	.13	.01	.00	.13**	.11	-.01	-.01
LEB	.05	.05	-.05	-.05	.01	.01	-.02	-.02
ML	-.01	-.03	.00	-.01	.04	.04	.00	.00
BUSL	.01	.00	.02	.01	.06	.05	-.01	-.01
Average Bull	-.01	-.01	-.02	-.02	.00	.00	-.01	-.01
Bear Patterns								
TBC	-.08	-.08	-.01	-.01	-.02	-.02	-.03	-.02
TID	-.02	.00	-.07	-.06	-.05	-.06	.01	.01
ES	.17**	.17**	.03	.03	-.11	-.10	-.02	-.02
ED	-.06	-.06	-.05	-.06	.02	.03	.11	.10
UGTC	-.20	-.48	.03	.03	.07	.15	.06	.10
BEC	.04	.03	-.02	-.01	-.04	-.03	-.06	-.05
BTS	-.02	-.01	-.01	.00	-.07	-.06	-.02	-.02
BEML	-.03	-.02	-.03	-.02	.01	.03	-.09	-.09
SS	.11	.08	.02	.02	-.08	-.11	-.04	-.04
LET	.02	.02	-.04	-.04	-.08	-.07	-.01	-.01
BESL	-.04	-.04	-.11	-.11	-.10	-.10	-.07	-.07
Average Bear	-.01	-.01	-.02	-.02	-.04	-.03	-.01	-.01
Average CL3	-.01	-.01	-.02	-.02	-.02	-.01	-.01	-.01
Bull Patterns				**CL10 Holding Strategy**				
TWS	-.04	-.05	-.01	-.02	-.02	-.02	-.03	-.03
TIU	.00	.00	-.01	-.01	-.05	-.05	.00	.00
MS	-.05	-.05	-.03	-.03	.01	.01	.00	.00
MD	.02	.03	.03	.03	.01	.02	.01	.01
BUC	.02	.02	.00	.00	.07	.07	.03	.03
ATS	-.02	-.02	-.02	-.02	.00	.00	.00	.00
BUML	.02	.02	.00	.00	-.01	-.01	.00	.00
HP	.04	.04	.00	.00	.02	.02	.01	.01
LEB	.00	-.01	-.03	-.03	.01	.02	.01	.01
ML	.01	.00	.02	.02	.03	.03	.02	.02
BUSL	.02	.02	.04**	.03*	.00	.00	.01	.00
Average Bull	.00	.00	.00	.00	.01	.01	.01	.00
Bear Patterns								
TBC	-.05	-.05	-.04	-.05	.02	.01	-.01	-.01
TID	-.05	-.05	-.05	-.04	-.01	-.01	.00	.00
ES	.05	.06	.01	.02	-.06	-.05	-.02	-.02
ED	-.08	-.08	-.01	-.01	.03	.03	-.01	-.01
UGTC	-.08	-.14	.09	.09	.05	.07	.00	.01
BEC	.00	.00	-.02	-.01	-.03	-.03	-.04	-.03
BTS	-.02	-.01	-.02	-.02	-.02	-.02	-.02	-.02
BEML	-.07	-.06	-.05	-.04	-.01	-.01	-.05	-.04
SS	.03	.02	-.02	-.02	-.03	-.05	-.02	-.03
LET	.03	.03	-.02	-.02	-.04	-.04	-.01	-.01
BESL	-.04	-.05	-.10	-.10	-.02	-.01	-.03	-.03
Average Bear	-.03	-.03	-.02	-.02	-.01	-.01	-.02	-.02
Average CL10	-.01	-.01	-.01	-.01	.00	.00	-.01	-.01

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$