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Momentum in Sweden: Past Returns and Continuing Overreaction

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Abstract

Comparing the performance of a traditional long-short momentum trading strategy to one based on a measure for continuing overreaction on OMXS 1997-2016, this study shows that traditional momentum only generates significant profits in the short-term. On the contrary, the continuing overreaction approach provides investors with significant profits for a variety of different holding- and formation periods, mainly attributable to its ability to pick winners. We show that these profits are not due to loading on common systematic risk factors and that the predictive power of the continuing overreaction measure outperforms momentum in the cross-section of future stock returns.

Keywords: Momentum, Trading Volume, Self-Attribution Bias, Continuing Overreaction, OMX Stockholm

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1 Introduction

Momentum is one of the most famous anomalies in the stock market and a debated topic worldwide. The momentum strategy has been studied and shown to generate significant positive profits across both emerging and developed markets, often by constructing zero-cost portfolios based on past returns (e.g. Jegadeesh and Titman, 1993; Asness, Moskowitz and Pedersen, 2013; Fama and French, 2012). The consistency of momentum returns has challenged financial researchers internationally and become a focal point in the discussion regarding market efficiency. The pursuit of an explanation for the phenomenon has generated several competing theories. Due to the magnitude of the momentum profits, the anomaly has been deemed unlikely to solely reflect systematic risk.[1] Thus, the majority of the academic literature on the topic is focusing on behavioural economic explanations (Chui, Titman and Wei 2010).

The DHS model, developed by Daniel, Hirshleifer and Subrahmanyam in 1998 (Daniel et al. 1998) theorises the markets under- and overreactions based on two psychological biases: investor overconfidence and biased self-attribution.[2] The biases imply that investors place exaggerated confidence in their private information. More specifically, investors tend to interpret public information that contradict their view as noise, while they simultaneously attribute favourable outcomes to their own ability. This entails that public signals trigger further trades on investors private information. The continuing overreaction causes positive short-lag autocorrelations – more commonly known as momentum. With the insights provided by Daniel et al. (1998), the DHS model has gained traction and is today considered one of the leading behavioural explanations of the momentum phenomenon (Byun et al. 2016).

Historically, momentum has commonly been measured using past returns. Taking stance in the DHS model, Byun et al. (2016) argue that if momentum is a result of investors continuing overreaction to private information, a more direct measure for this should be a stronger predictor for future returns than past returns. They form a measure for continuing overreaction (CO) based on a weighted average of signed trading volumes. In doing so, they attempt to capture the self-attribution bias and thus the underlying mechanism of momentum return predictability as theorised by DHS (1998). Byun et al.

[1] About 12% per annum in the United States and Europe (Chui et al. 2010)

[2] A cognitive process where the individual tend to see themselves in an overly favourable manner in order to build confidence

(2016) indeed find that the CO measure is a stronger predictor of future returns than past returns on the US market.

Chui, Titman and Wei (2010) investigate how momentum trading is affected by cross-cultural behavioural differences. Specifically, they hypothesise that countries with higher individualism scoring based on an index developed by Hofstede (2001) is more likely to generate excess momentum profits, as investors in these countries tend to exhibit higher overconfidence as a result of self-attribution bias. They provide evidence in favor of their hypothesis, showing that individualism is positively related to both volatility and trading volume, as well as the magnitude of momentum profits (Chui et al. 2010). Sweden is among the top countries in terms of individualism presented in the study, and using overlapping portfolios with 6-month holding- and formation horizons constructed in accordance with Jegadeesh and Titman (1993), Chui et al. find evidence of positive and statistically significant momentum profits in their sample of Swedish stocks (2010). A number of studies with varying methodologies reconfirm these findings (e.g. Leippold & Lohre, 2011; and Gong, Liu & Liu, 2015), whereas others contradict (e.g. Rouwenhorst, 1998 and Griffin, Ji & Martin, 2003). Further, Liu, Liu and Ma (2011) argues that momentum excess returns is highly dependent on portfolio formation methodology.

With the widely used momentum strategy and the inconclusive research body on the Swedish market in mind, we aim to fill parts of the research gap and provide an investor perspective on the matter. By mimicking the portfolio formation methodology in Jegadeesh and Titman (1993) and the continuing overreaction variable in Buyn et al. (2016), we form a trading strategy building on investor overreaction, as originally theorised by DHS (1998). The goal is to investigate and compare the momentum- and CO-trading strategies on OMXS rigorously. Our sample consists of all common equity stocks (listed and delisted) on the main stock exchange in Sweden, OMX Stockholm (OMXS). The time-frame commences in January 1997, ending in December 2016. We construct decile portfolios based on both traditional momentum (past returns) and continuing overreaction, and form zero-cost portfolios by shorting the loser (downward) momentum (CO) portfolio and longing the winner (upward) momentum (CO) portfolio. Comparing zero-cost portfolio raw- and risk adjusted returns for both strategies, we find that the traditional momentum strategy only produces significantly positive profits for short holding periods and that the risk adjusted abnormal returns for the strategy reverses quickly. Simultaneously, the zero-investment CO strategy performs well, providing significantly positive raw returns as well as risk adjusted returns through a wide range of holding- and formation periods. In addition, we provide benchmark-adjusted returns to both strategies. We see that CO drives away momentum returns to a larger extent than the reversed and, in particular, that upward CO portfolios outperform momentum winner portfolios considerably. As the empirical results point to the superiority of the CO strategy compared to traditional momentum on OMXS during the examined period, we proceed by exploring the strategy in more detail.

To control the endurance of the CO measure, we conduct cross-sectional regressions on 6-month holding period stock returns over time, adding a number of firm specific variables as well as running analysis on double-sorted portfolios on alternative explanatory measures.[3] The regression results show that the CO variable has significant predictive power for future returns across a wide variety of regression specifications, including traditional control variables such as beta, book-to-market, size, illiquidity and idiosyncratic volatility. However, including all firm-specific variables, CO loses its significance and we conclude that some of its predictive power is subsumed by alternative explanation variables.

As DHS (1998) argue that it is harder for investors to cover their position in small and less liquid firms, we conduct subsample analyses on variables controlling for size and illiquidity. We find that zero-investment portfolios formed with small and illiquid stocks generate returns superior to the big and liquid equivalents.

We conclude that the CO zero-investment portfolios generate higher and more consistent returns than traditional momentum portfolios throughout the studied period, partly attributable to the CO measures superior ability to pick winners. With these findings, we contribute to the momentum research body in the intersection between Byun et al. (2016) and Chui et al. (2010), showing that CO indeed is a more profitable strategy than traditional momentum on the Swedish market throughout the studied period.

2 Previous Literature

In this section, we review previous literature regarding equity factor strategies, centering around the momentum factor and focus particularly on research with a behavioural finance approach to the anomaly. Furthermore, we summarize the discussion regarding momentum's presence on European stock markets, looking in-depth on the research for Sweden.

[3] PRET, POS_ID, NEG_ID, POS_RC, NEG_RC, NPOS_NEG, BETA, SIZE, BM, REV, ILLIQ, IVOL and TURN as motivated in subsection Additional Variables

2.1 Equity Factor Strategies

Fama and French presented their three stock market factors in 1993, building the foundation for equity factor strategies, which since has been a current topic in financial research. The excess returns to the momentum trading strategy, originally found by Jegadeesh and Titman (1993), motivated the inclusion of a fourth risk factor. Carhart (1997) contributed with the Carhart four factor model by extending the Fama and French three factor model with a momentum risk factor. Since the discovery, the momentum factor premia has been studied globally using a vast number of different methodologies, generating numerous competing theories for their existence (Asness et al. 2014). All in all, the momentum strategy is one of the most studied capital market phenomenon globally.

2.1.1 Momentum as a Strategy

In the 1980's, psychological theories proposing that individuals tend to overreact to information started to gain traction (Kahneman and Tversky, 1982; De Bondt and Thaler, 1985; Shiller, 1981). As a direct extension, De Bondt and Thaler (1985, 1987) suggested that this overreaction is mirrored in stock prices, and that contrarian strategies therefore generate abnormal return over a 3- to 5-year holding period (Jegadeesh and Titman, 1993). As an alternative to the long-term return reversal strategy as proposed by De Bondt and Thaler (1985), Jegadeesh and Titman (1993) analyse relative strength trading strategies (buying past winners and selling past losers), as conducted by practitioners. In their research, the holding periods stretch 3- to 12-months in quarterly intervals, and they find evidence of both economically and statistically significant abnormal returns in the US.

Since the discovery, momentum as a strategy has grown in popularity, which in turn has resulted in an expansive body of research. Simultaneously, momentum has been criticised in many ways, for example for being too small a factor, only working well among small stocks and that it does not survive trading costs. Asness et al. (2014) devote their article *Fact, Fiction and Momentum Investing* to bust the myths surrounding momentum trading and they find that momentum portfolio raw returns and sharpe rations are in fact larger than both the size- and value factor dittos on US data in different samples up to 2013. Israel and Moskowitz (2013) study momentum's relation to size in detail, and find that the momentum strategy indeed holds for portfolios of different firm sizes. Further, as momentum is a high turnover strategy, many has been led to believe that the trading costs overwrites the possible profits. However, Frazzini et al. (2013) show that the per dollar trading cost for momentum is low, meaning that momentum trading survives trading costs with good margin. Asness et al. (2014) further elaborate on, and bust, 11 additional myths surrounding momentum. Myth busting like this is highly relevant given the practitioners perspective of this paper.

To date, it is discussed whether equity factor premium is evidence against the market efficiency hypothesis, showing irrational tendencies amongst investors, or if equity factors are in fact proxies for systematic risk factors. The momentum founding fathers, Jegadeesh and Titman, argued that the abnormal returns in their momentum portfolios were not due to systematic risk or delayed stock price reactions to common factors (1993). Since, several behavioural explanations have been developed. For example, Barberis, Shleifer and Vishny (1998), and Hong and Stein (1999) find that momentum arises as a result of investors' initial underreaction to events and information.

Daniel et al. (1998) contribute with another behavioral view, originally theorising equity markets under- and overreactions based on investor overconfidence in private information and biased self-attribution. More specifically, due to biased self-attribution, if an investor receives confirming public information to a trade based on private information, it will increase his confidence. Respectively, if the same investor receives disconfirming public information on a trade, her confidence drops only slightly - if at all. This entails that public information can prompt further overreaction subsequent to a trade based on private information, thus creating momentum in the short-term. However, Daniel et al. (1998) also show that such momentum reverses as private information becomes irrelevant with time, and more recent public information eventually drives security prices back to fundamentals.

Byun et al. (2016) test if continuing overreaction causes momentum as predicted by the DHS (1998) model, and if so, if a more direct measure of continuing overreaction than past returns better predicts future returns. DHS (1998) show that momentum arises when the investor overconfidence is increasing. Hence, the trend, rather than the level, of overconfidence is the desired objective to capture. The new measure is constructed in two main steps. Firstly, Buyn et al. (2016) construct a signed volume variable by multiplying trading volume by the sign of the contemporaneous return. Secondly, they take the weighted sum of signed volumes and assigns a higher weight to recent months. Then, through normalizing the weighted sum of signed volumes by the average volume over the same period, they capture the trend rather than the level of overconfidence. They call the measure CO, for continuing overreaction, and argue that it should be superior to past returns in predicting future returns as it captures the direction of investor overconfidence (Byun et al. 2016).

They show that the measure of continuing overreaction indeed is a better predictor of future returns than past returns, and additionally that the effect of continuing overreaction subsumes the price momentum effect (Buyn et al. 2016). Again, this study focuses on US equities. As we aim to contribute to the momentum research body using Swedish data, we further investigate momentum in Sweden in the next section.

2.2 Momentum in Sweden

Market anomaly studies are predominantly conducted on US equity markets (Asness et al., 2013), and the research on international equity markets is scarce in comparison, albeit a few papers have been written based on international market data. Further, the research results regarding momentum on the Swedish market is mixed.

We have identified a number of relevant studies showing results for aggregated European, Scandinavian and developed market portfolios including Sweden. Fama and French (2012) show that their European winner minus loser portfolios provide excess return that is positive and significant 1990-2011. Asness, Moskowitz and Pedersen (2013) confirm this finding in a study providing compelling evidence regarding momentum excess returns on the European market. Novy-Marx (2012) too finds that momentum strategies generate excess return on developed markets in a conclusive sample stretching throughout 1926-2010. On the same note, Bird & Casavencchia (2007) presents evidence of a momentum premium in portfolios aggregating the Scandinavian equity markets 1989-2004. However, none of these studies provide country-specific findings, and as the Swedish equity market generally receives a fairly low weight in the aggregated portfolios due to its limited size, the insight into momentum in Sweden from these studies is limited.

In a widely cited paper, Rouwenhorst (1998) examines the momentum strategy on international equity markets 1978-1995. Rouwenhorst studies momentum in depth in 12 European markets, finding that Sweden is the only country where the momentum portfolio return is not significantly different from zero.[4] Subsequent to Rouwenhorst (1998), a few studies have confirmed this result, where the Swedish equity market diverts from most other European markets in not showing evidence for a significant momentum premium

[4] Studied countries include Austria, Belgium, Denmark, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom

(e.g. Dahlquist, Engström & Söderlind, 2000; Griffin, Ji & Martin, 2003; Barber, George, Lehavy & Trueman, 2013; and Goyal & Wahal, 2015).

Simultaneously, several papers contradict the results presented in the previously mentioned studies. González and Parmler (2007) examine the excess return patterns of momentum using all stocks listed on the Stockholm Stock Exchange 1979 – 2003. Following the portfolio formation methodology used by Jegadeesh and Titman (1993) for different holding periods, they show that momentum strategies generate positive and statistically significant profits in Sweden. Gong, Liu and Liu (2015) form momentum portfolios on the intermediate and short-term horizon and verify the presence of excess momentum returns in Sweden, in both the short- and intermediate term. Liu, Liu and Ma (2011) investigate the momentum anomaly in Sweden further using different portfolio formation methodologies. It turns out that the momentum portfolio formed replicating the George and Hwang (2004) methodology yields returns significantly larger than zero - but they find no evidence of excess momentum returns with other methodologies used.[5]

Chui, Titman and Wei (2010) takes a behavioural finance approach and examines how cultural differences influence the momentum strategy return across markets. They measure cross-country cultural differences using an individualism index, developed by Hofstede (2001), relating to overconfidence and self-attribution bias. The study provides compelling evidence that individualism is positively correlated with trading volume and volatility, as well as the magnitude of momentum profits. Sweden is one of the countries with the highest individualism scoring in the study, meaning that individuals and investors tend to overestimate their abilities and thus be more overconfident. Chui et al. (2010) indeed find that momentum profits are positive and statistically significant on the Swedish equity market using portfolios with six-month holding- and formation periods. They also argue and show that differences in momentum returns across countries can partially be explained using the Hofstede (2001) individualism index (Chui et al. 2010).

With the contradictory and inconclusive momentum research in Sweden, we aim to partly fill the research gap and further study the anomaly focusing solely on the Swedish equity market. Specifically, we set out to contribute in the intersection between Chui et al. (2010) and Byun et al. (2016), examining whether a momentum trading strategy using the continuing overreaction measure motivated by Byun et al. (2016) generates profits by exploiting investor overconfidence and the self-attribution bias found on the Swedish

[5] Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999)

market in the study by Chui et al. (2010).

3 Data

In the following section, we describe our choice of data source, sample design and data treatment. We then present some descriptive statistics of our two main data samples.

3.1 Data Source

We collect data for all firms listed on the main stock exchange in Stockholm 1997-2016 using Datastream lists for both currently traded and delisted stocks to minimize survivorship bias.[6,7] In order to align our methodology with predecessors research, we collect accounting- and financial markets data on both monthly and daily frequency. Based on this data, we construct the Market (MRKT), HML and SMB factors in accordance with Fama-French (1993) and the PR1YR factor in accordance with Carhart (1997). The market factor is constructed with data collected from the Swedish Riksbank and the Swedish Investment Fund Association.[8,9] However, when constructing BETA and IVOL, explicitly explained in subsection 4.3, we collect daily frequency market data from Nasdaq OMXS.[10]

Our full, untreated, data sample consists of 664 companies, with observations spanning over 240 months with an average of 21 trading days per month, summing to a total of 5020 trading days.

3.2 Sample Design and Data Treatment

The full sample average number of traded firms amount to approximately 212 per month. We take a number of actions to mold our sample, in order to remove outliers, prior to constructing our portfolios.

To commence, we remove the few duplicate observations produced when collecting the

[6] All firms traded on Stockholm Stock Exchange's Small-, Mid-, and Large cap

[7] List LSWSEALI for current stocks and LDEADSD for delisted stocks, respectively

[8] SixGX index collected from http://fondbolagen.se/en/Statistics/Indices/

[9] T-bill rates collected from http://www.riksbank.se/en/Interest-and-exchange-rates/

[10] The reason for using returns from Nasdaq OMX Stockholm_PI as daily market return is that the Swedish Investment Fund Association does not provide daily frequency data

data from Datastream. We also remove firms that lack stock price data throughout the entire period January 1997 - December 2016. The majority of companies omitted from our sample are firms that delisted from OMXS early in 1997. Following this exercise, the sample includes 627 companies.

Following the reasoning in Fama and French (1993), we further omit observations where firms show negative book-to-market values, which is a rarity throughout the entire sample. Next, we exclude observations that would otherwise distort our results through omitting observations outside of the 5^{th} and 95^{th} percentile in book-to-market, corresponding to the cutoff points 0.035 and 4.484, respectively. This is done as we do not wish to trade in companies with extreme book-value measures. With regards to the cross-sectional regressions that we conduct in section Regression Results, this is the sample that we use, still with 627 constituents.

With respect to portfolio formation however, we apply one last constraint to the individual stocks in our sample. As we wish to provide a practitioners perspective to the trading strategy and avoid trading in penny stocks, we set a lower threshold for the stock price. Thus, following the reasoning of Byun et al. (2016), we remove observations where the monthly price is less than SEK 10. This results in a sample with a total of 623 constituents. All the manipulations performed could haven been made by any trader allocating his or her capital. In other words, our data treatment has not been contingent on future events unknown to a hypothetical trader, for instance demanding a minimum number of observations in order to be included in the sample. For a full treated sample overview, see Table 1.

Table 1: Descriptive Statistics of Untreated and Treated Data

Panel A of Table 1 reports descriptive statistics for the untreated OMXS sample collected on both current- and delisted/bankrupt stocks 1997-2016, containing $n = 627$ constituents. Panel B, respectively, reports descriptive statistics for the treated sample, where negative book-to-market observations have been omitted and extreme book-to-market observations have been excluded. Further, we exclude all observations where price is less than SEK 10. This sample contains $n = 623$ constituents.

	Mean	St. Dev.	Min	5%	25%	50%	75%	95%	Max
Panel A. Untreated sample									
Price	120.5	1,192.6	0.01	2.9	18.5	44.2	92.0	250.0	114,480.5
Return	1.00	15.3	-94.3	-18.4	-5.6	0.0	6.5	21.7	686.0
Market Cap	13,897.64	53,345.56	0.36	59.42	323.13	1,223.41	6,021.80	57,467.36	1,540,000.00
Book-to-Market	3.56	47.83	-701.42	0.02	0.17	0.43	0.91	4.38	1,950.55
Dollar Volume	939,285.57	4,252,341.89	0.550	537.90	5,532.53	30,929.00	215,794.43	5,083,925.30	184,529,441.52
Panel B. Portfolio formation sample									
Price	140.1	1,288.6	10.0	13.4	28.1	54.3	104.5	273.5	114,480.5
Return	1.0	13.0	-94.0	-17.0	-5.0	0.2	6.0	19.0	490.0
Market Cap	15,249.55	50,277.36	0.36	127.04	519.70	1,990.27	8,084.83	64,921.77	1,540,000.00
Book-to-Market	0.66	0.68	0.04	0.07	0.21	0.44	0.84	2.00	4.48
Dollar Volume	1,130,081.73	4,740,042.78	2.23	884.92	8,012.44	46,158.53	319,036.46	6,262,839.65	184,529,441.52

4 Methodology

In the methodology section, we provide an overview of the construction of the continuing overreaction variable as well as risk factors following Fama and French (1993) and Carthart (1997). We further present the additional variables we use in our cross-sectional regression analysis, and go deeper into our portfolio formation methodology.

4.1 Continuing Overreaction Variable

Self-attribution bias is a psychological phenomenon stating that individuals tend to credit themselves for favourable outcomes whilst blaming externalities for unfavourable outcomes. Daniel et al. (1998) argue that a direct consequence of this bias is that investors' overreact to private information because it makes them overly confident in their abilities on average. Due to self-attribution bias, the public signals following a trade increase the investors' confidence on average, as they regard disconfirming information as noise while attributing favourable information to their own ability. This, in turn, causes investors to conduct further trades based on their private information, leading to further overreactions. This continuing overreaction entails that past returns predict future returns as high (low) past returns leads to positive (negative) investor overreactions, triggering trades that push returns higher (lower) creating further overreactions in the same direction. DHS (1998) theorises that the process of continuing overreaction is the underlying mechanism driving momentum return predictability.

Thus, seeking a better predictor for future returns, constructing a more direct proxy for continuing overreaction than past returns is of interest. As a first step, following Buyn et al. (2016), we construct a measure for signed volume, denoted SV, by multiplying monthly trading volume for a stock i by the sign of its contemporaneous return. The idea is that a higher positive (negative) magnitude of SV indicates a larger investor overconfidence in positive (negative) non-public information. The signed volume for stock i in month t is therefore defined as:

$$\text{SV}_t = \begin{cases} VOL_t & \text{if } R_{i,t} > 0, \\ 0 & \text{if } R_{i,t} = 0, \\ -VOL_t & \text{if } R_{i,t} < 0, \end{cases}$$

where $R_{i,t}$ is the monthly stock return and VOL_t is the monthly SEK trading volume, defined as the sum of daily trading volume times the closing end-of-day stock price per stock, within each month. As stated, DHS (1998) argue that the key driver of intermediate-term return predictability is biased self-attribution, which leads to continuing overreaction characterized by an increasing trend in overconfidence. As we wish to capture the trend of overconfidence, we assign increasing weights for trading volumes in more recent months, in line with the methodology of Byun et al. (2016). By summing the weighted signed volumes and dividing by average trading volume, we capture the intended trend rather then the level of investor overconfidence. The continuing overreaction measure, denoted CO, is thus defined as:

$$\text{CO}_t = \frac{sum(w_J \times SV_{t-J}, \ ... \ , w_1 \times SV_{t-1})}{mean(VOL_{t-J}, \ ... \ , VOL_{t-1})},$$

where $\text{SV}_{t,i}$ is the signed volume for stock i in month t, J is the length of the formation period, and w_j is a weight that takes a value of J - j + 1 in month t - j (i.e., w_J=1, w_{J-1}=2, ... , w_1=J). Hence, more weight is allocated to more recent observations.

In line with previous research (e.g. Jegadeesh and Titman, 1993; Carhart, 1997; and Byun et al. 2016) the 12 months formation period will be the primary focus of the paper ($J = 12$). However, for comprehensiveness, we also present results using different formation periods in Table 3 and Table 4.

4.2 Risk Factor Construction

In order to control that the portfolio returns are not simply due to fundamental risk factor loadings, we construct Market, Size and Book-to-market factor portfolios mimicking common risk factors in accordance with Fama and French (1993).

The market factor (MRKT) is constructed in accordance with the CAPM:

$$\text{MRKT}_t \quad = \quad R_{m,t} - R_{f,t},$$

where the market return, $\text{R}_{m,t}$, is the monthly general index return 1997-2016 collected from the Swedish Investment Fund Association, and the risk-free return, $\text{R}_{f,t}$, is the monthly Swedish 1-month T-bill rate collected from the Swedish Riksbank.

To construct the Small Minus Big (SMB) and High Minus Low (HML) factors, we split the entire sample into two based on market capitalization, with the median as cut-off point. We also divide the entire sample into three based on book-to-market, with the cut-off points being 30 and 70 percent. Subsequently, six portfolios (*SmallValue*, *SmallNeutral*, *SmallGrowth*, *BigValue*, *BigNeutral*, and *BigGrowth*) are formed of the intersections between these different sets. For instance the *BigGrowth* consists of the companies that are both in the top half with respect to market cap and the bottom 30 percent in book-to-market. We compute the book-to-market value in June each year *t*, following Fama and French (1992). The book value is computed as book value of equity plus deferred taxes for the firm's latest fiscal year, ending in the prior calendar year. We use the market capitalisation in December each year *t-1*. The stocks are sorted into the portfolios each June, and monthly value-weighted returns on the six portfolios are calculated from July year t until June year *t+1*. Each portfolio is rebalanced in the end of June in *t+1*. The SMB and HML factors are the equal-weighted averages of the portfolios as follows:

$$\begin{aligned} \text{SMB} \quad = \quad & \frac{1}{3} \times (SmallValue + SmallNeutral + SmallGrowth) \\ - \quad & \frac{1}{3} \times (BigValue + BigNeutral + BigGrowth) \end{aligned}$$

$$\begin{aligned} \text{HML} &= \frac{1}{2} \times (SmallValue + BigValue) \\ &- \frac{1}{2} \times (BigValue + BigGrowth) \end{aligned}$$

The above procedures are in line with the Fama and French (1993) methodology.

In addition, we construct the momentum factor (PR1YR) and extend the Fama French 3 Factor model, as originally done by Carhart (1997). The computation resembles the HML and SMB process; we use the same cut-off points for the Small and Big sub-samples where we simply divide the samples in two. Further, we sort the top and bottom 30% performing stocks based on past return into winner and loser portfolios, respectively, and the middle 40% is sorted into a neutral portfolio. This produces six independent, value-weighted, portfolios using the analogue methodology as for the SMB and HML factors. The PR1YR factor is hence the equal-weighted average of the intersecting portfolio returns as follows:

$$\begin{aligned} \text{PR1YR} &= \frac{1}{2} \times (SmallHigh + BigHigh) \\ &- \frac{1}{2} \times (SmallLow + BigLow) \end{aligned}$$

4.3 Additional Variables

In addition to the portfolios mimicking common, fundamental, risk factors as described in the latter section and the CO variable, we form a number of supplementary variables. These will be used in cross-sectional regressions with the intention to assess the predictive power of the CO variable and past returns on future stock returns. Further, we set out to investigate the underlying drivers of the CO strategy's profitability, analysing the CO returns using a selection of the variables presented below.

$BETA_t$

The market beta is estimated for each stock by regressing its daily excess returns in month t on daily market excess returns, hence it is reestimated on a monthly basis. We use the

Nasdaq OMX Stockholm all share index return as the market return and 1-month Swedish T-bill rates from Sveriges Riksbank as the risk-free rate.[11,12]

ILLIQ$_t$

Amihud (2002) argues that expected excess stock return is partly due to an illiquidity premium by showing that expected market illiquidity affects ex ante excess returns positively over time. DHS (1998) states that inefficiencies and overconfidence is larger in more illiquid stocks as it is harder for investors to cover their positions in such firms. Hence, we can assume that the return predictability based on CO is higher amongst illiquid firms. To control for this, we construct a monthly illiquidity variable, ILLIQ, following Amihud (2002):

$$\text{ILLIQ}_t = \frac{1}{D_t}\sum_{d=1}^{D_t}\frac{|R_{t,d}|}{VOLD_{t,d}},$$

where D_t is the number of trading days in month t, $R_{t,d}$ is the return on day d in month t and $VOLD_{t,d}$ is the SEK trading volume on day d of month t.

IVOL$_t$

Previous empirical research stress the positive relation between overconfidence and volatility (Odean, 1998 and Daniel et al., 1998). To control for the idiosyncratic volatility, we construct the variable IVOL following Bali, Cakici and Whitelaw (2011), using a single-factor return-generating process to estimate monthly idiosyncratic volatility:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i(R_{m,d} - R_{f,d}) + \varepsilon_{i,d},$$

where $R_{i,d}$ is the daily stock return of stock i, $R_{m,d}$ is the daily market return, $R_{f,d}$ is the daily risk free return and $\varepsilon_{i,d}$ is the idiosyncratic return on day d. The idiosyncratic volatility of stock i in month t is defined as the standard deviation of daily residuals:

[11] Nasdaq OMX Stockholm_PI index collected from http://www.nasdaqomxnordic.com/indexes/

[12] T-bill rates collected from http://www.riksbank.se/en/Interest-and-exchange-rates/

$$\text{IVOL}_{i,t} = \sqrt{\text{var}(\varepsilon_{i,d})}$$

NPOS_NEG$_t$

The number of positive-return months minus the number of negative-return months over the past 12 months from month *t-12* to month *t-1*. The variable is introduced in order to further investigate the nature of CO, following Byun et al. (2016).

POS_ID$_t$*/NEG_ID*$_t$

Following the methodology of Da, Gurun, and Warachka (2014), POS_ID$_t$ (NEG_ID$_t$) is defined as:

$$\text{POS\_ID}_t = \begin{cases} \%POS - \%NEG & \text{if } R_{t-12,t-1} > 0, \\ 0 & \text{otherwise} \end{cases}$$

$$\text{NEG\_ID}_t = \begin{cases} \%NEG - \%POS & \text{if } R_{t-12,t-1} < 0, \\ 0 & \text{otherwise} \end{cases}$$

where %POS (%NEG) denotes the percentage of days, from *t-12* to *t-1* with positive (negative) returns, and $R_{t-12,t-1}$ is the return over the months *t-12* to *t-1*.

POS_RC$_t$*/NEG_RC*$_t$

Following the methodology of Grinblatt and Moskowitz (2004), this dummy variable intends to capture the return consistency of stock i. POS_RC$_t$ (NEG_RC$_t$) takes the value 1 if the stock has experienced at least 8 months of positive (negative) return from month *t-12* to month *t-1* and if the previous 12-month return (PRET) is positive (negative).

PRET$_t$

To compare our CO strategy to past stock performance (momentum) we construct a past return variable, PRET, defined as cumulative return over the previous 12 months, from month *t-12* to month *t-1*.

REV_t

Lehmann (1990) presents evidence that 'winner' and 'loser' stocks show large return reversals in the short-term. He suggest that this *"probably reflects inefficiency in the market for liquidity around large price changes"* (Lehmann, 1990). To control for such short-term reversals, we construct a variable REV, controlling for one-month return reversals. It is defined as the return on a stock in month *t*, following Byun et al. (2016).

$TURN_t$

Several studies, both empirical and theoretical, argue that overconfidence increases stock trading volume (e.g. Benos, 1998; Gervais and Odean, 2001; Barber and Odean, 2013; Glaser and Weber, 2009; Grinblatt and Keloharju, 2009 and Statman et al. 2006). To control for trading volumes in individual stocks we construct the variable TURN, defined as average monthly turnover over the previous 12 months from month *t-12* to month *t-1.*

4.4 Portfolio Formation

We split our sample into deciles and form ten portfolios based on both CO and the traditional momentum measure (past return). The CO decile portfolio 1 (10) shows the strongest negative (positive) continuing overreaction while the momentum decile portfolio 1 (10) has the highest (lowest) past return. The zero-investment CO (momentum) portfolios - 10-1 - is constructed by shorting the weakest CO (lowest momentum) decile portfolio while longing the strongest CO (highest momentum) decile portfolio. Previous momentum research on the Swedish market normally divide the sample into quintiles due to the relatively low number of constituents, as argued by Bird and Casavecchia (2007). However, forming decile portfolios give us around 20 companies per portfolio, which is quite a large number from a practitioners perspective and thus sufficient in our view. We construct overlapping portfolios in accordance with predecessors (e.g. Jegadeesh and Titman, 1993; Carhart, 1997) and also non-overlapping portfolios for robustness, generating similar results (not presented). The overlapping portfolio methodology is adopted in order to increase the power of our tests and works in the following manner: for instance, a July portfolio return with three-month holding period (*K=3*) is the equally-weighted return from the first month return of the portfolio formed in June, the second month return for the portfolio formed in May and the third month return from the portfolio formed in April. In the case with overlapping portfolios, we present simple t-statistics as this portfolio formation methodology reduce autocorrelation, as argued by Byun et al. (2016).[13] The overlapping portfolio formation methodology is the most widely used by predecessors and we therefore focus on the overlapping portfolio results in this study.

For exhaustiveness, we show results for different holding periods in quarterly intervals, i.e. K = *3, 6, 9, 12* and for different formation periods J = *6, 9, 18, 24*, in line with previous research (e.g. Jegadeesh and Titman, 1993; Byun et al. 2016). As in Jegadeesh and Titman (1993) all stocks with return observations available for the previous J months precedent to the portfolio formation date are included in the sample that the decile portfolios are constructed from.

5 Empirical Findings

5.1 Descriptive Statistics and Variable Correlations

In Panel A of Table 2, we present summary statistics for the CO measure. We observe a mean of 12.1, standard deviation of 33.4 and the most extreme percentile values -57.6 and 94.6 for the 1st and 99th percentile, respectively. Panel B shows CO decile portfolio means for the market capitalization (SIZE), Book-to-market (BM), market beta (BETA), previous 12-month cumulative return (PRET, in Table 2 presented as monthly average), the short-term reversal variable (REV), the illiquidity measure as originally introduced by Amihud (2002) (ILLIQ), the idiosyncratic volatility (IVOL), the stock turnover measure (TURN) and the number of positive return months minus the number of negative return months in the past 12 months (NPOS_NEG). These variables are introduced and discussed in subsection 4.3.

In the PRET, REV and NPOS_NEG variables, there is a clear increasing pattern going from the downward continuing overreaction portfolio (1) to the upward continuing overreaction portfolio (10), as expected. However, the relationship in the ILLIQ variable to the decile portfolios is not as clear. The downward CO portfolio (1), has the largest ILLIQ measure, albeit we do not detect a clear pattern amongst the other decile portfolios. The absence of a trend is also true for the SIZE, BM, BETA, TURN and IVOL variables.

[13]In accordance to Jegadeesh and Titman, we have performed t-test using the Newey-West methodology as well, which generates similar results. However, to keep the results comparable to predecessor research (Buyn et al., 2016), we present the simple t-statistics in our tables.

Table 2: Summary Statistics

In Panel A of Table 2, we present summary statistics for the CO measure for the companies used in the portfolio formation process. Panel B show time-series averages for each CO-decile for the market capitalization (SIZE), the book-to-market ratio (BM), the market beta (BETA), the previous 12-month cumulative return in percent (PRET, as monthly average), the 1-month reversal variable in percent (REV), the illiquidity measure (ILLIQ), the idiosyncratic volatility (IVOL), the turnover in percent (TURN) and the number of positive-return months minus the number of negative-return months. Panel C presents the time-series averages of the Pearson and Spearman correlations between the variables introduced in Panel B. The Spearman rank correlations are presented above the diagonal, while the Pearson correlations are presented below the diagonal.

Panel A. Summary Statistics

			Percentiles								
	Mean	Std. Dev.	1st	5th	10th	25th	50th	75th	90th	95th	99th
CO	12.073	32.417	-57.597	-37.395	-27.877	-10.491	10.443	32.815	54.476	68.255	94.647

Panel B. Summary Statistics for Decile Portfolios of Stocks Sorted by CO

Decile	SIZE	BM	BETA	PRET	REV	ILLIQ	IVOL	TURN	NPOS_NEG
1 (Downward)	21.227	0.669	0.532	-1.020	0.599	2.230	0.023	6.733	-3.243
2	21.597	0.606	0.589	-0.491	0.618	1.734	0.022	8.646	-1.971
3	21.736	0.587	0.596	0.106	0.800	1.919	0.022	9.171	-1.066
4	21.859	0.601	0.601	0.524	0.615	1.450	0.021	9.834	-0.269
5	21.847	0.602	0.604	0.987	0.839	1.405	0.021	10.836	0.402
6	21.886	0.628	0.587	1.411	0.602	1.626	0.020	10.433	1.015
7	21.899	0.639	0.584	1.979	0.911	1.448	0.020	11.304	1.698
8	21.749	0.643	0.577	2.590	1.382	1.926	0.020	10.100	2.435
9	21.541	0.649	0.533	3.313	1.313	1.809	0.021	8.993	3.182
10 (Upward)	21.337	0.678	0.487	5.444	1.732	1.816	0.021	9.589	4.129

Panel C. Time-Series Averages of Cross-Sectional Correlations

	CO	SIZE	BM	BETA	PRET	REV	ILLIQ	IVOL	TURN	NPOS_NEG
CO		0.016	0.022	-0.017	0.526	0.027	-0.002	-0.038	0.039	0.694
SIZE	0.008		-0.121	0.328	0.134	0.029	-0.810	-0.454	0.318	0.207
BM	0.010	-0.086		-0.040	-0.035	-0.010	0.128	0.017	-0.379	-0.051
BETA	-0.017	0.326	-0.006		0.033	-0.001	-0.377	-0.021	0.231	0.031
PRET	0.467	0.069	-0.007	0.034		0.047	-0.098	-0.095	0.122	0.674
REV	0.036	0.006	-0.006	0.001	0.053		-0.048	0.018	0.026	0.044
ILLIQ	-0.010	-0.380	0.121	-0.184	-0.081	-0.040		0.412	-0.607	-0.159
IVOL	-0.031	-0.399	0.039	0.023	-0.026	0.063	0.273		-0.143	-0.159
TURN	0.040	0.267	-0.250	0.190	0.164	0.021	-0.200	-0.074		0.133
NPOS_NEG	0.687	0.205	-0.047	0.029	0.584	0.046	-0.103	-0.161	0.122	

Panel C of Table 2 provides time-series averages of cross-sectional correlations, with Spearman rank correlations above the diagonal and Pearson correlations below. As expected, CO is positively correlated with PRET and NPOS_NEG and (to a limited extent) negatively correlated with ILLIQ. Idiosyncratic volatility (IVOL) and beta (BETA) are, too, negatively correlated with CO whereas SIZE, BM and TURN are showing a positive relationship to our continuing overreaction measure. To get a deeper insight into how firm specific characteristics affect stock returns on the Swedish market, we conduct cross-sectional regressions with various specifications in subsection 5.6.

5.2 CO- and Momentum Raw Returns

In Panel A of Table 3, we present raw returns for the overlapping CO decile portfolios for different holding periods, $K = 3, 6, 9, 12$, with the formation period $J = 12$ as well as for different formation periods, $J = 6, 9, 18, 24$, with holding period $K = 6$. Studying the results for different holding periods, we see an almost monotonic relationship between CO and raw portfolio returns. More specifically, the zero-cost CO portfolios (10-1) with holding periods of 3, 6, 9 and 12 months provide significant monthly average returns of 1.06%, 0.98%, 0.74% and 0.53%, respectively. The fact that return magnitudes and statistical power of the long-short CO portfolios decrease with longer holding periods is expected, due to the previously mentioned return reversals. Another indication of this is that the return to the downward CO portfolio (1) increases with holding period. In line with previous research, we find that the 6-month holding period long-short CO-portfolio shows the highest statistical power in terms of return predictability (Byun et al. 2016), and we therefore focus on this holding period when testing for different portfolio formation periods.

When looking at different formation periods for CO decile portfolio raw return, we observe positive significant returns on the 5% level for the long-short (10-1) CO-portfolios throughout all but one formation periods with holding period $K = 6$. The portfolio using a formation period of $J = 24$ is significant on the 10% level. We observe the highest zero-investment portfolio t-statistic for $K = 6$ and $J = 12$. When examining different J, the sample period with portfolio returns available for $J = 24$ is shorter than the other ($J = 6, 9, 12, 18$). For result consistency, we restrict our sample to the period where the 2-year formation portfolios have available data.

Table 3: Overlapping Portfolio Returns: CO and Momentum

Panel A of Table 3 presents average monthly returns, in percent, for portfolios formed using the CO measure for the period 1997-2016. Each month, with the start in January 1998, the stocks are sorted by their CO measure into deciles and divided into 10 portfolios. Portfolio 1 (10) consists of the stocks with the lowest (highest) CO-measures. J represents the number of months used in the construction of the CO-variable, while K stands for the number of months each portfolios is held. Each K-month return is the equally-weighted average of returns from K overlapping portfolios implemented over K months. The overlapping portfolios increases the power of the tests and motivates the use of ordinary t-statistics, which are given in parenthesis. The last row of Panel A shows the result for the zero-cost portfolio that is long in the 10-portfolio and short the 1-portfolio. Panel B is analogue to Panel A, but the portfolios are based on the stocks' past returns.

	J = 12				K = 6			
	K = 3	K = 6	K = 9	K = 12	J = 6	J = 9	J = 18	J = 24
Panel A. *CO Raw Return*								
1 (Downward)	0.459(1.094)	0.437(1.023)	0.632(1.485)	0.650(1.553)	0.613(1.434)	0.553(1.258)	0.503(1.110)	0.632(1.317)
2	0.533(1.201)	0.695(1.582)	0.873(2.090)	0.899(2.171)	0.787(1.833)	0.777(1.787)	0.781(1.774)	0.734(1.712)
3	0.578(1.413)	0.765(1.854)	0.857(2.151)	0.816(2.053)	0.687(1.615)	0.828(1.953)	0.841(2.014)	0.728(1.761)
4	0.702(1.706)	0.836(2.030)	0.991(2.497)	0.905(2.302)	0.932(2.264)	0.845(2.019)	0.922(2.173)	0.816(2.032)
5	0.676(1.688)	0.816(2.045)	0.923(2.384)	0.917(2.373)	0.867(2.176)	0.907(2.273)	0.865(2.135)	0.978(2.444)
6	0.955(2.503)	0.917(2.447)	1.001(2.766)	0.947(2.614)	0.854(2.236)	0.887(2.287)	1.030(2.820)	1.088(2.867)
7	0.770(2.167)	0.821(2.330)	0.926(2.714)	0.924(2.655)	1.039(2.828)	1.019(2.744)	0.892(2.464)	1.011(2.868)
8	1.101(3.057)	0.989(2.762)	1.067(3.098)	0.962(2.786)	1.100(2.887)	0.941(2.623)	0.972(2.740)	0.803(2.280)
9	1.252(3.438)	1.201(3.394)	1.200(3.514)	1.072(3.113)	1.223(3.422)	1.246(3.407)	0.996(2.859)	1.043(2.942)
10 (Upward)	1.519(4.141)	1.418(3.949)	1.373(3.952)	1.182(3.397)	1.336(3.627)	1.362(3.749)	1.324(3.723)	1.258(3.560)
10-1	1.059(3.437)	0.981(3.542)	0.741(2.798)	0.532(2.218)	0.723(2.893)	0.809(3.000)	0.821(2.755)	0.626(1.841)
Panel B. *'Momentum' Raw Return*								
1 (Loser)	0.257(0.380)	0.555(0.842)	0.748(1.179)	0.804(1.315)	0.409(0.612)	0.606(0.906)	0.804(1.210)	0.852(1.274)
2	0.495(1.061)	0.614(1.308)	0.761(1.659)	0.823(1.783)	0.814(1.634)	0.646(1.307)	0.717(1.527)	0.824(1.815)
3	0.607(1.470)	0.733(1.782)	0.875(2.212)	0.863(2.193)	0.796(1.944)	0.756(1.785)	0.913(2.239)	0.751(1.911)
4	0.752(2.004)	0.840(2.251)	0.991(2.758)	0.976(2.708)	0.864(2.285)	0.914(2.384)	1.104(3.100)	1.104(3.088)
5	1.009(2.970)	0.979(2.859)	1.069(3.236)	0.986(3.001)	0.969(2.766)	0.996(2.814)	1.022(3.100)	0.916(2.788)
6	0.860(2.604)	0.923(2.816)	1.034(3.284)	1.010(3.180)	0.985(2.984)	1.028(3.064)	1.019(3.082)	1.059(3.261)
7	0.899(2.745)	0.928(2.832)	0.991(3.142)	0.964(3.021)	0.946(2.783)	0.987(3.054)	1.035(3.136)	1.080(3.292)
8	0.920(2.763)	0.867(2.584)	1.016(3.125)	0.908(2.784)	1.144(3.404)	1.128(3.299)	0.895(2.614)	0.913(2.719)
9	0.931(2.685)	0.980(2.706)	0.935(2.679)	0.800(2.293)	1.160(3.438)	1.183(3.451)	0.884(2.478)	0.851(2.340)
10 (Winner)	1.356(3.243)	1.075(2.576)	1.030(2.446)	0.837(1.927)	1.477(3.596)	1.280(3.080)	1.027(2.174)	0.968(2.083)
10-1	1.100(2.050)	0.520(1.018)	0.282(0.591)	0.033(0.075)	1.069(2.244)	0.674(1.372)	0.223(0.439)	0.116(0.227)

In Panel B of Table 3, we present the decile raw returns for the traditional momentum portfolios, as constructed in Jegadeesh and Titman (1993) and further studied by e.g. Carhart (1997). Interestingly, we find that momentum on the main Swedish exchange is neither persistent in the intermediate- nor the long-term. Statistically significant results are observed for the zero-cost portfolio with holding period K = *3* and J = *12*, and when holding period K = *6* is paired with the 6-months formation period J = *6*. The latter result is in line with the finding of Chui et al. (2010) that uses this portfolio formation methodology. Otherwise, we find that traditional momentum does not generate significant profits in any of the zero-investment portfolios. Further, we cannot reject that the 'winner' portfolio (10) with 12-month holding period is statistically different from zero on a 5% level, stressing the short-termism of the traditional momentum strategy on OMXS. Despite the insignificant results for the holding period K = *6*, we use this holding period when examining different formation period for alignment purposes. Looking at the different formation periods J = *6, 9, 18, 24*, we see that J = *6* is the longest formation period for which the zero-cost momentum portfolio return is statistically significant, given a holding period of K = *6*.

Comparing the raw returns for the strategies, it is evident that CO performs better than traditional momentum in terms of return predictability on the Swedish main stock exchange. When comparing the two measures, we see that both decrease in statistical and economic significance with time. However, the zero-cost CO portfolios are statistically significant, on the 5% level, throughout all holding periods and all but one formation period, whereas only two of the studied traditional zero-cost momentum portfolios are statistically significant. Later in the study, from subsection 5.4, we focus on holding period K = *6* and formation period J = *12* since this is where the zero-cost CO portfolio shows the highest statistical power.

5.3 Risk Factor Alphas

In Table 4, we provide monthly alphas, in percent, from regressions of both CO and momentum overlapping portfolios, using the Fama and French three factor regression specification (1993):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_M \times MRKT_t + \beta_{SMB} \times SMB_t + \beta_{HML} \times HML_t + \varepsilon_{i,t} \qquad (1)$$

The main reason for conducting these regressions is to control that the excess returns generated by the strategies are not merely compensation for loading on fundamental risk factors. In Panel A, we present the return alphas for CO portfolios with different holding periods K = *3, 6, 9, 12* when J = *12* as well as formation periods J = *6, 9, 18, 24*, when K = *6*. Again, we observe the strongest statistical power where holding period equals six months (K = *6*) and formation period equals twelve months (J = *12*) despite a magnitude lower than for the three month holding period. With the regression specification used, the alphas obtained can be considered as risk-adjusted returns from the CO strategy relative to these factors. Looking at the K = *6*, J = *12* zero-investment portfolio, we see that the returns adjusted for common risk factors, as argued by Fama and French (1993), is slightly higher than the results presented in Table 3 (0.996% per month, compared to 0.981%). For the other holding periods, the risk adjusted returns are marginally lower than the respective raw returns. Thus, we conclude that adding the widely used common risk proxies for market risk, HML and SMB does not drive away excess returns for the continuing overreaction strategy and the return of the CO long-short portfolio is still highly statistically significant across all examined holding periods. Notably, the alpha for the formation period J = *24* too is significant on the 5% level, which is an improvement compared to Table 3.

Interestingly, turning to Panel B of Table 4 and the output for the strategy based on past returns, we get different results. With the traditional momentum specification, the only zero-cost portfolios with statistically significant results on the 5% level is where K = *3* and J = *12*, and K = *6* and J = *6*. These results are expected given the findings in Table 3. In fact, when the portfolio holding period exceeds the 9-month mark, the abnormal return of the long-short momentum portfolio turns negative. This is in line with previous research arguing that the momentum strategy experience reversals toward fundamentals in the long term (e.g. Daniel et al. 1998). The fact that the 'winner' momentum portfolio (10) alphas are not significant on the 5% level for holding periods exceeding K = *3* when J = *12* is quite striking, highlighting the weakness of relative strength trading strategies based on

Table 4: Fama and French Three Factor Alphas

Panel A (B) of Table 4 reports the monthly Fama-French three factor alphas, in percent, for the overlapping portfolios from table 4, using CO (past return) as the "constructing" variable. J represents the number of months used in the formation period, while K stands for the holding period. Each K-month return is the equally-weighted average of returns from $K = 6$ portfolios implemented and held over $K = 6$ months. The overlapping portfolios increases the power of the tests and motivates the use of ordinary t-statistics, which are given in parenthesis. In the last row, we present the alphas for the strategy that is long in the 10^{th} CO (past return) decile portfolio and short in the 1^{st} CO (past return) decile portfolio.

	J = 12				K = 6			
	K = 3	K = 6	K = 9	K = 12	J = 6	J = 9	J = 18	J = 24
Panel A. CO FF3F Alphas								
1 (Downward)	0.249(0.563)	-0.287(-1.362)	0.374(0.859)	0.534(1.260)	-0.179(-0.898)	-0.230(-1.058)	-0.303(-1.206)	-0.170(-0.586)
2	0.290(0.622)	-0.017(-0.076)	0.628(1.480)	0.789(1.883)	0.019(0.096)	0.038(0.183)	0.005(0.022)	-0.056(-0.249)
3	0.318(0.743)	0.067(0.365)	0.604(1.491)	0.702(1.742)	-0.063(-0.337)	0.068(0.372)	0.123(0.675)	-0.003(-0.015)
4	0.455(1.054)	0.152(0.876)	0.723(1.794)	0.777(1.946)	0.183(1.083)	0.096(0.522)	0.193(1.050)	0.144(0.818)
5	0.426(1.019)	0.142(0.810)	0.668(1.707)	0.783(1.993)	0.144(0.841)	0.175(1.067)	0.168(0.969)	0.288(1.803)
6	0.692(1.735)	0.254(1.519)	0.723(1.973)	0.812(2.211)	0.101(0.614)	0.154(0.878)	0.367(2.276)	0.394(2.527)
7	0.492(1.322)	0.154(0.965)	0.665(1.920)	0.778(2.203)	0.327(2.186)	0.302(1.891)	0.184(1.162)	0.329(2.047)
8	0.847(2.249)	0.294(1.788)	0.795(2.255)	0.814(2.321)	0.347(2.052)	0.213(1.317)	0.227(1.273)	0.100(0.575)
9	0.995(2.608)	0.520(3.015)	0.934(2.672)	0.925(2.642)	0.497(3.107)	0.503(2.888)	0.236(1.369)	0.271(1.437)
10 (Upward)	1.286(3.376)	0.709(3.576)	1.115(3.141)	1.047(2.964)	0.588(2.998)	0.599(3.152)	0.560(2.901)	0.509(2.589)
10-1	1.036(3.208)	0.996(3.622)	0.741(2.753)	0.512(2.105)	0.766(3.053)	0.829(3.087)	0.863(2.895)	0.679(1.989)
Panel B. 'Momentum' FF3F Alphas								
1 (Loser)	-0.024(-0.035)	-0.379(-0.972)	0.514(0.794)	0.737(1.194)	-0.547(-1.395)	-0.399(-1.055)	-0.208(-0.520)	-0.223(-0.552)
2	0.205(0.419)	-0.136(-0.555)	0.499(1.069)	0.694(1.481)	0.054(0.215)	-0.093(-0.353)	-0.098(-0.387)	-0.014(-0.054)
3	0.340(0.783)	0.069(0.341)	0.635(1.577)	0.733(1.835)	0.076(0.404)	0.058(0.282)	0.188(0.938)	0.006(0.033)
4	0.509(1.292)	0.207(1.126)	0.727(1.990)	0.832(2.272)	0.190(1.131)	0.205(1.184)	0.436(2.616)	0.460(2.581)
5	0.767(2.163)	0.337(2.045)	0.796(2.361)	0.841(2.517)	0.319(2.058)	0.317(1.934)	0.368(2.230)	0.298(1.779)
6	0.616(1.782)	0.308(1.880)	0.771(2.415)	0.865(2.678)	0.307(2.116)	0.361(2.229)	0.364(2.195)	0.395(2.572)
7	0.699(2.031)	0.341(2.035)	0.745(2.322)	0.831(2.567)	0.261(1.625)	0.334(2.045)	0.383(2.382)	0.488(2.982)
8	0.681(1.950)	0.257(1.516)	0.735(2.226)	0.777(2.346)	0.412(2.572)	0.422(2.500)	0.252(1.347)	0.307(1.782)
9	0.679(1.868)	0.314(1.510)	0.673(1.901)	0.670(1.901)	0.428(2.596)	0.439(2.620)	0.182(0.966)	0.178(0.872)
10 (Winner)	1.111(2.543)	0.370(1.502)	0.787(1.824)	0.694(1.583)	0.625(2.949)	0.456(1.936)	0.232(0.828)	0.186(0.709)
10-1	1.136(2.016)	0.749(1.529)	0.272(0.557)	-0.043(-0.098)	1.172(2.628)	0.855(1.856)	0.439(0.875)	0.409(0.814)

past returns on OMXS.

When comparing the strategies respective abnormal returns, it is clear that the continuing overreaction strategy outperforms traditional momentum on the main exchange in Sweden for the studied period. The fact that the return magnitude of the zero-cost momentum strategy with a 3-month holding period is larger than the CO ditto is suppressed by the long-term consistency of the CO measure, as well as the observed reversals of the momentum alphas within 12-months. Obviously, the continuing overreaction measure delivers positive risk-adjusted excess returns on OMXS, whereas traditional momentum does not.

In addition to the traditional Fama and French (1993) risk factor adjustments, we construct a momentum factor (PR1YR) for OMXS following Carhart (1997) and compute four factor alphas for CO and momentum respectively. However, as previous results of momentum strategies on the Swedish equity market are mixed, and the research on the momentum factor on OMXS limited, we present the four factor abnormal returns in Table 9 in Appendix A. As expected, the momentum strategy zero-investment alphas are more affected by the inclusion of the PR1YR factor, whereas the abnormal CO returns remain high and statically significant. It becomes apparent that the CO measure is resilient to the PR1YR inclusion and hence not a result of loading on these risk factors.

5.4 Benchmark-adjusted Returns

Table 5 present benchmark-adjusted returns for each of the two strategies, CO and traditional momentum, based on the 12-month formation- and 6-month holding period portfolios. This in done in order to further deepen the comparison between the two strategies. We compute benchmark-adjusted stock returns by subtracting the return of the benchmark strategy portfolio each individual stock belongs to. Explicitly, the CO (momentum)-adjusted stock return is calculated as the monthly return of the individual stock minus the equally weighted monthly return of the CO (momentum) portfolio that the stock is sorted into. The CO (momentum)-adjusted portfolio return is then obtained by calculating the overlapping portfolio return using CO (momentum)-adjusted stock returns. The monthly portfolio return is the equally-weighted average of the returns from $K = 6$ portfolios implemented and held over $K = 6$ months.

In Panel A of Table 5, we provide both raw- and benchmark-adjusted returns for the full-sample CO and momentum portfolios. As we use the 6-month holding period and

12-month formation period portfolios for these tests, the reported unadjusted portfolio returns for CO and momentum is equal to the second columns of Table 2 quadrant one and three, respectively. Turning to the momentum-adjusted returns for the CO portfolios, we note that the portfolios for decile 9 and 10 are still highly significant, generating monthly average returns of 0.30% and 0.54%, respectively. The same is true for the zero-investment portfolio (10-1), which generates 0.75% per month. Interestingly, the CO-adjusted momentum returns are not significant for any of the decile portfolios, nor the long-short portfolio which was expected given the unadjusted zero-cost portfolio results. In terms of patterns, the momentum-adjusted CO portfolios still show an increasing pattern from decile 1 to 10.

Previous research on US equity markets have shown that momentum returns primarily stem from shorting the loser portfolio; stating that a large share of the momentum profits come from delisting, or bankruptcy, profits (Eisdorfer, 2008). In that sense, one could have expected the loser portfolios to generate larger negative returns. In our case, we observe high, statistically significant, profits from the momentum-adjusted zero-investment CO-portfolio, while none of the CO-adjusted momentum portfolios provide returns statistically different from zero throughout our sample period.

We further split our sample into two different time periods, in order to better observe how the strategies have evolved over time. In Panel B, we provide results for the period 1997-2007. The unadjusted return for the CO strategy is highly statistically significant for the top two upward continuing overreaction portfolios (9 and 10), generating approximately 1.08% and 1.53% return per month, respectively. Simultaneously, the zero-cost portfolio, too, provides statistically significant and positive profits of about 1.32% on average per month. The upward momentum-adjusted CO portfolio for the 1997-2007 subsample, too, provides investors with positive returns and the zero-cost portfolio provides 1.09% per month. Again, neither the zero-cost portfolio for momentum raw returns nor benchmark-adjusted returns generate significant profits. Additionally, the decile portfolios does not show monotonically increasing patterns in terms of returns. Worth noting is that none of the top three decile momentum portfolios generates return statistically different from zero. These results reconfirm the lack of existence of excess momentum profits on the Swedish main exchange in the traditional sense, as found by several predecessors (e.g. Rouwenhourst, 1998; Griffin, Ji & Martin, 2003; Barber, George, Lehavy & Trueman, 2013 and Goyal & Wahal, 2015).

Table 5: Benchmark-Adjusted Returns

Panel A of Table 5 reports Momentum (CO) adjusted returns for the CO (Momentum) decile portfolios formed with OMXS stocks 1997-2016. The Momentum (CO) adjusted stock returns are calculated as the individual monthly stock return, minus the monthly return of the momentum (CO) decile portfolio each stock belongs to. The Momentum (CO) adjusted portfolio return, is then simply obtained by calculating the overlapping portfolio return using Momentum (CO) adjusted stock returns instead of unadjusted stock returns. The monthly return is the equally-weighted average of the returns from $K = 6$ portfolios implemented and held over $K = 6$ months. In Panel B and C, we report results for the years 1997-2007 and 2008-2016 respectively. Ordinary t-statistics are given in parentheses.

CO Portfolio	Unadjusted Returns	Mom-Adjusted Returns	Mom-Portfolio	Unadjusted Returns	CO-Adjusted Returns
Panel A. 1997-2016					
1 (Downward)	0.437(1.023)	-0.215(-1.642)	1 (Loser)	0.555(0.842)	-0.171(-0.480)
2	0.695(1.582)	-0.068(-0.756)	2	0.614(1.308)	-0.149(-0.835)
3	0.765(1.854)	-0.039(-0.435)	3	0.733(1.782)	-0.084(-0.767)
4	0.836(2.030)	0.013(0.155)	4	0.840(2.251)	-0.022(-0.234)
5	0.816(2.045)	-0.033(-0.421)	5	0.979(2.859)	0.087(0.921)
6	0.917(2.447)	0.068(0.836)	6	0.923(2.816)	-0.018(-0.169)
7	0.821(2.330)	-0.037(-0.476)	7	0.928(2.832)	-0.016(-0.162)
8	0.989(2.762)	0.120(1.358)	8	0.867(2.584)	-0.102(-0.870)
9	1.201(3.394)	0.296(2.730)	9	0.980(2.706)	-0.013(-0.082)
10 (Upward)	1.418(3.949)	0.538(4.010)	10 (Winner)	1.075(2.576)	0.052(0.263)
$10-1$	0.981(3.542)	0.753(3.703)	$10-1$	0.520(1.018)	0.223(0.501)
Panel B. 1997-2007					
1 (Downward)	0.205(0.312)	-0.383(-1.956)	1 (Loser)	0.285(0.264)	-0.246(-0.397)
2	0.636(0.929)	-0.035(-0.249)	2	0.595(0.803)	-0.009(-0.028)
3	0.539(0.878)	-0.172(-1.251)	3	0.598(0.977)	-0.075(-0.454)
4	0.705(1.149)	-0.005(-0.036)	4	0.781(1.465)	0.038(0.254)
5	0.766(1.317)	0.021(0.174)	5	0.988(2.183)	0.206(1.299)
6	0.944(1.712)	0.195(1.524)	6	0.850(1.958)	-0.012(-0.070)
7	0.605(1.223)	-0.172(-1.426)	7	0.954(2.170)	0.110(0.676)
8	0.892(1.861)	0.097(0.705)	8	0.789(1.657)	-0.043(-0.231)
9	1.083(2.303)	0.250(1.516)	9	0.900(1.672)	0.009(0.034)
10 (Upward)	1.525(2.993)	0.704(3.118)	10 (Winner)	0.980(1.536)	0.046(0.145)
$10-1$	1.320(2.897)	1.087(3.272)	$10-1$	0.695(0.816)	0.292(0.395)
Panel C. 2008-2016					
1 (Downward)	1.261(2.395)	-0.086(-0.549)	1 (Loser)	1.441(1.929)	-0.141(-0.387)
2	1.354(2.609)	-0.162(-1.449)	2	1.354(2.550)	-0.224(-1.288)
3	1.711(3.293)	0.158(1.476)	3	1.575(3.160)	-0.058(-0.402)
4	1.664(3.253)	0.056(0.556)	4	1.621(3.377)	-0.043(-0.380)
5	1.570(3.128)	-0.046(-0.443)	5	1.649(3.490)	-0.023(-0.229)
6	1.558(3.363)	-0.060(-0.599)	6	1.638(3.568)	-0.064(-0.562)
7	1.773(3.808)	0.161(1.569)	7	1.468(3.145)	-0.262(-2.211)
8	1.837(3.819)	0.206(2.102)	8	1.545(3.519)	-0.249(-1.704)
9	1.978(3.942)	0.321(2.284)	9	1.756(3.857)	-0.003(-0.022)
10 (Upward)	1.992(4.292)	0.374(2.632)	10 (Winner)	1.939(3.828)	0.169 (0.672)
$10-1$	0.732(2.492)	0.460(2.347)	$10-1$	0.498(0.842)	0.310(0.585)

Lastly, Panel C focus on the second half of our sample, 2008-2016. All portfolio raw returns across both strategies, except the momentum loser portfolio, are positive and significant. This diverts from the findings in Panel B, where the majority of portfolio raw returns were insignificant. The difference observed is however larger for the momentum strategy, where the 'winner' portfolio did not generate significantly positive return 1997-2007, while now producing a 1.94% monthly average return. Comparing the raw returns for the upward CO portfolio and the winner momentum portfolio, we observe returns that are very close in magnitude. However, as the t-statistic for the CO portfolio is larger, we conclude that the CO strategy provides higher Sharpe Ratio. Turning to the two zero-investment portfolios, the CO portfolio provide positive and significant return of a higher magnitude (0.73%) than the momentum equivalent (0.50%), which is not statistically different from zero. The benchmark-adjusted returns show a pattern similar to what we observed in the previous panels of the table, namely that the momentum-adjusted CO returns are still significant in the top three upward portfolios (8-10) and the zero-investment portfolio. Simultaneously, all but the 'winner' (10) CO-adjusted momentum portfolios generate negative returns.

Comparing the early subsample to the more current one (Panel B and C, respectively), we see that the zero-investment raw returns from both CO and momentum have decreased in magnitude in recent years. Looking at both strategies raw returns, we see that the lower decile (loser) portfolios have performed strongly in recent years compared to the earlier subsample (1997-2007). This is partly attributable to a strong overall performance of the Stockholm main exchange in the post-crisis period.[14]

Figure 1 is a graphical representation of the decile portfolio returns for the full sample. In the left graph, monthly average raw returns for both CO and momentum strategies are plotted. With this representation, it becomes obvious that the most extreme downward- and upward CO portfolios under- and outperforms the momentum dittos, respectively. Through the graphical representation, it becomes even clearer that the underlying reason why the long-short CO strategy outperform the corresponding momentum portfolio on OMXS is primarily attributable to the stronger performance of the upward CO portfolio. As previously stated, researchers have found that the majority of momentum profits in the US come from the loser portfolios (Eisdorfer, 2008). However, this does not seem to be a plausible explanation for neither of the strategies on the Swedish market.

[14]Swedish Investment Fund Association, www.fondbolagen.se/en/

The rightmost graph plots the benchmark-adjusted returns, where the magnitude of the returns are, of course, dampened albeit with a clear resemblance in pattern to the raw return graph. The three top upward CO portfolios clearly outperform the top three momentum winner-portfolios. Again, the loser and downward momentum portfolios perform quite similarly.

Figure 1: Full Sample Comparison of Raw Returns and Benchmark Adjusted Returns

The left graph of Figure 1 displays the monthly average return of CO and momentum portfolios for the whole sample, 1997-2016, while the right graph shows the performance of momentum-adjusted CO and CO-adjusted momentum portfolios.

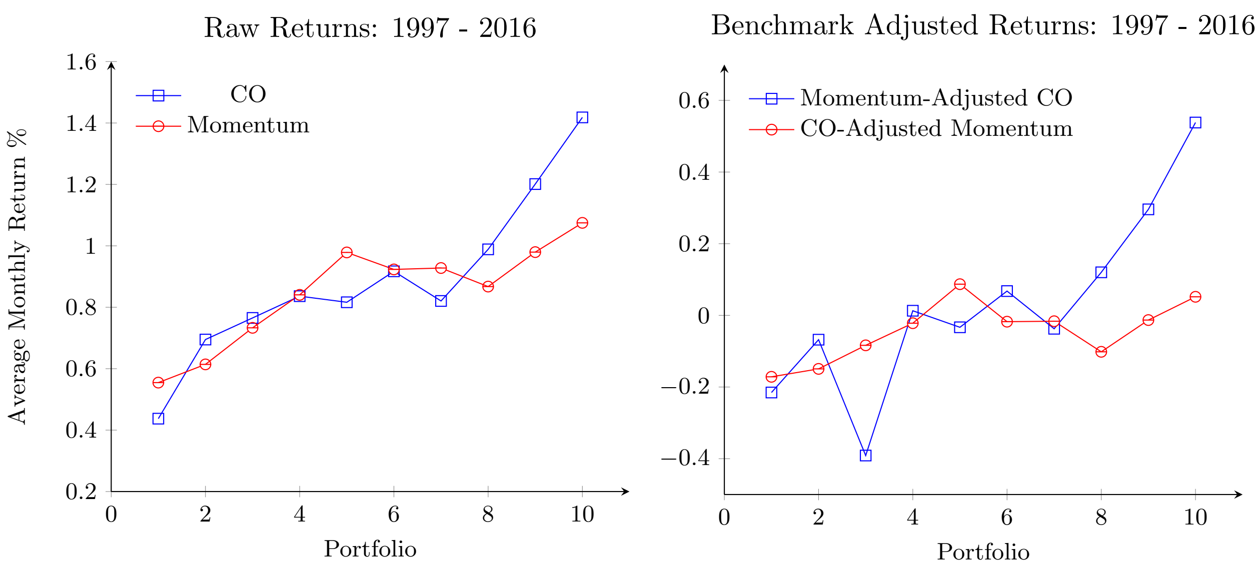


Figure 2 plots the average monthly returns for the decile portfolios formed on CO and momentum in the first half of our sample period. The pattern for both the raw returns and benchmark-adjusted returns resembles the full-sample results. We observe slightly lower returns to the downward CO portfolio than the loser momentum portfolio, both in raw- and benchmark adjusted returns. In the 2-7 decile portoflios, the CO and momentum returns track each other quite closely. However, the top three upward CO portfolios once again outperform the momentum winner portfolios (8-10) quite significantly, in line with the full-sample findings.

Figure 2: Comparison of Raw Returns and Benchmark Adjusted Returns, 1997-2007

The left graph of Figure 2 displays the monthly average return of CO and momentum portfolios for the sub-sample consisting of the years 1997-2007, while the right graph shows the performance of momentum-adjusted CO and CO-adjusted momentum portfolios.

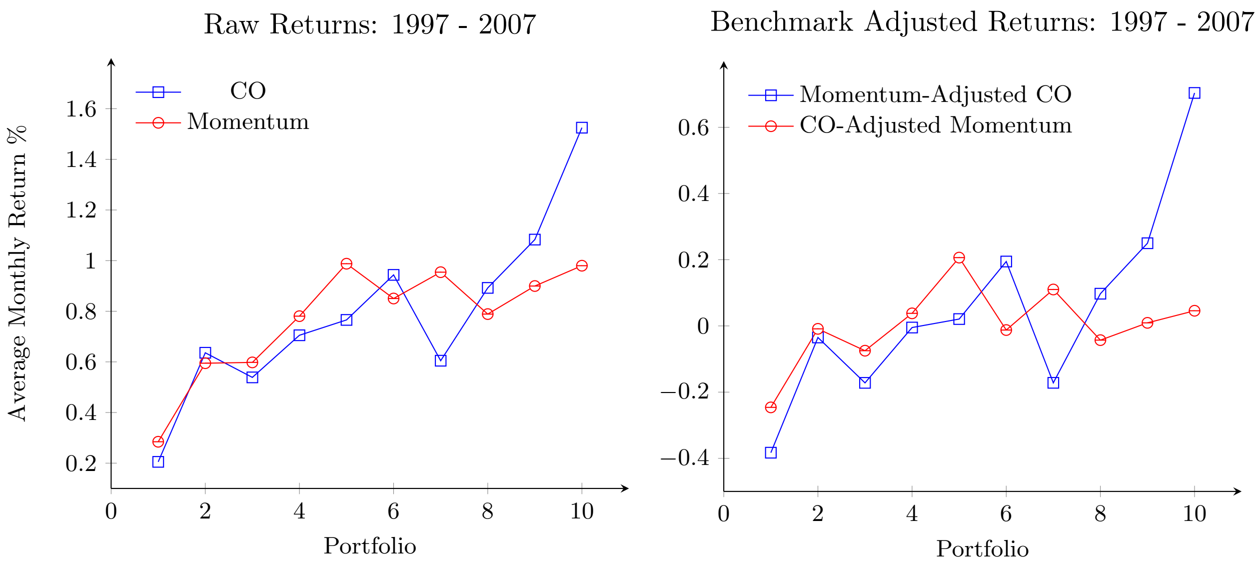
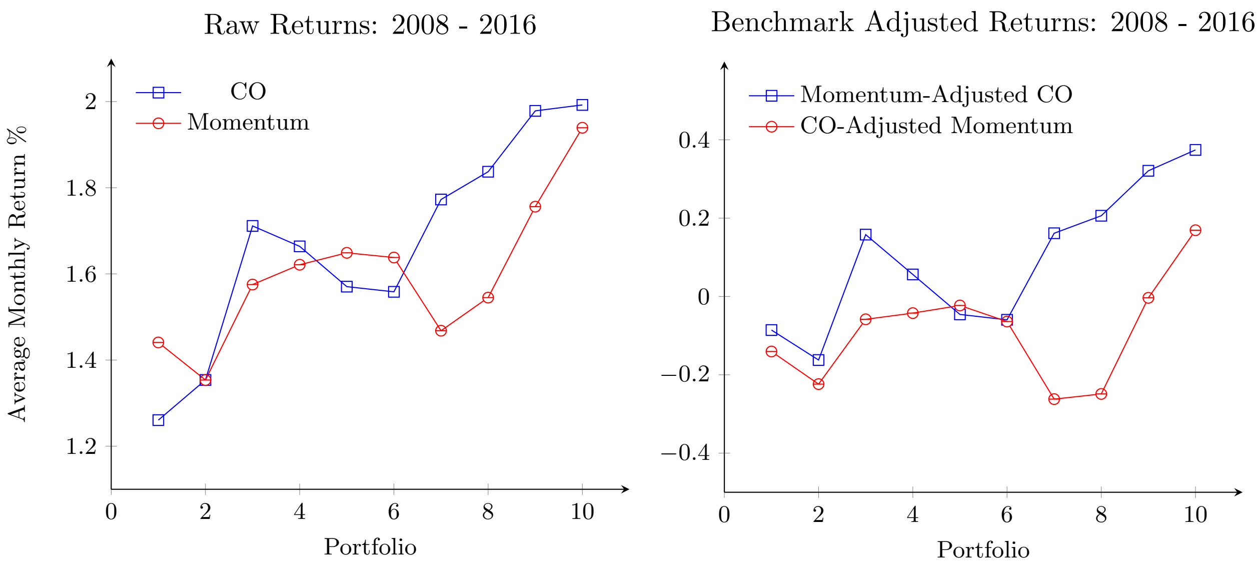


Figure 3 plots average monthly raw- and benchmark adjusted returns from CO and momentum trading strategies in the latter half of our sample period. It is once again obvious that the upward CO portfolios provide investors with higher average raw returns, even if the performance of the two top portfolios (10) are quite similar. Here, however, we see that the downward CO portfolio contributes quite significantly to the fact that the zero-investment CO strategy outperforms momentum. Looking at the general market index for OMXS, the Swedish stock market has performed quite strongly since the financial crisis which contributes to relatively high returns, even in the downward CO and loser momentum portfolios. Though, in comparison, we see that the downward CO portfolio return is substantially smaller than the average monthly return to the momentum loser portfolio (1.26% compared to 1.44%).

Figure 3: Comparison of Raw Returns and Benchmark Adjusted Returns, 2008-2016

The left graph of Figure 3 displays the monthly average return of CO and momentum portfolios for the sub-sample consisting of the years 2008-2016, while the right graph shows the performance of momentum-adjusted CO and CO-adjusted momentum portfolios.

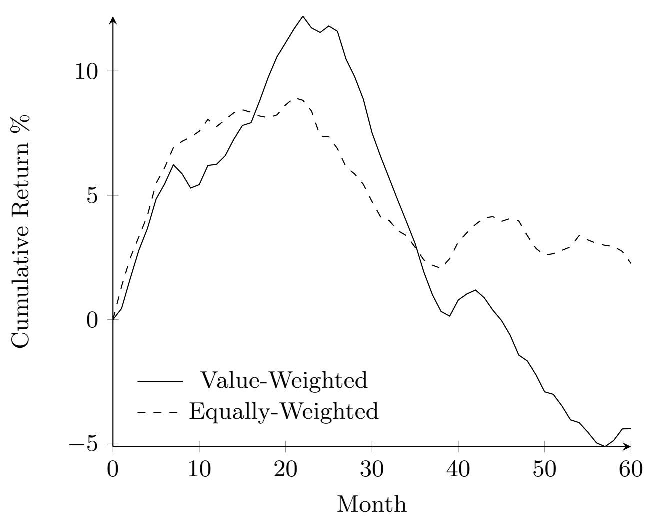


Comparing the results from the first half of our sample period to the latter half, the graphical representation of returns show that throughout the entire sample, long-short trading on CO consistently outperforms the momentum strategy on OMXS. It seems that the primary reason for this is the consistently higher returns to the upward CO decile porfolios, as these have outperformed their momentum equivalents in terms of average monthly returns across the full sample and both subsamples.

To provide further insight into the characteristics of CO returns, we investigate the long-term reversal effects of the zero-investment strategy. DHS (1998) states that the self-attribution bias and investor overconfidence leads to momentum in the short run and reversals to stock fundamentals in the long-term. Therefore, we provide a graph of average value- and equally-weighted cumulative returns to the CO long-short portfolio in Figure 4 with a 60-month holding period following portfolio formation. We find that the returns to both the equal- and value weighted CO strategies exhibits positive drifts up to slightly over 24 months, and reverses thereafter. In the US, the CO strategy experiences the corresponding upward drift approximately up to a year after portfolio formation before reversing (Byun et al. 2016). As can be observed, the magnitude of value weighted cumulative returns is larger than the equally-weighted ditto after approximately 12 months. However, the value weighted returns reverses in a much higher pace, which is expected as the value weighted methodology put increasing weights in stocks that perform well, amplifying the reversal effect illustrated by the steepness of the drop in the graph around month 27. As we do not find a significant momentum effect on the Swedish exchanges for zero-investment portfolios with holding period longer than $K = 3$, comparing the cumulative returns to the momentum portfolio equivalent is somewhat superfluous. However, for conclusiveness, we provide graphical representations of the momentum cumulative returns for a holding period of 60 months, with formation period $K = 6$, $J = 12$ in Appendix B. From Figure 4, we conjuncture that the reversal period for the CO strategy on the Swedish stock exchange is substantially longer than for the momentum strategy, and additionally longer than for the CO reversal period found on the US market (Byun et al. 2016).

Figure 4: Average Cumulative Returns on 12-Month CO Zero-Cost Portfolios

Figure 4 shows the average 60 month cumulative return for the long-short strategy, based on the continuing overreaction variable, formed over the last $J = 12$ months. Both value-weighted and equally-weighted portfolios are constructed and depicted below. The sample period is 1997-2016.



5.5 CO and Alternative Explanations

The continuing overreaction variable shares some traits with various variables introduced in the academia in recent years in order to explain cross-sectional stock returns. We hence wish to investigate whether the profitability of the CO-strategy can be explained by these other variables. Grinblatt and Moskowitz (2004), for instance, highlight the role that return consistency plays for expected returns. They introduce dummy variables for return consistency, POS_RC and NEG_RC. POS_RC (NEG_ID) takes the value 1 if a stock has experienced eight or more months with positive (negative) return and simultaneously has a positive (negative) 12-month return. A stock with a majority of positive return months is naturally more likely to have a high CO-value. We examine this relationship, between CO and return consistency, by sorting our sample based on the variable NPOS_NEG. NPOS_NEG is the number of months with positive return, minus the number of months with negative return over the last 12 months. Another study of interest is Da et al. (2014) and their measure of positive and negative information discreteness, POS_ID and NEG_ID, respectively. They try to detect if the stream of information could be considered as continuous or discrete, arguing that the higher the POS_ID (NEG_ID), the more continuous positive (negative) information, which in turn increases the likelihood of future positive (negative) returns. POS_ID (NEG_ID) is constructed as the percentage of days with positive (negative) return minus the percentage of days with negative (positive) return, if the past 12-month return is positive (negative), otherwise the variable takes the value of zero. Studying the CO and the information discreteness variables in our sample, we find that stocks with relatively many positive return days, that is high POS_ID, also tend to have large CO, at the same time as high NEG_ID tends to coincide with low CO (explicit explanations for these variables are found in subsection 4.3).

We commence by looking at the connection between continuing overreaction and return consistency, and, as stated above, analyse the CO-strategy based on NPOS_NEG. This is done by, firstly, dividing our sample into five quintiles based on NPOS_NEG and then, within each quintile, further sort the stocks into quintiles using the CO-measure with formation period $J = 12$. After this, we calculate portfolio performances for the 25 quintile portfolios and the five zero-cost portfolios respectively, using $K = 6$ months as holding period. The resulting average monthly returns (and t-statistics for the long-short portfolios) are presented in Panel A of Table 6. Studying the results, we see that the only zero-investment returns statistically different from zero on the 5% level are the portfolios

Table 6: Returns of Portfolios Double-Sorted on CO and Alternative Explanations

Double sorted portfolios are constructed monthly from 1997-2016 by sorting stocks based on CO after number of positive- and negative return months (NPOS_NEG) and information discreteness (NEG_ID and POS_ID), respectively. In Panel A of Table 6, we divide the stocks into five groups based on NPOS_NEG. In Panel B, we sort the stocks into four groups based on NEG_ID and POS_ID. Across both panels, all stocks are then sorted into quintiles based on the CO measure. Based on this sorting, the table presents average monthly returns (percentages) over a holding period of six months. Ordinary t-statistics are given in parenthesis for the zero-cost portfolios.

Panel A. First Sort NPOS_NEG

	NPOS_NEG				
CO Portfolio	1	2	3	4	5
1	0.397	0.564	0.666	0.828	0.696
2	0.658	0.603	0.997	1.148	0.886
3	0.712	0.928	0.863	0.903	1.047
4	0.578	0.788	0.961	0.852	1.462
5	0.587	0.809	1.035	1.270	1.602
5-1	0.190	0.245	0.369	0.442	0.906
	(0.595)	(0.964)	(1.756)	(2.004)	(3.743)

Panel B. First Sort POS_ID and NEG_ID

	PRET<0 (NEG_ID)		PRET>0 (POS_ID)	
CO Portfolio	2	1	1	2
1	0.331	0.485	0.672	0.816
2	0.233	0.749	0.766	1.015
3	0.208	0.860	0.714	0.712
4	-0.068	0.592	0.945	1.229
5	0.291	0.968	1.186	1.577
5-1	-0.040	0.484	0.513	0.762
	(-0.103)	(2.059)	(2.084)	(3.661)

in the top two NPOS_NEG groups (CO-portfolio 5 has statistically significant returns for NPOS_NEG quintiles 3-5). From this, we conclude that return consistency indeed influences CO and, in particular, that the long-short CO-strategy return increases with the NPOS_NEG score in this setting. In Table 2 we see that CO-deciles and NPOS_NEG are positively correlated, telling us that the groups with significant long-short returns mainly consist of stocks with large CO variables. We know from Table 3 and Figure 1, that the top CO-decile portfolios produces significant returns and that the relationship is monotonic. This monotonicity is likely one of the drivers of the performance of the double sorted long-short portfolios in NPOS_NEG group 4 and 5.

For information discreteness, we split all stocks with positive (negative) 12-month past returns into two based on POS_ID (NEG_ID). In this way our sample is divided in four and each group is then sorted into quintiles based on CO. Panel B of Table 6 presents average monthly returns for the quintile and long-short portfolios for each ID-group, as well as the t-statistics for the long-short portfolios. The ID groups are presented in such way that the leftmost group (NEG_ID 2) has the highest number of days with negative return, while the group most to the right (POS_ID 2) has the highest number of days with positive return. We see that the strategy that is long in the 5^{th} quintile portfolio and short in the 1^{st} quintile portfolio produces positive and significant returns for three of the four information discreteness groups. The deviating group consists of firms with negative return over the last 12 months, and at the same time the highest number of days with negative return. Intuitively, this group should consist of stocks with low CO values, which is indeed the case for our sample. With this in mind, the absence of positive and significant returns for the zero cost portfolio for this group is partly attributable to the absence of significant returns for the lower CO-decile portfolios, presented in Table 3.

We conclude that CO incorporates some of the effect stemming from the number of positive and negative past return months as well as information discreteness. When sorting the sample based on these variables, the internal relative strength of the CO measure is not maintained within all groups. In these groups, the CO values are not dispersed enough to generate significant zero-investment profits, highlighting the link between these additional variables (NPOS_NEG in particular) and CO.

5.6 Regression Results

In order to control the endurance of the CO measure's return predictability, we conduct firm-level cross-sectional regressions of the six month buy-and-hold stock returns over time, using variations of the following regression specification from Byun et al. (2016):

$$\begin{aligned} R_{i,t+1,t+6} &= \lambda_{0,t} + \lambda_{1,t}CO_{i,t} + \lambda_{2,t}PRET_{i,t} + \lambda_{3,t}POS\_ID_{i,t} + \\ &+ \lambda_{4,t}NEG\_ID_{i,t} + \lambda_{5,t}POS\_RC_{i,t} + \lambda_{6,t}NEG\_RC_{i,t} + \\ &+ \lambda_{7,t}NPOS\_NEG_{i,t} + \lambda_{8,t}BETA_{i,t} + \lambda_{9,t}SIZE_{i,t} + \lambda_{10,t}BM_{i,t} + \\ &+ \lambda_{11,t}REV_{i,t} + \lambda_{12,t}ILLIQ_{i,t} + \lambda_{13,t}IVOL_{i,t} + \lambda_{14,t}TURN_{i,t} + \\ &+ \epsilon_{i,t+1,t+6}, \end{aligned} \tag{2}$$

where the dependent variable, $\mathrm{R}_{i,t+1,t+6}$, is the return on stock i from month *t+1* until month *t+6*. Explanatory variables include the continuing overreaction measure $\mathrm{CO}_{i,t}$; the previous return measure, $\mathrm{PRET}_{i,t}$, corresponding to the cumulative return over the previous 12 months; $\mathrm{POS\_ID}_{i,t}$ ($\mathrm{NEG\_ID}_{i,t}$) proxies for positive (negative) information discreteness; $\mathrm{POS\_RC}_{i,t}$ ($\mathrm{NEG\_RC}_{i,t}$) is a dummy variables that takes the value 1 if a stock has had at least 8 months of positive (negative) return from month *t-12* to month *t-1* and the previous 12-month return (PRET) is positive (negative); $\mathrm{NPOS\_NEG}_{i,t}$ corresponds to the number of positive return months minus the number of negative return months, from month *t-12* to month *t-1*; $\mathrm{BETA}_{i,t}$ is the market beta estimated in month t on daily returns; $\mathrm{SIZE}_{i,t}$, defined as the natural logarithm of market capitalization; $\mathrm{BM}_{i,t}$, the book-to-market ratio in a given month t; $\mathrm{REV}_{i,t}$ is the return reversal variable, specified as individual stock return in a given month t; $\mathrm{ILLIQ}_{i,t}$ is a measure for illiquidity, constructed following Amihud (2002); $\mathrm{IVOL}_{i,t}$ measures idiosyncratic volatility in month t using daily data; and $\mathrm{TURN}_{i,t}$ is the equally weighted mean of monthly turnover from month *t-12* to month *t-1*. Each variable specification is further elaborated in subsection 4.3.

Table 7 reports the time-series averages of the regression coefficients. Since the time series naturally suffer from autocorrelation, supported by unreported Durbin-Watson tests, we report the estimates' corresponding Newey-West (1987) adjusted t-statistics with lag $L = 3$, in parenthesis. The first two columns present results for univariate regressions on CO and PRET, respectively. Regression specification (1) shows that CO has statistically significant explanatory power for six-month holding cross-sectional stock returns, with an average coefficient amounting to 0.052 and a t-statistic of 3.35. In the second univariate regression, the coefficient is not statistically significant, with a magnitude of 0.016 and t-statistic of 0.83.

To control that the PRET variable does not subsume predictive power from the CO variable, we perform a regression on both variables (specification 3). We see that the magnitude of the CO variable decreases to 0.04, yet it remains highly statistically significant with a t-statistic of 3.08. PRET further loses power and the coefficient decreases to 0.006, with a t-statistic of 0.32. The results from regression specifications 1-3 highlights the superiority of the continuing overreaction approach to traditional momentum for predicting future returns on OMXS, previously indicated, by e.g. the higher CO risk adjusted returns reported in subsection 5.3.

In regression 4, we add the information discreteness variables as defined by Da et al., (2014). We find that neither positive nor negative information discreteness has significant predictive power for future return on the main Swedish exchange. The magnitude for the positive and negative information discreteness is -0.11 and -0.08, respectively. The sign on POS_ID is quite surprising, yet as the t-statistics for the variables amounts to -0.69 and -0.62, respectively, the variables' predictive power is weak. The coefficients on CO and PRET are in line with previous findings (0.04 and 0.01 respectively). The CO variable is highly statistically significant, whereas the PRET variable is not, with t-statistics corresponding to 2.80 and 0.72.

In specification 5, we add the return consistency variables POS_RC and NEG_RC to regression specification 3. Again, the CO variable prevails with a magnitude of 0.04 and t-statistic of 2.88 while the PRET variable is once again insignificant. The return consistency variables show intuitive signs, yet without statistical significance.

For exhaustiveness, we conduct a regression using information discreteness, return consistency and NPOS_NEG in regression specification 6. As expected given previous results, the only variable with significant predictive power for future returns in this regression is the CO variable, with a coefficient of 0.04 and corresponding t-statistic of 2.44.

Having studied the respective effects of the PRET, information discreteness and return consistency variables comprehensively without finding these variable to be significant across any of the previous specifications, we omit these variables in regression 7. Instead, we add the BETA, SIZE, BM, REV, ILLIQ, IVOL and TURN variables to this regression specification. The CO variable is still statistically significant with a t-statistic of 3.519 which is an increase compared to the previous specification, while the magnitude of the

Table 7: Cross-Sectional Return Regressions

Each column of Table 7 corresponds to the times series average of coefficients from firm level cross-sectional regressions, and their t-statistics in parenthesis, conducted on a monthly basis from July 1998 until June 2016. All regressions have the 6-month holding period return for as the dependent variable. The explanatory variables considered are; continuing overreaction for $J = 12$ (CO), past 12-month return (PRET), information directness (POS_ID/NEG_ID), return consistency (POS_RC/NEG_RC), number of positive-return months minus number of negative-return months over the last 12 months (NPOS_NEG), market beta (BETA), company market value (SIZE), book-to-market ratio (BM), the reversal variable (REV), Amihud's illiquidity measure (ILLIQ), idosyncratic volatility (IVOL) and turnover (TURN). The t-statistics are Newey-West t-statistics with lag equal to 3. Time-series averages of the adjusted R-squared are presented in the last row. Significance level 0.1%, 1%, 5% and 10% are marked by ***,**,* and ^{o}, respectively.

	1	2	3	4	5	6	7	8
CO	0.052***		0.040**	0.036**	0.043**	0.038*	0.039***	0.027
	(3.347)		(3.082)	(2.803)	(2.876)	(2.437)	(3.519)	(1.576)
PRET		0.016	0.006	0.012	0.007	0.008		0.040
		(0.831)	(0.316)	(0.723)	(0.345)	(0.441)		(1.627)
POS_ID				-0.111		-0.131		-0.072
				(-0.694)		(-0.742)		(-0.270)
NEG_ID				-0.083		-0.064		-0.106
				(-0.617)		(-0.443)		(-0.594)
POS_RC					0.010	0.004		-0.005
					(0.899)	(0.341)		(-0.421)
NEG_RC					-0.012	0.005		0.011
					(-1.190)	(0.386)		(0.684)
NPOS_NEG						0.002		-0.001
						(0.781)		(-0.417)
BETA							-0.010	-0.007
							(-0.974)	(-0.754)
SIZE							-0.933**	-1.033**
							(-2.616)	(-2.859)
BM							-0.780	-0.613
							(-0.885)	(-0.762)
REV							0.107**	0.089*
							(2.769)	(2.391)
ILLIQ							0.359	0.398^{o}
							(1.489)	(1.657)
IVOL							-0.049	0.153
							(-0.113)	(0.375)
TURN							0.173**	0.142*
							(2.630)	(2.108)
Adj. R^2	0.012	0.031	0.035	0.048	0.037	0.050	0.106	0.136

coefficient remains in the same region as the most recent specifications (0.04). Further, some of the newly added variables are, too, statistically significant. As expected, the SIZE variable's coefficient has a negative sign and is highly significant, with a magnitude of -0.93 and t-statistic of -2.62. The REV and TURN variables also have significant effect on future stock returns in the cross section, with coefficient means of 0.11 and 0.17 and t-statistics of 2.77 and 2.63 respectively. The time-series averages for BETA, BM, ILLIQ and IVOL on the other hand, are not statistically significant for the current regression specification.

Lastly, in regression 8, we include all examined variables in a regression equivalent to the full formula as formulated in Equation 2. We find that the CO measure is no longer significant, which deviates from previous findings on US equity markets (Byun et al. 2016). Some of the predictive power of the continuing overreaction measure is hence subsumed by PRET (which is now higher than in previous specifications) and the alternative explanation variables added from specification 7 to 8 (information discreteness, return consistency and NPOS_NEG). SIZE is still significant with coefficient -1.033 and t-value -2.86, both increasing in magnitude from the previous specification. Both REV and TURN are still significant, but now on a five percent significance level (compared to one percent before). We can also see that ILLIQ, with a coefficient of 0.4, is significant on a ten percent level. Remaining variables do not have significant coefficient averages in this setting. It is worth noting that the coefficient for BETA is negative, however small and statistically insignificant, which also is true for specification 7. This tells us that BETA estimated using daily observations in month t is a weak explanatory variable for stock returns over month $t+1$ to $t+6$, with sign contradicting the generally presumed relationship between BETA and returns in the cross section on the Swedish market.

5.7 Further Subsample Analysis

Daniel et al. (1998) argue that it is harder for investors to cover their positions in small and less liquid firms and investments in these firms should hence be more prone to self-attribution bias and overconfidence. Therefore, we wish to investigate whether size and liquidity affect the CO portfolio performance. Thus, we conduct a subsample analysis of the CO portfolios based on these two measures, presented in Table 8. The size subsample is sorted into small and big firms, with the cutoff point being the median market capitalization on OMXS (small is below, whilst big is above). The liquidity subsample is based on the

ILLIQ measure as constructed by Amihud (2002). Stocks that are above the median in the ILLIQ measure on OMXS are sorted into the low liquidity sample. Stocks with a low ILLIQ measure is sorted into the high liquidity sample. In line with the reasoning by DHS (1998), we find that the return to the continuing overreaction strategy is higher for smaller

Table 8: Subsample Analysis of CO Portfolio Based on Size and Liquidity

Table 8 presents average monthly portfolio performance for CO-decile portfolios, with $J = 12$ and $K = 6$, for sub-samples based on size and liquidity (under and above the respective median). For both variables, the complete sample is divided into two before decile portfolios are formed for each respective sub-sample. The monthly return is the equally-weighted average of the returns from $K = 6$ portfolios implemented and held over $K = 6$ months. In the last two rows, we present the average monthly return for the zero-cost portfolio that is long the 10^{th} decile and short the 1^{st} decile and the corresponding 3-factor alpha, their t-statistics are given in parenthesis.

	Size		Liquidity	
CO-Portfolio	Small	Big	Low	High
1 (Downward)	0.525	0.520	0.622	0.368
2	0.595	0.751	0.630	0.718
3	0.743	0.813	0.709	0.762
4	0.592	0.864	0.727	0.939
5	0.756	0.872	0.862	0.794
6	1.013	0.891	0.987	0.823
7	0.825	0.788	0.946	0.804
8	1.280	0.764	1.375	0.626
9	1.636	0.880	1.488	0.820
10 (Upward)	1.570	1.058	1.671	1.220
10-1	1.045	0.538	1.048	0.852
	(3.157)	(1.698)	(3.645)	(2.458)
3-Factor alpha	1.102	0.564	1.033	0.927
	(3.244)	(1.821)	(3.468)	(2.782)

stocks. The magnitude of return to the zero-investment portfolio for small stocks is much higher than the corresponding return for the big stocks. In fact, the return to the big zero-cost portfolio is not statistically different from zero on the 5% significance level, with a coefficient of 0.54% and a t-value of 1.70. The corresponding figures for the small zero-investment portfolio is 1.05% and 3.16, respectively. We also present Fama and French three factor alphas, and observe similar results where the small zero-investment portfolio generates alphas of 1.10% on average per month with a t-value of 3.24, and the big 10-1 portfolio equivalent is 0.56 and 1.82. From this, we conclude that the CO strategy indeed generate higher returns for smaller firms on OMXS during the studied period.

With regards to the liquidity variable, we find that the low liquidity subsample provide investors with higher returns, again re-confirming the reasoning in DHS (1998). The pattern in terms of the CO portfolios is clearly increasing from the downward portfolio (1) to the upward portfolio (10) for both subsamples, however, the magnitude of profits to the low liquidity stocks is higher than the high liquidity stocks in the majority of cases. We find that the zero-investment CO portfolios for both low and high liquidity stocks are significant, generating profits of 1.05% and 0.85% per month on average, respectively. Though both subsamples generate significantly positive returns to the zero-investment CO strategy, the Sharpe Ratio for the low liquidity subsample is higher primarily attributable to the t-statistics (3.65 for low liquidity stocks and 2.46 for the high liquidity ditto). The results for the three factor alphas are in line with these findings, where the zero-investment continuing overreaction portfolio constructed with low liquidity stocks generates 1.03% monthly average returns, compared to 0.93% for the high liquidity equivalent. Again, the t-statistic for the low liquidity 10-1 portfolio is higher (3.47) than the high liquidity portfolio t-statistic (2.78). We conclude that less liquid firms provide higher zero-cost CO portfolio returns than highly liquid firms.

Comparing the two subsample analyses, size appears to be of higher importance when explaining returns to the CO strategy. The subsample for small stocks outperforms the big stock equivalent by a higher magnitude than the liquidity ditto. In other words, there is an obvious larger difference between CO returns to small and big stocks than between low and high liquidity stocks. This finding is aligned with the higher significance of SIZE than ILLIQ in regression specification 8 in Table 7.

6 Discussion and Conclusion

The first key insight in this study is that the zero-cost momentum strategy, based on 12-month past returns, only generates significantly positive profits with short-term portfolio holding horizons on OMXS. Thus, we reconfirm that the Swedish equity market diverts from other European stock markets in the fact that momentum does not generate consistent, statistically significant excess returns. This finding is in-line with several studies providing country-specific results for Sweden (e.g. Rouwenhorst, 1998, Griffin, Ji & Martin, 2003; Barber, George, Lehavy & Trueman, 2013 and Goyal & Wahal, 2015).

Further, perhaps the finding worth most emphasis is the performance of the continuing overreaction strategy on OMXS. The CO measure, constructed in accordance with Byun et al. (2016), is argued to capture returns stemming from trades based on self-attribution bias as theorised by DHS (1998). Chui et al. (2010) find evidence that the individualism index developed by Hofstede (2001) is a proxy for self-attribution bias and that it is highly related to momentum profit magnitudes. As Sweden scores among the top countries in the study by Hofstede (2001), the CO investment strategy examined in this paper fits well in the intersection between Chui et al. (2010) and Byun et al. (2016), both relying on insights provided by DHS (1998). We find that both raw returns and Fama and French three factor alphas are positive and statistically significant for zero-investment CO portfolios across a variety of holding- and formation periods. Thus, it is evident that the CO measure is indeed a stronger predictor for future returns on the OMXS than past returns, successfully capturing the momentum effect arising from investor overconfidence and self-attribution bias.

This finding holds for the entire sample period, as well as subsamples dividing the time-period into two. The time-split subsample results, in turn, show that the zero-investment CO strategy has been superior to the traditional momentum strategy in both the earlier- and latter part of our sample period. We find that neither the long-only nor the long-short momentum strategy provide investors with significantly positive returns in the 1997-2007 subsample, whereas the equivalent CO portfolios do. In the more recent sample, both momentum and CO long-only strategies generate positive, significant returns, which can partly be attributable to a strong overall performance of the OMXS in the post-crisis period. However, we do observe that all CO decile portfolios provide significant returns, and the magnitude to the zero-investment portfolio is larger for CO than the momentum equivalent in the subsample 2008-2016.

The superiority of the CO strategy is further highlighted by the benchmark-adjusted performance. We find that the CO drives away momentum return to a greater extent than the reversed. For both adjusted and unadjusted portfolios, it becomes obvious that the primary source for the CO strategy's excess returns is the ability for the strategy to pick winners. Hence, the superiority of CO compared to momentum is largely attributable to the upward CO portfolio's outperformance of the traditional momentum 'winner' portfolio. This finding holds true throughout the entire sample period, and we see that the top 3 upward portfolios in CO outperform the momentum equivalents. Hence, the long-short CO return cannot solely be attributable to poor performance in the downward portfolios, which has been the case in many previous momentum studies (e.g. Eisdorfer, 2008).

Further, conducting cross-sectional regressions over time, we test the endurance of the CO measure and find that it prevails as statistically significant in all but the last regression specification. It appears that some of the predictive power of CO is subsumed by PRET and the alternative explanation variables, sharing traits with CO by construction.

Motivated by DHS (1998), we conduct subsample analysis on Size and ILLIQ, respectively. The results show that size indeed affects the CO-strategy portfolio performance as the small stock zero-investment portfolio provide large, significant raw- and Fama French three factor abnormal returns, whereas the big stock equivalents are only significant on the 10% level. In terms of liquidity, both zero-investment CO-portfolios formed with low- and high liquidity stocks generate positive, statistically significant raw- and Fama and French three factor abnormal returns. Nonetheless, aligned with theory, the returns are larger for the less liquid sample.

To conclude, our findings show that the examined hands-on trading strategy based on continuing overreaction on OMXS provide positive and statistically significant returns during the studied period. We also find that CO outperforms traditional momentum using a variety of holding- and formation periods. In fact, traditional momentum only generates significant profits in the short-term. A topic for further research would hence be to examine the CO strategy on markets where the momentum strategy have generated positive returns, but where the individualism scoring is low. This would provide further insight into the relationship between CO and traditional momentum, as well as CO's dependence on cross-cultural differences and how the self-attribution bias differs from country to country. Furthermore, a natural extension of obvious importance to a practitioner would be to assess the strategy's profitability accounting for trading costs.

Relying on the theory developed by DHS (1998), this study contributes in the intersection between Byun et al. (2016) and Chui et al. (2010), showing that the CO measure captures the continuing overreaction arising from investor overconfidence and self-attribution bias, argued to be high in Sweden by Chui et al. (2010). By exploiting this fact, a trading strategy based on CO on the Swedish market generates significant profits throughout the examined period.

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8 Appendix

8.1 Appendix A

In Table 9, we extend the Fama French three factor regression specification, adding the Carhart (1997) PR1YR factor:

$$
\begin{aligned}
R_{i,t} - R_{f,t} &= \alpha_i + \beta_M \times MRKT_t + \beta_{SMB} \times SMB_t + \beta_{HML} \times HML_t + \\
&+ \beta_{PR1YR} \times PR1YR_t + \varepsilon_{i,t},
\end{aligned}
$$

These regressions are conducted in order to control the extent to which the excess returns of these strategies can be attributed to risk factors, including the momentum factor. In Panel A, we present the return alphas for CO portfolios with different holding periods *K = 3, 6, 9, 12* when *J = 12* as well as formation periods *J = 6, 9, 18, 24*, when *K = 6*. The similarities to the patterns in Table 4 are striking. We observe the strongest statistical power as well as the highest return magnitude for the zero-cost portfolio where the holding period equals *K = 6* and formation period equals 12 months *J = 12*. As in the Fama French three factor case, the alphas obtained can be interpreted as the risk-adjusted returns from the CO strategy relative to the factors used, in this case including the PR1YR factor. Turning to the traditional momentum strategy, we see that the abnormal return to the zero-cost portfolio is no longer statistically significant for any of the holding periods *K = 3, 6, 9, 12*, using the formation period *J = 12*. Moreover, using the holding period *K = 6*, we see that the abnormal returns gravitate towards zero for formation periods longer than *J = 9*. The magnitude of the abnormal returns for the zero-cost momentum strategy is monotonically decreasing as the formation- and holding period increases, stressing the short-term nature of the traditional momentum strategy on OMXS. We conclude that the CO strategy is resilient to the PR1YR factor, while the momentum strategy is not.

Table 9: Overlapping Portfolios, Carhart 4-Factor Alphas

Panel A (B) of Table 9 reports the monthly Carhart 4-factor alphas, in percent, for the overlapping portfolios, using CO (past return) as the "constructing" variable. J represents the number of months used in the formation period, while K stands for the holding period. Each K-month return is the equally-weighted average of returns from $K = 6$ portfolios implemented and held over $K = 6$ months. The overlapping portfolios increases the power of the tests and motivates the use of ordinary t-statistics, which are given in parenthesis. In the last row, we present the alphas for the strategy that is long in the 10^{th} CO (past return) decile portfolio and short in the 1^{st} CO (past return) decile portfolio.

	J = 12				K = 6			
Panel A. CO C4F Alphas	K = 3	K = 6	K = 9	K = 12	J = 6	J = 9	J = 18	J = 24
1 (Downward)	0.283(0.634)	-0.298(-1.404)	0.309(0.708)	0.555(1.298)	-0.205(-1.026)	-0.268(-1.231)	-0.326(-1.289)	-0.210(-0.721)
2	0.325(0.691)	-0.041(-0.181)	0.576(1.350)	0.805(1.906)	-0.001(-0.004)	0.017(0.080)	-0.011(-0.051)	-0.050(-0.222)
3	0.354(0.822)	0.056(0.304)	0.554(1.362)	0.723(1.782)	-0.078(-0.413)	0.056(0.305)	0.138(0.751)	-0.002(−0.010)
4	0.498(1.147)	0.154(0.879)	0.684(1.686)	0.791(1.967)	0.167(0.981)	0.084(0.456)	0.172(0.929)	0.145(0.815)
5	0.474(1.127)	0.136(0.770)	0.610(1.551)	0.789(1.992)	0.154(0.893)	0.176(1.065)	0.173(0.993)	0.290(1.802)
6	0.732(1.825)	0.257(1.526)	0.673(1.828)	0.822(2.221)	0.107(0.648)	0.175(0.991)	0.365(2.242)	0.390(2.485)
7	0.525(1.401)	0.175(1.094)	0.630(1.809)	0.793(2.227)	0.363(2.434)	0.330(2.069)	0.192(1.200)	0.332(2.048)
8	0.867(2.286)	0.317(1.924)	0.762(2.148)	0.831(2.352)	0.374(2.204)	0.230(1.411)	0.254(1.424)	0.133(0.763)
9	0.995(2.587)	0.563(3.279)	0.893(2.541)	0.945(2.679)	0.502(3.118)	0.534(3.059)	0.269(1.559)	0.292(1.543)
10 (Upward)	1.304(3.399)	0.748(3.767)	1.049(2.954)	1.067(2.998)	0.603(3.056)	0.635(3.339)	0.611(3.188)	0.570(2.939)
10-1	1.022(3.139)	1.045(3.796)	0.740(2.728)	0.512(2.086)	0.808(3.214)	0.903(3.393)	0.937(3.160)	0.780(2.312)
Panel B. 'Momentum' C4F Alphas								
1 (Loser)	0.027(0.038)	-0.438(-1.119)	0.482(0.738)	0.747(1.200)	-0.627(-1.601)	-0.482(-1.278)	-0.259(-0.646)	-0.254(-0.624)
2	0.251(0.511)	-0.154(-0.625)	0.476(1.013)	0.705(1.492)	0.021(0.082)	-0.120(-0.453)	-0.086(-0.339)	0.024(0.092)
3	0.389(0.891)	0.056(0.273)	0.592(1.462)	0.752(1.870)	0.074(0.391)	0.039(0.191)	0.176(0.871)	0.002(0.012)
4	0.523(1.319)	0.206(1.115)	0.683(1.861)	0.848(2.298)	0.195(1.154)	0.219(1.255)	0.434(2.582)	0.466(2.596)
5	0.780(2.182)	0.352(2.120)	0.743(2.197)	0.856(2.543)	0.329(2.108)	0.330(2.002)	0.379(2.278)	0.321(1.915)
6	0.637(1.829)	0.330(2.004)	0.719(2.247)	0.886(2.724)	0.322(2.206)	0.373(2.290)	0.373(2.234)	0.407(2.630)
7	0.717(2.067)	0.356(2.109)	0.689(2.145)	0.840(2.574)	0.265(1.640)	0.363(2.217)	0.400(2.474)	0.489(2.967)
8	0.712(2.025)	0.283(1.667)	0.674(2.040)	0.780(2.336)	0.444(2.776)	0.433(2.547)	0.272(1.448)	0.307(1.763)
9	0.720(1.973)	0.299(1.429)	0.614(1.730)	0.670(1.885)	0.446(2.693)	0.466(2.771)	0.210(1.117)	0.167(0.813)
10 (Winner)	1.125(2.554)	0.383(1.542)	0.741(1.708)	0.709(1.605)	0.633(2.962)	0.456(1.922)	0.193(0.687)	0.163(0.616)
10-1	1.023(1.835)	0.299(0.571)	0.193(0.395)	0.186(0.418)	1.259(2.827)	0.938(2.037)	0.452(0.893)	0.417(0.822)

8.2 Appendix B

Figure 5: Cumulative Returns on 12-Month Momentum Zero-Cost Portfolios

Figure 5 shows the average 60 month cumulative return for the long-short strategy, based on pased performance over the latest $J = 12$ months. Both value-weighted and equally-weighted portfolios are constructed and depicted below. The sample period is 1997-2016.