**Universidade do Minho**
School of Economics and Management

Márcio António de Oliveira Santos

# Overreaction and Underreaction in the UK

Junho 2017

Márcio António de Oliveira Santos **Overreaction and Underreaction in the UK**

Uminho | 2017

**Universidade do Minho**
School of Economics and Management

Márcio António de Oliveira Santos

# Overreaction and Underreaction in the UK

Master in Finance

Professor supervisor:
**PhD Cristiana Cerqueira Leal**

Junho 2017

**Acknowledgments**

I would like to express my gratitude to Professor Cristiana Cerqueira Leal for her valuable and constructive suggestions during the planning and development of this research work. Her guidance has been very much appreciated.

I wish to thank my family for their trust, support and encouragement throughout my study.

# Overreaction and Underreaction in the UK


**Abstract**

In this research work we challenge the Efficient Market Hypothesis (EMH) of Fama (1970) in its weak-form by assessing if price and earnings momentum and reversals are robust in the UK stock market over December 1985 to June 2016; and whether these phenomena can be explained by behavioral finance theory regarding the Underreaction and Overreaction Hypothesis. We analyze the short- and long-term profitability of momentum strategies by forming and testing relative strength portfolios based either on price and earnings variables. Our results indicate that the profits from momentum strategies have generated consistently superior returns as those achieved by the overall market for the last 31 years in the UK; and that momentum can be largely attributed to extreme past winners' stocks that have suffer from favorable earnings surprises. After controlling for risk, extreme past winners' stocks exhibit steady positive abnormal returns and extreme past losers' stocks tend to exhibit normal performance. Evidence provided is consistent with the argument that momentum profits are not explained by asset pricing models as Fama-French (1993) three-factor model and Carhart (1997) four-factor model; and with the argument that the Fama-French (1993) three-factor model is effective in explaining the tendency for stock returns to reverse. We confirm the existence of stock price relation between stock price momentum and market underreaction to firm-specific information. Multivariate analysis performed point on a systematic drift of stock prices associated with the release of unexpected positive earnings surprises. Our results are compatible with the underreaction hypothesis. We found evidence that investors tend to underweight positive earnings surprises and, consequently, that conservatism bias causes prices to systematically show a continuation pattern and origin momentum profit opportunities of about 1% a month, by means of a multivariate momentum arbitrage procedure based mutually on price and earnings variables. We conclude that momentum effect is persistent and an exploitable anomaly in the UK from December 1985 to June 2016; is robust to risk-adjustments; and brought up (at least in part) by the presence of investors that systematically underreact to favorable and unexpected firm-specific information related to earnings.



Keywords: Momentum; Momentum strategies; Reversals; Earnings surprises; Overreaction; Underreaction; Market efficiency; Behavioral finance.

# Overreaction and Underreaction in the UK


## Resumo

Neste estudo desafiou-se a teoria de eficiência de mercado de Fama (1970) na sua forma fraca. Avaliou-se se a continuidade e reversão dos retornos são fenómenos robustos no mercado de ações do Reino Unido entre dezembro de 1985 e junho de 2016; e se esses fenómenos estão relacionados e podem ser explicados pelas teorias das finanças comportamentais em relação às hipóteses de sub-reacção e sobre-reação do mercado.

Através de um conjunto de testes de rendibilidade de carteiras de ações formadas com base em variáveis como o "preço das ações" e os "resultados líquidos obtidos", testou-se se empresas classificadas como "ganhadoras" ou "perdedoras" experienciaram continuidade nos retornos a curto-prazo e reversões a longo-prazo.

Os resultados corroboram a existência do efeito de continuidade no Reino Unido e indicam que os lucros das estratégias de momentum geraram retornos superiores aos alcançados pelo mercado global nos últimos 31 anos de forma consistente; e que o efeito momentum pode ser atribuído em grande parte a empresas classificadas como vencedoras que sofreram de surpresas favoráveis nos resultados. Depois de controlar os resultados para fatores de risco, as empresas vencedoras exibem retornos positivos anormais e as empresas perdedoras tendem a apresentar desempenho normal. A evidência fornecida é consistente com o argumento de que os lucros de momentum não são explicados por modelos de valorização de ativos como o modelo de três fatores de Fama and French (1993) e o modelo de quatro fatores de Carhart (1997); e com o argumento de que o modelo de três fatores de Fama and French (1993) é eficaz para explicar a tendência de reversão nos retornos a longo-prazo.

Confirma-se a existência de uma relação entre a continuidade dos preços das ações e a divulgação de informação específica das empresas. Análises multivariadas apontam para um desvio sistemático dos preços das ações associado com o anúncio de resultados que constituem surpresas positivas. Os resultados são compatíveis com a hipótese de sub-reação do mercado inglês. Constata-se que os investidores tendem a subponderar as surpresas positivas nos resultados, e que esse conservadorismo faz com que os preços exibam sistematicamente um padrão de continuidade

e originem oportunidades de lucro de cerca de 1% ao mês, por meio de um procedimento de arbitragem multivariada baseado no preço das ações e em surpresas nos resultados.

Conclui-se que o fenómeno da continuidade dos retornos é persistente e consiste uma anomalia explorável no Reino Unido de dezembro de 1985 a junho de 2016; é robusto para ajustes de risco; e surge (pelo menos em parte) pela presença de investidores que sistematicamente sub-reagem a informações favoráveis e inesperadas relacionadas com os resultados das empresas.

## Contents

## Tables

## Abbreviatures

ACAR – Average Cumulative Abnormal Returns

CAR – Cumulative Abnormal Returns

CAPM – Capital Asset Pricing Model

C4FM – Carhart (1997) four-factor model

EMH – Efficient Market Hypothesis

FF3FM – Fama and French (1993) three-factor model

FTSE – Financial Times Stock Exchange

LMC – Low Market Capitalization

LSE – London Stock Exchange

MCSS – Market Capitalization Size-Segment

MMC – Medium Market Capitalization

PEAD – Post-earnings-announcement-drift

SMC – Small Market Capitalization

SP – Sub-Period

SUE – Standardized Unexpected Earnings

TMC – Total Market Capitalization

TRI – Total Return Index

# 1. Introduction

Technical analysts have long searched for patterns in stock prices and trading strategies to exploit them. In accordance with the efficient market theory (Fama, 1970), it is impossible to predict future price movements by using available information in the market. However, a bulk of empirical evidence suggests that it can be possible to predict future performance from historical information. Among them, financial researchers and practitioners have found two broad type of phenomena that still challenge the notions of market efficiency: the momentum effect (or continuation) and reversals.

The momentum effect is documented to be present on returns and on earnings information variables. For instance, Ball and Broun (1968) document that firms reporting unexpectedly high earnings subsequently outperform firms reporting unexpectedly low earnings; and Jegadeesh and Titman (1993) refer the tendency for stocks with recent low (high) returns to have low (high) returns over the subsequent 3- to 12-months period. In the long-term, DeBondt and Thaler (1985, 1987) document a tendency for stocks to reverse, an instance in which long-term past losers outperform long-term past winners over long horizons up to 3- to 5-years period. Jegadeesh and Titman (2001) also find a tendency for stocks that show good/bad performance in short horizons to reverse at longer horizons (a momentum-reversals effect).

Several explanations have been proposed to explain returns predictability. To date, no measure of risk has been found that completely explain momentum returns. Grundy and Martin (2001) and Jegadeesh and Titman (2001) study the risk of momentum strategies and conclude that while factor models can explain most of the variability of momentum returns, they fail to explain their mean returns.

On the other side of the spectrum, others suggest that a plausible explanation for stock returns to exhibit autocorrelations is consistent with a rational deviation of investors when updating new information in their investment prospects that are not explained by the arguments of the Efficiency Market Hypothesis. This behavioral explanation is supported by a large number of overreaction and underreaction studies (e.g. Tversky and Kahneman, 1975; Barberis, Shleifer and Vishny, 1998; Daniel, Hirshleifer and Subramanyam, 1998; Hong and Stein, 1999; Antoniou, Doukas and Subrahmanyam, 2013). Overall, both underreaction and overreaction studies rely on evidence that when investors receive firm-specific information, they do not respond as much as Bayesian statistics predicts, creating patterns in stock returns that can be exploited by sophisticated investors.

Our main purpose is to investigate if the UK stock market overreacts and/or underreacts to firm's fundamental information. This research work relates the evidence on momentum and reversals in stock prices to the evidence on market underreaction and overreaction to earnings-related information. We start providing evidence for returns continuation and reversals in the UK stock market by assessing the existence of autocorrelations in returns over short- and long term horizons. Then, we study the relation between price momentum and earnings momentum. We finally resort to the main behavioral theories to conclude about the underreaction and/or overreaction hypothesis documented in the literature concerning the market under study.

For reasons to discuss later in the Methodology and Data' sections (Sections 3 and 4, respectively), we assign individual stocks based on their past performance into portfolios and we test several investment strategies by going long/short with those portfolios according to their relative performance. To conclude about the Underreaction and Overreaction hypothesis, our analysis is based on two-way investment strategies. This procedure constructs portfolios of stocks that are commonly identified by a price variable (i.e., past stock returns) and an information variable (i.e., earnings surprises). Our study considers all the current UK stocks that compose the All-Share index of the London Stock Exchange at December 2016. The time-period considered runs for approximately 31 years beginning in December 1985 to June 2016. Our data for individual firms consists of stock returns, market capitalization value and earnings figures.

Our results show that momentum returns are robust to the traditional risk-return paradigm given by commonly used multifactor models. Additional robustness tests exposed an interesting size effect related to momentum returns. When double-sorting stocks based on past returns and a market capitalization size variable, our findings reveal that momentum effect is mainly attributed to medium and small segments of the market capitalization. Momentum is also documented to be pervasive over the entire sample.

We make a link between momentum returns and investors conservatism reaction to firm-specific information by using an earnings variable that sort stocks that have suffered from earnings surprises. We noticed that investors tend to underweight positive earnings surprises and, consequently, that conservatism bias causes prices to systematically drive away from fundamentals, creating a continuation pattern in returns and originating momentum profit opportunities. According to tests performed, a sophisticated investor can, on average, obtain superior returns of about 1% a month by implementing a multivariate momentum arbitrage strategy that goes long with a portfolio of recent winning stocks and short with a portfolio of recent losing stocks that have suffered from favorable/unfavorable earnings surprises, respectively. Although, transaction costs or limits to arbitrage are not considered in this study.

Our findings are compatible with the underreaction hypothesis in the UK stock market. This study provides empirical evidence for the UK stock market that contradicts the EMH of Fama (1970) in its weak form level which states that abnormal returns cannot be obtained based on past returns observation.

The study proceeds as follows. Section 2 provides a brief review of the relevant literature, Section 3 presents the methodology, Section 4 the data description and the tests we run and in Section 5 we show our empirical results and discuss the main findings. In Section 6 we present our main conclusions.

## 2. Literature Review

The concept of market efficiency is central to finance. Starting in the 1960s, the EMH was the central proposition of finance for nearly thirty years. This traditional framework defines an efficient market as one in which security prices reflects all available information and change in response to new information quickly and accurately (Fama, 1965). Since new information is unpredictable by nature, stock prices must move randomly and unpredictably as well. As such, any valuable information that could be used to predict future stock performance should already be reflected in stock prices.

The theoretical base case for the EMH (Fama, 1970) relies on three arguments. First, investors are assumed to be rational and hence to value securities rationally. As Barberis and Thaler (2003) elucidate, rationality means that when agents receive new information, they update their beliefs correctly, in the manner described by Bayes' law and, given their beliefs, agents make choices that are normatively acceptable. Second, to the extent that some investors are not rational, their trades are random and therefore cancel each other out without affecting prices (Fama, 1998).

Third, to the extent that investors are irrational in similar ways, they are met in the market by rational arbitrageurs who eliminate their influence on prices, as stated by Fama (1965).

Besides the definition of efficient markets, in the 1970' Eugene Fama distinguish among three versions of EMH: the weak, semistrong, and strong forms of the hypothesis. These versions differ by their notions of what is meant by the term "all available information".

Under the weak-form efficiency, current prices fully incorporate information that could be derived by examining market trading data such as the past history of prices. This version of the hypothesis means that any effort analyzing trends in stock prices is fruitless. Since security prices are the most public and easily available information in the market, all investors would have incorporated that information into their investment prospects.

The semi-strong form states that all publicly available information regarding the prospects of a firm must be already incorporated in the stock price. Such information includes, in addition to past prices, fundamental data of firms. Again, if investors have that information from publicly available sources, one would expect it to be reflected in stock prices. The weak-form efficient is obviously contained in this definition since historical prices are a subset of publicly available information about a security.

Finally, the strong-form version of the EMH states that stock prices reflect all information relevant to the firm, including publicly available information in the market and even information available only to company insiders (i.e., private information). This version implies both the semi-strong and the weak-form of the EMH and is the most comprehensive version of the hypothesis. While an investor cannot profit from trading on publicly available information, one could profit by acting upon privileged information supplied by insiders that have not been yet released to the general public, which is illegal in most markets.

The EMH has some implications for investors. It implies that any effort dedicated to analyzing, picking and trading securities is ineffective and the way an investor can possibly obtain higher returns is by purchasing riskier investments (Fama, 1970). As said by Malkiel (2003, p.3) an efficient capital market is a market in which "prices fully reflect all known information, and even uninformed investors buying a diversified portfolio at the tableau of prices given by the market will obtain a rate of return as generous as that achieved by the experts". Although, this is not well accepted by some professional portfolio managers and economists who believe that stock prices are somewhat predictable on the basis of past stock price patterns (e.g. DeBondt and Thaler, 1985; Jeagadesh and Titman, 1993 and 2001). For instance, many professionals called *chartists* or *technical analysts* still study records or charts of past stock prices, hoping to find patterns they can exploit to make a profit. This type of information is publicly available information at minimal cost and therefore should has been already incorporated in stock prices and one should not expect abnormal returns by studying that subset of information (Fama, 1970).

From its conception to the 1990's, finance research was dominated by this EMH framework. Since the mid-1980's, considerable effort was expended testing market efficiency. The 1990's witnessed the proliferation of reported market anomalies and were a time of important academic discussion of the consistency of the efficient markets model.

## 2.1. Challenges to Market Efficiency Theory

### 2.1.1. Price Momentum and Reversals

An endless debate among finance academics concerns market efficiency. Early tests of efficiency were tests of the weak form. Fundamentally, were tests designed to find trends in past prices that would enable investors to earn abnormal profits. One way of discerning trends in stock prices is by measuring the serial correlation of stock market returns. Serial correlation refers to the tendency for stocks to be related to past returns. Positive serial correlation in returns means that positive returns tend to follow positive returns - a momentum type of propriety. Negative serial correlation means that positive returns tend to be followed by negative returns - a reversion or "correction" property (Bodie, Kane and Marcus, 2011 ch.11).

Early empirical evidence confirms the market efficiency conjecture. For example, Jensen (1968) found that mutual funds do not outperform the market. Also, Ball and Brown (1968) and Fama, Fisher, Jensen, and Roll (1969) confirm that firm-specific announcements do not, on average, cause stock prices to move.

However, since the mid-1980's the notion of market efficiency has been challenged. Studies have reported a set of anomalies that were difficult to relate to the traditional finance framework. Among them, the relation between stock returns and past performance has called researchers attention and a large amount of empirical work has documented ways in which asset returns can be predicted based on publicly available information, as follow.

The ability in predicting the cross section of future returns based on past returns was first shown in the US common stock return from 1965 to 1989 by Jeagadesh and Titman (1993). In their findings, one can obtain superior returns by holding a zero-cost portfolio that consists of long positions in stocks that have outperformed in the past 3- to 12-months (winners) and short positions in stocks that have underperformed during the same period. They conclude that while the individual performance of stocks is unpredictable, portfolios of best-performing stocks in the recent past appear to outperform other stocks with enough reliability to offer profit opportunities.

Since its discovery, Momentum effect remains a big puzzle in efficient markets.

Momentum is documented to be pervasive and robust over time. Subsequently, Jeagadesh and Titman (2001) confirms the efficacy of momentum portfolios in the 1990 to 1998 period and Israel and Moskowitz (2013) shows its robustness prior to Jeagadesh and Titman (1993) studies from 1927 to 1925, and after from 1990 to 2012;

The momentum effect has been documented in numerous other studies in which good and bad recent performance of stocks continues over short periods of time (e.g., George and Hwang, 2004; Novy-Marx, 2012).

Momentum effect is also documented in developed and emerging countries (Rouwenhorst, 1998 and 1999), in global markets and individual countries throughout the world (Haugen and Baker, 1996 and Griffin and Martin, 2003) and consistent across markets and asset classes and present in the bounds market (Asness, Moskowitz, and Pedersen, 2013). However, there are some important exceptions, most notably in Asia, of those in Japan and Korea (Chui, Wei, and Titman, 2000);

Momentum is also found in industry portfolios (Moskowitz and Grinblatt, 1999), in country indexes (Asness, Liew, and Stevens, 1997), in commodities (Erb and Harvey, 2006), in exchanged traded futures contracts (Moskowitz, Ooi, and Pedersen, 2012).

As for the long-horizon returns (over multiyear periods), empirical studies have found suggestions of negative serial autocorrelations. For instance, DeBondt and Thaler (1985) were the first to document systematic price reversals in the US stock market, indicating that stocks that have performed poorly in the past 3- to 5-years tend to significantly outperform stocks that have performed well in the same period. Subsequently, Jegadeesh and Titman (2001) also document the tendency for long-term reversals in stock returns. To a certain extent, those set of phenomena constitute examples of possible violations of the tenets of market efficiency theory in its weak form.

The endless debate faced by researchers and practitioners is whether these anomalies are caused by problems with asset pricing theories and measures of performance or they can be explained by behavioral aspects or either by chance. Still, there is an ongoing debate about the possible reasons of observed market anomalies and there is much to be done in this area.

### 2.1.2. Risk-based Explanations

Since revealed, many academics have tried to account for momentum and reversals effects with risk-based explanations. First studies on mutual fund performance were based solely on the return of a portfolio relative to the return of a benchmark, as postulated by the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), which has long been a basic tenet of finance. However, with the development of portfolio theory, evidence shows that differences in average returns are determined not only by the market risk, as prescribed by the CAPM, but also by firm-level market capitalization, book-to-market (Fama and French, 1993 and 1996), and prior return (Carhart, 1997). As result, risk emerges as an important parameter in performance evaluation.

Overall, it has become evident that risk-based explanations and traditional asset pricing models cannot account for all the profits of the reported anomalies presented. For instance, Jegadeesh and Titman (1993) comment that the evidence is consistent with delayed price reactions to firm-specific information and Jegadeesh and Titman (2011) conclude that momentum effect is quite pervasive and very unlikely to be explained by risk. In their findings, Chopra, Lakonishok and Ritter (1992) demonstrate that contrarian profits are possible even when size, beta and past returns are accounted for. Fama and French (1993, 1996) show that, except for the momentum effect, the impact of security characteristics on expected returns can be explained within a risk-based multifactor model. Fama and French (1996) argue that the three factor model captures the long term return reversal documented in DeBondt and Thalar (1985) but is unable to explain the evidence of return continuation present in Jagadeesh and Titman (1993).

Size related effects are also described to have an important impact in return continuation and reversals. A recent study from Booth, Fung, and Leung (2016) investigates the risk-return explanations for the momentum-reversals phenomena (i.e., momentum effect followed by reversals) in the US from January 1962 through December 2013. Their procedure form portfolios using a double-sort technique in which stocks are identified and assigned to portfolios by past returns and other characteristics such as firm size, that serves as a proxy for risk. Their results show that momentum followed by reversals is largely attributable to the interaction of the price momentum and the market capitalization and other size related effects. Booth, Fung, and Leung' (2016) results are consistent with the literature that, on average, small firms yield more positive returns than large firms (e.g. Fama and French, 1993).

Microstructure bias such as the liquidity effect also seems to relate to return continuation and reversals. Zhao, Wang and Tan (2016) conclude that liquidity factors consistently emerge as key driver of return reversal, which is in support of the *liquidity effect*. They also conclude that institutional investors appear to trade primarily the stocks of large firms, which leads them to lower returns as a result of not exploitation of the small-firm effect, which is consistent with the *neglected-firm effect*. Because small firms tend to be neglected by large institutional traders (Arbel and Strebel, 1983), information about smaller firms is less available so this information deficiency makes smaller firms riskier investments that command higher returns. In this sense, neglected firms might be expected to earn higher returns as compensation for the risk associated with limited information (Merton, 1987). In accordance with this hypothesis, Amihud and Mendelson (1986, 1991) showed that small stocks have a strong tendency to exhibit abnormally high risk-adjusted rates of return. Accordingly, Pástor and Stambaugh (2003) conclude that expected US stock returns from 1966 to 1999 are related cross-sectionally to the sensitivities of returns to fluctuations in aggregate liquidity. In their findings, stocks that are more sensitive to aggregate liquidity have substantially higher expected returns, even after they account for exposures to the market return as well as size, value, and momentum factors. They find smaller stocks to show less liquidity and to have high sensitivities to aggregate liquidity. They also demonstrate that lower liquidity induces greater return reversals and that the liquidity risk factor account for half of the profits to a momentum strategy over the period tested.

### 2.1.3. Price and Earnings Momentum

The literature has documented not only price-momentum drift but also a price drift after earnings announcements. Earnings momentum or the post-earnings-announcement-drift (PEAD) was first documented by Ball and Brown (1968) and refers to the fact that firms reporting unexpectedly high earnings subsequently outperform firms reporting unexpectedly low earnings. In specific, the authors document that even after earnings are announced, estimated Cumulative Abnormal Returns (CAR) continue to drift up for "good news" firms and down for "bad news" firms.

Main literature suggests that buying stocks with recent good earnings news, while simultaneously shorting stocks with recent bad earnings news, can generate positive profits that are unrelated to risk (Chan, Jegadeesh and Lakonishok, 1996; Chordia and Shivakumar, 2006; Hong, Lee and Swaminathan, 2003; Chordia and Shivakumar, 2006). Additionally, studies have shown that the market's informational inefficiency is one main factor for PEAD (e.g., Bernard and Thomas, 1989; Freeman and Tse,1989; Bhushan, 1994).

Price and earnings momentum are documented to be related (Chan, Jegadeesh and Lakonishok, 1996). A subsequent study performed by Chordia and Shivakumar (2006) confirm the relation between price and earnings momentum and support the argument that price momentum is a manifestation of the earnings momentum. Moreover, their findings show that the payoff for both anomalies are known to follow a very similar pattern, in that for both earnings momentum and price momentum, disproportionately large payoffs occur at earnings announcements subsequent to portfolio formation. This is consistent with the results in Hong, Lee and Swaminathan (2003) who examine earnings and price momentum in eleven international equity markets and find that price momentum exists only in those countries where earnings momentum is profitable.

Chordia and Shivakumar (2006) results suggest that the Fama-French (1993) model does not capture the impact of earnings surprises on returns. Even after controlling for price momentum, a strategy of buying firms reporting unexpectedly high earnings and selling firms reporting unexpectedly low earnings would earn a significant payoff of 0.80% per month.

More recent studies focus on the three firm-performance information that receive most attentions from investors – revenue, earnings and price. They attempt to understand how investors incorporate those information variables altogether in stock prices. Thus, multivariate momentums are therefore used as a venue in the exploration (Chen, Chen, Hsin, and Lee, 2015).

Chen, Chen, Hsin, and Lee (2015) show that the information conveyed by revenue surprises and/or earnings surprises only makes a limited contribution to price momentum. Further, they observe that fundamental performance information (Standardized Unexpected Earnings (SUE)) is positively associated with the accompanying market performance information (prior returns), and the reverse holds as well. For example, earnings momentum strategies with winner stocks yield higher returns than with loser stocks; and a price momentum strategy with stocks with higher SUE yields higher returns than with lower SUE stocks. This reveals that that investors underestimate the joint implications of fundamental information (as revenue surprises and earnings surprises) and prior returns particularly when they point in the same direction.

### 2.1.4. Momentum and Reversals in the UK stock market

There is much work on momentum and reversal effects for the US stock market. Evidence for the UK stock market is comparatively scarcer and contradictory.

Clare and Thomas (1995) and Dissanaike (1997) both find some evidence of returns predictability in the UK, though the focus of their work is on long-run rather than short-term momentum effect. Using a random sample of up to 1000 stocks in any one year from 1955 to 1990, Clare and Thomas (1995) find that losers outperform previous winners over a two-year period by a statistically significant 1.7% per annum. Although, they find that those results may be a manifestation of the small firm effect. Dissanaike (1997) using larger and better-known listed companies to minimize the influence of bid-ask biases and infrequent trading that are constituents of the FT500 Index, over the period 1975-1991 find that there is some evidence of momentum (rather than reversal) up to the 24-month horizon.

Campbell and Limmack (1997) studied the long-term reversals in the abnormal returns of UK companies classified as 'winners' and 'losers' over the period from January 1979 to December 1990. It was found that a reversal in the abnormal returns of winner and loser portfolios was experienced over each of years 2-5, supporting the momentum-reversals effect. Overall, the evidence appears to be consistent with the overreaction hypothesis. The excess returns documented by Campbell and Limmack (1997) are robust even when they control for size effect, suggesting that overreaction phenomenon' in the UK is not simply a manifestation of the well documented size effect. Their results indicate that the winner-loser effect is an exploitable anomaly in the UK stock market.

In the short-run, Campbell and Limmack (1997) find that in the 12 months following portfolio formation loser companies continued to experience negative abnormal returns and winner companies persisted in generating positive abnormal returns, thus appearing to confirm the findings of US studies which support the momentum effect.

Another study by Liu, Strong and Xu (1999) identifies the presence of momentum profits in UK stock returns over the period of January 1977 to December 1996. Controlling for systematic risk, size, book-to-market ratio, did not eliminate momentum profits. They also confirm its robustness by examining momentum profits in sub-samples of their dataset.

The possible influence of firm size is also documented for the UK stock market by splitting the winner and loser portfolios into groups based on equity market capitalization. Campbell and Limmack (1997) found that the very smallest loser companies did experience a reversal in their abnormal returns over the following 12 months, but that no such reversal existed for the smallest winner companies.

A more recent study by Spyrou, Kassimatis, and Galariotis (2007) on short-term overreaction and underreaction and efficient reaction to information in the UK stock market indicates that investors in large capitalization stocks in the UK react efficiently to information contained in market shocks. However, investors in medium and small capitalization stocks exhibit a very different behavior by reacting less strongly to market shocks. They document an underreaction effect for medium and small capitalization stocks. The return momentum is documented to be more pronounced following positive shocks (for extended periods of 15-20 days after the shock).

Additionally, Spyrou, Kassimatis and Galariotis (2007) find that microstructure biases do not explain findings, which contradicts Zarowin's (1989 and 1990) results.

### 2.1.5. Behavioral Approach

In the 1990s, a lot of the focus of academic discussion shifted away from econometric models toward developing models of human psychology as it relates to financial markets (Shiller, 2003). "Behavioral Finance" has been raised in the hope to explain for market anomalies that are left unaccountable by econometric models and in response to the difficulties faced by the traditional paradigm in understanding individual trading behavior.

#### *2.1.5.1. Investors' (limited) Rationality*

Although EMH state that, while they may exist, irrational investors deviate randomly, it is suggestive that individuals systematically violate the Bayes rule and other maxims of probability theory in their prediction of uncertain outcomes. Human experiments lead by Tverskyand and Kahneman (1975) and Kahneman and Tversky (1982) explain that individuals act per investor sentiment rather than Bayesian rationality. Black (1986) argues that investors trade on noise rather than information, fail to diversify, buy and sell actively and expensively, sell winnings stocks and hold losing stocks, and seek and follow price patterns instead of pursuing passive strategies in a systematic and pervasive way. Shiller (1987) sustains that, rather than randomly, investors deviate in the same way, buying and selling the same securities roughly at the same time, following rumors or imitating their neighbors. According to behavioral approach, investors suffer some cognitive limitations and illusions when they have to make decisions. Those cognitive limitations lead them to a distortion in perception or understanding when judging information and cause erroneous investment decisions.

#### 2.1.5.2. Market (In)Efficiency

To a certain degree, investors' systematic erroneous investment decisions are barriers to arbitrage and cause markets to be informationally inefficient. The Fama (1965) point of view is that when a mispricing occurs rational investors immediately exploit the opportunity thereby correcting the mispricing. Behavioral finance argues that, even when identified, mispricing's can remain unchanged due either to risk or cost of implementing strategies designed to correct them or the inexistence of similar substitutes for securities affected with the effects of noise trading. The central argument of behavioral finance states that, in contrast to EMH, arbitrage is limited to be implemented and mispricing can persist instead of being efficiently corrected. As such, some features of asset prices are most plausibly interpreted as deviations from fundamental value, brought about by the presence of traders who are not fully rational (Barberis and Thaler, 2003).

### 2.1.6. Behavioral Explanations

As we have mentioned before, the risk-based explanation cannot account for all of momentum and reversals' profits. Therefore, researchers start to look to behavioral aspects hoping to better explain the reported phenomena. In brief, to behavioral finance, momentum and reversals are brought about by the presence of investors that do not update their investments prospects correctly when judging new information, creating patterns in stock returns.

Studies of human psychology found that individuals tend to either underreact or overreact to information. As such, two set of hypotheses have been put forward to understand returns momentum and reversals: the underreaction hypothesis and the overreaction hypothesis. In what follows, we present the fundamental behavioral models that relate the underreation and overreaction hypothesis.

Concerning the underreaction hypothesis, Barberis, Shleifer and Vishny (1998) discuss how a "conservatism bias" might lead investors to underreact to information and origin momentum profits. This conservatism bias suggests that investors tend to underweight new information when they update their priors. This way, new information is slowly and gradually incorporated into stock prices during the holding period, but once the information is fully incorporated in prices there is no further predictability about stock returns.

A possible behavioral explanation for the overreaction hypothesis is derived from the "representativeness" heuristic, as advocated by Tversky and Kahneman (1975). This theory asserts that the stock market may overreact to relevant news. That overreaction leads to positive serial correlation (momentum effect) over short time horizons. Subsequent correction of the overreaction (i.e., the occurrence of return reversal) leads to poor performance following good performance (in case of overreaction to good news) and vice versa (in the case of overreaction to bad news). As such, a momentum-reversals effect is observed.

DeBond and Thaler (1985, 1987) stand on the cognitive psychology findings of Tversky and Kahneman (1975) who believe that investors would overweight recent information, neglecting or attributing less importance to past news in their prospects revisions, resulting in excessive optimism over good news and extreme pessimism over bad news. This would impact the stock market to such a degree that stock prices would deviate temporarily from their intrinsic values in the short-term, creating a "mean-reverting" effect (i.e., a subsequent correction of the security prices) in the medium-long term.

Another Behavioral model is proposed by Daniel, Hirshleifer and Subramanyam (1998). The authors argue that informed traders are overconfident and can be characterized by a "self-attribution" bias. In their model, investors receive information that either conforms or disconfirms their prospects. Because of their cognitive bias, they become overconfident about their selection ability in the presence of confirming news. That is, in the short run the overreaction increases following the arrival of confirming news and that leads to further overreaction that will result in return momentum. Based on their increased confidence, they push the prices of the winners above their fundamental values. In the long run, as investors realize their illusions, a return reversal is observed.

Hong and Stein (1999) develop a model that predict initial underreaction to information and subsequent overreaction. In their model, they assume that there are two types of investors that trade on different sets of information: one that either relies exclusively on their private information (news watchers) or rely exclusively on past information (momentum traders). Since each group uses only partial information in updating their prospects, information is obtained and transmitted into prices at different points in time, creating a momentum effect. Technical traders that observe past prices will act on past information, pushing prices of past winners above their fundamentals. Eventually, the prices of past winners will overshoot its fundamentals. In time, these episodes of apparent overshooting will be followed by correction giving the stock market the appearance of fluctuating around its fair value.

'Does sentiment affect financial asset prices?' Antoniou, Doukas, and Subrahmanyam (2013) address this question by examining the relation between momentum profits and sentiment. "Sentiment, broadly defined, refers to whether an individual, for whatever extraneous reason, feels excessively optimistic or pessimistic about a situation" (Antoniou, Doukas, and Subrahmanyam, 2013 p.246). Their analysis indicates that momentum profits are significant only when investors are optimistic (i.e., when the sentiment measure is high). Their results show that long-run price reversals occur only after optimistic periods. This is consistent with the idea that the actions of momentum traders exacerbate price continuations during optimistic periods, and subsequently, prices correct toward fundamentals.

## 3. Methodology

In this study, we test the null hypothesis of week form stock market efficiency by assessing if the UK stock market underreacts and/or overreacts to good or bad performance in so far as companies classified as winners and losers experience continuation in returns over short-horizons and reversals in long-horizons. We analyze the short and long-term profitability of momentum strategies by forming and testing relative strength portfolios based on price and/or earnings-related information.

First, we provide evidence on price momentum and reversals. Then, we study price momentum and whether price momentum and earnings momentum are linked. Finally, we relate our results to the empirical evidence on market underreaction and overreaction hypothesis.

Our first research question is explored by testing momentum returns and reversals dominance in the UK stock market. To test momentum and reversals, we assign individual stocks into portfolios based on their past performance and test several investment strategies by going long/short with those portfolios according to their relative performance, as done by Jegadeesh and Titman (1993) and DeBondt and Thaler (1985), respectively. We also replicate the work of Fama and French (1996) asset-pricing tests for the price momentum anomaly by regressing the returns of each momentum portfolio on the Fama-French (1993) three-factor model. We also employ the momentum factor proposed by Carhart (1997).

The existence of momentum and reversals is not sufficient condition to support the underreaction and overreaction effect. To infer the existence of the underraction and overreaction effect, momentum and reversals in returns must be linked to fundamental firm-specific news (e.g. Tversky and Kahneman, 1975; Barberis, Shleifer and Vishny, 1998; Daniel, Hirshleifer and Subramanyam, 1998; Hong and Stein, 1999).

Our second research question inquires how the UK stock market reacts to fundamental information and to the joint implications of fundamental information and past performance of prices. First, we formulate an earnings momentum strategy analogous to the one designed by Chordia and Shivakumar (2006). In this procedure, stocks are sorted into deciles based on their standardized unexpected earnings (SUE), which is defined as the seasonal change in earnings standardized by its standard deviations in prior quarters, and its performance is tested in the subsequent periods after portfolio formation. This way, we are evaluating the effect of earnings surprises on stock returns.

Finally, we consider the possibility that stock prices systematically underreact to firm-specific information as earnings surprises. We construct double sorted portfolios based mutually on an information variable (earnings surprises) and prior returns. This way, we are testing the joint implications of fundamental information and prior returns. This multivariate analysis follows a similar procedure as in Chen, Chen, Hsin, and Lee (2015).

The above procedure raises the questions of whether a factor based on price momentum subsumes the payoffs of momentum strategies; whether the results are robust across market capitalization size-segments; whether the results are robust over time. To answer these questions, we test the Carhart's (1997) four-factor model ability to explain returns across double sorted portfolios; we test the robustness of the results across specific market size-segments; and we construct a subperiod analysis, respectively.

### 3.1. Momentum and Reversals' tests

To test momentum and reversals we construct several investment strategies as in Jegadeesh and Titman (1993). So, we start by defining an event window composed of two different periods that describe an investment strategy: an observation period $J$ and a test period $K$; each period of $JxK - \text{months}$ defines an investment strategy (or an event-window).

Stocks are grouped in relative-strength portfolios based on their CAR $CAR_{it}$ over the observation period $J$, and hold into the future during a test period $K$.

In this procedure, at the end of each observation period in month $t$, stocks are equally ranked into deciles $X$ in ascending order based on the respective $CAR_{it}$ during the observation period. Each decile corresponds to a portfolio type $PX$ of stocks, being $P1$ designated the loser portfolio containing the $10\%$ worst performing stocks during the observation period, and $P10$ the winner portfolio containing the $10\%$ best performing portfolios during the observation period.

The performance of an investment strategy is given by the average performance of a portfolio type of stocks during the test period $K$, over the entire sample.

### 3.2. Earnings Momentum' tests

To test earnings momentum, stocks are grouped every month $t$ in portfolios based on earnings surprises and hold into the future during for $K - \text{months}$.

Earnings surprises are given by the SUE of stock $i$ in month $t$, computed using the same method as in Chan, Jegadeesh, and Lakonishok (1996). The $SUE$ for stock $i$ in month $t$ is thus defined as:

$$SUE_{it} = \frac{e_{iq} - e_{iq-4}}{\sigma_{it}} \qquad (1)$$

Where, $e_{iq}$ is the quarterly earnings per share most recently announced as of month $t$ for stock $i$, $e_{iq-4}$ is earnings per share four quarters ago, and $\sigma_{it}$ is the standard deviation of unexpected earnings (i.e., $e_{iq} - e_{iq-4}$) over the preceding eight quarters.

Stocks are equally ranked into deciles $X$ in ascending order based on the respective $SUE$ during the observation period. Each decile corresponds to an individual portfolio type $PX$ of stocks, being $P1$ designated the loser portfolio containing the 10% stocks that have reported the worst $SUE$ in month $t$, and $P10$ the winner portfolio containing the 10% stocks that have reported best $SUE$ in month t.

### 3.3. Assessing portfolio' performance

The portfolio formation procedure is repeated throughout the sample at the end of each observation period, in month $t$, using non-overlapping observation periods. The reason why we use non-overlapping periods instead of overlapping periods is because for explanatory variables with serial correlation, non-overlapping regressions perform better in producing low standard errors (Smith and Yadav, 1996).

CAR for each stock in the observation period is given by:

$$CAR_{i,t} = \sum_{t-j}^{t} \mu_{i,t} \qquad (2)$$

Were $j$ is the number of months in the observation period and $\mu_{it}$ is the market-adjusted return for the stock $i$ in month $t$ computed as:

$$\mu_{i,t} = R_{i,t} - R_{m,t} \qquad (3)$$

Where $R_{i,t}$ is the log-normal return for the stock $i$ in month $t$ defined as $\ln(TRI_{i,t}) - \ln(TRI_{i,t-1})$ and $R_{m,t}$ is market log-normal return in month $t$, defined as $\ln(TRI_{m,t}) - \ln(TRI_{m,t-1})$. $TRI_{i,t}$ is the Total Return Index of the stock $i$ in month $t$ and $TRI_{m,t}$ is the Total Return Index of the aggregate market in month $t$.

The performance of each portfolio type $PX$ is given by the mean $CAR$ of all stocks within the portfolio $PX$ of all the test periods performed throughout the time horizon comprehended in our sample, as:

$$CAR_{PT} = \sum_{T=1}^{T} \frac{\sum_{i=1}^{N} CAR_{i,t}}{N} \qquad (4)$$

Were $P$ denotes the portfolio type, $T$ denotes the number of months the portfolio is held and $N$ the number of stocks within the portfolio $PX$.

The monthly average $CAR_{PT}$ of a specific portfolio (i.e., the $ACAR_{PT}$) is simply the $CAR_{PT}$ divided by the number of months the respective portfolio is held ($T$), as:

$$ACAR_{PT} = \frac{CAR_{PT}}{T} \qquad (5)$$

To assess the statistical significance of the ACAR returns in the test period for the winner and the loser portfolio, we used a t-statistic defined as:

$$t_{PT} = \frac{ACAR_{PT}}{S_t/\sqrt{N}} \quad (6)$$

Where $S_t/\sqrt{N}$ represents the sample estimate of the standard error of $ACAR_{PT}$.

Besides portfolio $P1$ to $P10$, we also form a winner-minus-loser portfolio, designated the arbitrage portfolio $PA$, whereby an investor goes long on the winner portfolio and takes on a short position on the loser portfolio.

To assess the statistical significance of the ACAR returns for the arbitrage portfolio, we used a t-statistic defined as:

$$t_{Pwinner-Ploser,T} = \frac{ACAR_{Pwinner,T} - ACAR_{Ploser,T}}{\sqrt{2S_T^2/N}} \qquad (7)$$

Where $2S_T^2/N$ is the variance of the difference of sample means.

**3.4. Multivariate Analysis: double-sort procedure**

In double-sort procedures, stocks are sorted two times before assignment to portfolios of stocks. First based on past performance of prices and subsequently based on SUE.

At the beginning of each month t, we sort the securities in the sample based on past 9 months' returns. Independently, we sort the securities another time to one of ten equally sized portfolios based on earnings surprises given by SUE in month t. So, we end up with two sets of 10 different portfolios: one set based on a price variable and another set based on an earnings variable. Then, according to prior classifications, each stock is finally assigned to one of ten individual portfolios: the 10% best performers in both price and earnings classifications are assigned to a winner portfolio; the 10% worst performers in both classifications are assigned to a loser portfolio.

This way, for a stock to be an extreme winner/loser, it must have been classified as an extreme winner/loser based both on price and earnings variables. With these extra criteria imposed, we capture specifically stocks that had suffered from extreme earnings surprises and from extreme gains/losses in their performance. As such, it is expected for an arbitrage strategy to pic more effectively stocks that will keep gaining/losing in the future and, therefore, to yield superior abnormal returns in comparison to the performance of one-way strategies presented in prior results.

With this procedure, we aim to select stocks that systematically reacts to firm-specific information. We raise the hypothesis that stocks that suffer from god/bad earnings surprises and simultaneously experience god/bad performance systematically underreact and/or overreact to information, creating the patterns described in previous results.

### 3.5. Robustness check

Several studies suggest the need to control for risk factors such as market risk, size, book-to-market or bias in performance such as bid-ask bounces. As Jegadeesh and Titman (1993) adjust for risk using the CAPM benchmark and Fama and French (1996) and Jegadeesh and Titman (2001) adjust for risk using the Fama-French three factor model benchmark, we examine whether cross-sectional differences in risk explain momentum profits by examining risk adjusted returns using several multi-factor models of performance.

To assess the stability of the model parameters with respect to time, we compute the parameter estimates over a rolling window with a fixed sample size of 36 months through the entire sample.

To test the robustness of our results, we perform the following robustness tests:

a) ***Fama-French (1993) three factor model***

Fama and French (1993) show that the CAPM is not sufficiently in explaining the cross-section in returns. Thus, to explain the differential returns between the loser and winner portfolios we control not only for risk factors such as market risk (given by CAPM) but also for size and book-to-market given by the Fama and French (1993) three factor model as:

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_i\left(R_{m,t} - R_{f,t}\right) + \gamma_i SMB_t + \delta_i HML_t + \varepsilon_i \qquad (8)$$

Where, apart from the excess returns from a market portfolio given by the CAPM, we employ the difference between the return on a portfolio of small stocks and the return on a portfolio of big stocks $SMB$, and the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks $HML$.

***b) Momentum-effect***

Fama and French (1996) admit that the three-factor model is unable to capture the continuation of short-term momentum anomalies. In last section we test further robustness of an optimal strategy using the Carhart (1997) four-factor model which is an extension of the Fama-French (1993) three-factor model that includes a momentum factor that tries to capture the tendency for stock price to continuing rising if it is going up and to continue falling if it is going down. The four factor model is given by:

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_i\left(R_{m,t} - R_{f,t}\right) + \gamma_i SMB_t + \delta_i HML_t + \lambda_i UMD_t + \varepsilon_i \qquad (9)$$

Where, apart from controlling for the excess returns from a market portfolio given by the CAPM and the differences in size and book-to-market given by the Fama-French (1993) three-factor model, we consider the continuation tendency in stock prices given by $UMD$ , a zero-cost portfolio that is long in previous 12-month return winners and short in previous 12-month loser stocks.

***c) Size-effect***

Being the FTSE All-Share an aggregation of the FTSE 100 Index (large capitalization stocks' index), FTSE 250 Index (medium capitalization stocks' index) and FTSE SmallCap Index (small capitalization stocks' index), the constituents of those indexes can be considered as a portfolio of stocks that represents a specific size-segment of the UK equity market. Thus, to highlight further issues related to each size-segment of the market, we analyze three individually sub-samples according to the constituents of those individual indexes: a large capitalization stocks' sub-sample (LMC), a medium capitalization stocks' sub-sample (MMC) and a small capitalization stocks' subsample (SMC) is generated after portfolio formation. Because size can be used as a proxy for other factors such as availability of information and presence of analysts, we can rationalize whereas the phenomena under study can be attributed to liquidity characteristics of a specific value size-segment.

***d) Time-effect***

At last, to access the robustness of the results across different moments in time, we divide our sample in 3 subsamples covering each one approximately 10 years of data: a subsample that runs from January 1986 to March 1996, other that runs from April 1996 to July 2006, and a last one that runs from August 2006 to June 2016. Similarly, the abnormal performance of each portfolio type $PX$ during the event-window is given by a mean weighted average market capitalization index of each individual stock within the portfolio. This analysis will determine if the underreaction effect is pervasive over time.

## 4. Data

We select all the constituent's stocks of the FTSE All-Share Index at 31st December 2016 as a proxy for the UK equity market. 'The FTSE All-Share Index represents the performance of all eligible companies listed on the London Stock Exchange's (LSE) main market, which pass screening for size and liquidity. Representing 98-99% of UK market capitalization, the FTSE All-Share index is the aggregation of the FTSE 100, FTSE 250 and FTSE Small Cap Indexes"[1]. The main reason to only choose the constituent' stocks of FTSE All-Share Index is to avoid potential bias attributed to microstructure effects and cross-sectional differences in individual stocks that could mislead our results. Table 1 provides summary statistics of the companies in the sample in five years' intervals from January 1986 (1986m1) to January 2016 (2016m1) and in June 2016 (2016m6). By a way of illustration, in June 2016, the last month considered in our sample, there are 627 stocks, which of them 98 are Large Capitalization Stocks, 98 Medium Capitalization Stocks and 401 Small capitalization Stocks. Large Capitalization Stocks are given by the

[1] Source: FTSE Russell as at 28 February 2017

constituent stocks of the FTSE 100 and Small Capitalization Stocks by the Small Cap Indexes. The remaining stocks of the FTSE All Share Index are classified as Small Capitalization Stocks within the sample.

Firm level data were collected from Thomson Reuters Database on a monthly basis for the highest period available, comprehending the dates between December 1985 to December 2016. For all stocks of the FTSE All-Share Index we collect the Total Return Index (TRI), Earnings figures and Total Market Capitalization (TMC). Monthly returns are calculated from the Total Return Index and market returns are calculated from a Value Weighted index of the constituent stocks in sample of the FTSE All-Share Index collected from Thomson Reuters Database. Excess returns are computed relative to risk-free rates.

To investigate whether our results can be explained by risk factors that have been found to explain asset price anomalies in the US, we examine whether cross-sectional differences in risk explain momentum and contrarian profits by examining risk adjusted returns under specific asset pricing models. The asset pricing models are identified with further detail in the Methodology section. The monthly Fama-French risk factors, momentum factor and risk-free rates for the UK market are collected from the *Xfi Centre for Finance and Investment Database* of the University of Exeter – Business School[2].

Since we have information available on Total Return Index and Earnings figures starting on December 1985 and risk factors until June 2016, our final data sample runs therefore from December 1985 to June 2016, comprehending approximately 31 years of montly data (367 months) for 627 stocks traded on the London Stock Exchange in December 2016.

*Table 1 – Summary statistics*

| Year | 1 | 6 | 11 | 16 | 21 | 26 | 31 | 31 |
|---|---|---|---|---|---|---|---|---|
| Date | 1986m1 | 1991m1 | 1996m1 | 2001m1 | 2006m1 | 2011m1 | 2016m1 | 2016m6 |
| Nº of stocks in sample | 196 | 246 | 317 | 384 | 447 | 514 | 620 | 627 |
| Nº large MCSS stocks | 44 | 52 | 61 | 75 | 83 | 89 | 98 | 98 |
| Nº medium MCSS stocks | 99 | 123 | 152 | 181 | 236 | 297 | 394 | 401 |
| Nº small MCSS stocks | 53 | 71 | 104 | 128 | 128 | 128 | 128 | 128 |

*This table reports the companies in the sample in five years' intervals from January 1986 (1986m1) to January 2016 (2016m1) and in June 2016 (2016m6) per Market Capitalization Size-Segment (MCSS).*

[2] http://business-school.exeter.ac.uk/research/centres/xfi/

## 5. Results

We document the returns of relative strength portfolios over December 1985 to June 2016 for 627 companies traded in the FTSE All-Share Index at 31/12/2016. All the stocks with available returns data in the j-months preceding the portfolio formation date are included in the sample. Loser, Winner and Arbitrage portfolios are constructed based on past performance during the observation period. The arbitrage portfolio illustrates a momentum investment strategy that takes long/short positions with the *winners* and *losers'* portfolios. Transaction costs, market frictions or limits to arbitrage are not considered in this study.

### 5.1. Return Momentum' tests

Table 2 reports the Market-adjusted ACAR of the loser, winner and arbitrage portfolios, for j-month/k-month strategies up to 12 months. The cumulative returns of the arbitrage portfolios for all strategies are positive. All these returns are statistically significant at 1 percent level except for the 12-month/6-month strategy. The winner portfolio (i.e., the portfolio of stocks that takes long positions in the market) generates positive returns for all strategies with 1 percent significance level except for the 12-month/12month strategy. The loser portfolio (i.e., the portfolio of stocks that takes short positions in the market) is the portfolio that generates returns with less statistical significance, manly for strategies that hold the stocks for 3 months after portfolio formation. All the strategies that select stocks based on the past 3 months produce statistically significant returns at 1 percent significance level and all the strategies that select stocks based on the past 3-months to 12-months and hold the stocks for 6-months or more generate equally statistically significant returns at 1 percent significance level. Strategies that form portfolios over the last 6 to 9 months and then holds them for equal period produce average returns of about 1% per month. The most successful arbitrage strategy is the 9-month/9-month strategy. This strategy yields on average 1.3% per month. *Figure 1 and 2 illustrates graphically the performance of each arbitrage strategy tested.*

Having stablished that investment strategies based on relative strength portfolios generate on average superior returns in the UK stock market, now on we will examine one specific set of strategies in detail – strategies that select stocks based on prior 9-month returns. Based on testes performed, strategies that form portfolios based on prior 9-month returns generates higher yields and therefore are the type of strategies one sophisticated investor would be most attracted to exploit.

Table 3 reports the Market-adjusted ACAR per portfolio for 9-month/k-month strategies. The statistical significance of the results suggests that the momentum effect is stronger for the 40% best performers, or winners, than for the 40% worst performers, or losers. This asymmetry in results suggests that momentum returns are mainly driven by continuation in returns observed for best performers. The 4 deciles that contains the 40% best performers produce statistically significant monthly average returns for all holding periods tested. As for the 40% worst performers, the results are relatively weaker. Only the bottom decile produces returns statistically different from zero for horizons ranging 6 to 12 months into the test period. Although, when we look to the returns dimension from both winner and loser portfolios, is observable that the loser portfolio is the one that more contributes to the yield of the arbitrage portfolio for horizons ranging 6 to 9 months into the test period. *Figure 3 illustrates graphically the portfolio performance of* 9-month/k-month strategies.

### 5.1.1. Robustness check

Empirical studies suggest that relative strength profits may be attributed to compensation for bearing risk and not be an indication of market inefficiency. To access whether the existence of relative strength profits implies market inefficiency, it is important to identify the sources of those profits.

Further, we present the relative strength abnormal profits given by commonly used multifactor models. Statistically significant abnormal returns are interpreted as evidence inconsistence with weak-form market efficiency, although the results may also be due to misspecifications of the performance measures or misestimation of the relevant alphas and betas.

Table 4 reports the ACAR of the loser, winner and arbitrage portfolios, for j-month/k-month relative strength portfolios, adjusted with Fama-French (1993) three-factor model. By analyzing this table, we investigate whether the behavior of the relative strength returns in our earlier results may be confounded with the effects of cross-sectional differences in stocks as those related to market risk, book-to-marker and firm size. If the unadjusted relative strength profits reported in table 2 are explained by market risk, size and book-to-market effects, then the ACAR reporting in table 4 should not be statistically different from zero.

In short, once controlling for risk factors with Fama-French (1993) three-factor model, the adjusted returns for arbitrage portfolios are comparatively lower in relation to the unadjusted returns but overall, they do not lose statistical robustness at 1% significance level (compare table 4 with table 2). In fact, except for 12-month/3-;6-month strategies, all the arbitrage returns are statistically significant at 1% significance level.

The most important finding reported in this table relates the returns of loser portfolios. When we look to the performance of extreme past losers for a 9-month/9-month strategy, we conclude that those stocks experience a correction right after portfolio formation as they do not produce statistically significant abnormal returns. In the other strategy, we see that this correction pushes the prices too high (or beyond the fundamentals) as we see the occurrence of statistically significant positive abnormal returns after portfolio formation. Nevertheless, those positive abnormal returns follow a decreasing pattern - as we increase the holding period, positive abnormal returns of extreme past loser portfolios seem to dissipate and therefore converge to zero (i.e., to the market mean return). This feature found in returns for extreme losing stocks is somewhat congruent with the overreaction effect, although for short-term horizons. The results for 3-month/3-month strategies suggest that stocks that have experienced extreme losses for shorter observations periods are the ones that exhibit a more evident reversal effect as they continuously generate statistically significant positive abnormal returns up to 9-months holding periods with 1% significance level.

As observed in table 2, table 4 confirms that 9-month/k-month strategies are the ones that generate higher yields of all set of strategies tested. The most profitable arbitrage strategy is the 9-month/9-month strategy that generates a monthly average yield of 1.242% (18.15 t-statistic). Table 5 presents the CAR with Fama-French (1993) three-factor model per portfolio for all 9-month/k-month strategies tested. As we can see, the worst performers do not show continuation in returns as they do not generate significant negative abnormal returns. In fact, their performance during the test period show an evident mean reversion effect as they do not generate, on average, statistically significant abnormal returns. Portfolios 4 to 10 (or winner portfolio) generate positive abnormal returns for all 9-month/k-month strategies reported. *See figure 4 and 5 annexed.*

Table 6 presents the intercept and regressors of the Fama-French (1993) three-factor model for 9-month/9-month strategies. This table shows that portfolio returns load significantly on systematic risk, size and book-to-market. The portfolio of winners has substantially lower market risk exposures regarding the beta ($\beta$ ) of null and losers' portfolios. The losers' portfolios aggregate smaller stocks than winner portfolios, so they load more heavily on size factor ($\gamma$ ). Compared to extreme winners, extreme losers load more significantly on book-to-market factor ($\delta$ ), so they load more heavily on value stocks. Extreme portfolios load more heavily on risk factors than the null sample, as expected. Since the betas of the portfolio of extreme past losers are higher than the betas of the portfolio of extreme past winners, the betas of the arbitrage portfolio are negative.

Table 7 presents further robustness tests of the 9-month/9-month strategy using the Carhart (1997) four-factor model. After controlling for the additional momentum factor, the arbitrage portfolio of the 9-month/9-month strategy generates a monthly average yield of 1.300%, statistically significant at 1% level (19.45 t-statistic). This excess return is largely attributed to the continuation pattern associated with past winners' stocks. They generate a monthly average yield of 1.284%, statistically significant at 1% level (13.64 t-statistic). The portfolio of past losers exhibits normal performance. Like in table 6, returns load significantly on systematic risk, size and book-to-market. In relation to momentum factor, the 30% worst performers seem to load positively and significantly on momentum factor; and the 30% best performers seem to load negatively and significantly on momentum factor. As result, all betas of the arbitrage portfolio are negative.

To a certain extent, the results confirm the existence of stock price momentum in the UK stock market, at least during the period in analysis, as past winners' stocks outperform past losers' stocks. In fact, strategies that exploit momentum effect thus seem to generate positive abnormal returns. All the winner portfolios tested earn superior abnormal returns. In what concerns to extreme past losers, we document a tendency for stock returns to converge to the mean returns of the aggregate market. The abnormal returns presented are statistically significant to robustness tests, suggesting that multifactor models are unable to explain return momentum in the UK stock market.

### 5.2. Return Reversals' tests

The above evidence is consistent with the momentum effect, where past winners tend to outperform past losing stocks for short-term periods up to 12 months. In this section, we investigate if reversals are found in longer horizons, an instance in which prior losers outperform prior winners. This is not inconsistent with the momentum effect, given that momentum and reversals are experienced at different horizons. If we find reversals in returns after risk-adjustment tests, then we can assume the Overreactions hypothesis to be present in the UK stock market.

Table 8 reports the Market-adjusted CAR of the winner, loser and arbitrage portfolios for relative strength portfolios based on past 24 and 36 months' return and holding periods up to 72 months. Table 8 confirms the existence of long-term return reversals in the UK stock market for the period analyzed since both winning and losing portfolios see their performance reversed at long-term horizons. That is, portfolios that have registered extreme positive (negative) abnormal returns in the past 24/36-month period, see their stocks incur in negative (positive) abnormal returns up in the test period. These findings also note that the performance of extreme losers and winners during the test period is asymmetric and follow the same trend as Debondt and Thaler (1995); the reversals are much larger for extreme losers than for extreme winners.

For portfolios formed based on past 24-month period, the reversals occur 24 months to 36 months after portfolio formation. For the 36-month observation period, the reversal effect is found even at 24 months after the portfolio formation. It suggests that if investors observe stocks for longer periods before portfolio formation, their stocks will incur in higher reversals, starting at shorter horizons up in the future. Thus, building a contrarian arbitrage strategy, i.e., selling the winners and buying the losers, will generate positive and statistically significant abnormal returns at long horizons; and, the longer we hold portfolios, the higher the abnormal returns (given by the market model) will be. For instance, a 36-month/72-month contrarian arbitrage strategy obtains risk unadjusted CAR around 41.523% (10.91 t-statistic). *See figure 6 and 7 annexed.*

### 5.2.1. Robustness check

To test the robustness of the results, we adjust the CAR to the Fama-French three-factor model as well as to the Carhart (1997) four-factor model; those results are presented in table 9 and 10, respectively. By controlling for risk factors with the three factor-model, we expect to explain the reversal effect previously documented in table 8 (using unadjusted returns), as stated by Fama and French (1996).

Table 9 shows that the reversal effect is not robust to the three-factor model, confirming the power of this model in explaining the Overreaction effect documented by DeBondt and Thaler (1985). The loser portfolio does not overperform the winner portfolio at longer horizons. Thus, implementing a contrarian arbitrage strategy does not generate abnormal profits. These results are congruent with Fama and French (1996). *See figure 8 and 9 annexed.*

Although, as shown in table 10, when we introduce the momentum factor suggested by Carhart (1997) in our multifactor model, we could capture a long-term reversal effect for strategies that observe stocks during the past 36-month period and hold them for more than 48-months. A 36-month/60-month contrarian arbitrage is documented to generate statistically significant CAR of 10.176%, with 1% significance level (2.73 t-statistic). *See figure 11.*

### 5.3. Earnings Momentum' tests

Yet, we have found evidence of returns momentum and reversals in the UK stock market for the period that goes from December 1985 to June 2016. To conclude about the Underreaction and Overreaction effect, momentum and reversals must be linked to firm-specific information as earnings information. In this section, we make that required relation by equating if buying stocks with recent good earnings surprises while simultaneously shorting stocks with recent bad earnings surprises can generate positive abnormal profits.

Table 11 reports the performance of relative strength portfolios based on prior earnings performance given by the SUE, without risk-adjustment. Both winner and loser portfolios generate abnormal returns after portfolio formation. Although, there is a clear difference between past winners and past losers in terms of abnormal performance. At shorter horizons, extreme past winners outperform extreme past losers until 36 months into the test period. Both portfolios seem to underreact to earnings information after portfolio formation as we see a continuation pattern in returns – winners/losers' portfolios generate positive/negative statistically significant abnormal returns at 1% significance level. Particularly, the continuation effect is stronger for extreme winning stocks when looking to the dimension of the abnormal returns generated by each type of portfolio. At longer horizons, extreme past losers outperform extreme past winners for holding periods greater than 36 months. This is a signal that the market overreacts to extreme pessimistic information since past losing stocks outperform past winning stocks. For instance, an arbitrage strategy based on past SUE that holds stocks for 9 months into the test period generates positive CAR of 3.104% (24.02 t-statistic). As for longer horizons, a similar arbitrage strategy that holds stocks for 60 months into the test period generates CAR of -3.124% (-5.68 t-statistic). *See figure 12 annexed.*

### 5.3.1. Robustness check

Table 12 shows the CAR of relative strength portfolios based on earnings performance given by the SUE with the Fama-French (1993) three-factor model. The results presented show that controlling for risk factors does not explain the continuation in returns found in table 11. In fact, past winner's stocks continue to outperform past losers. Although, this table shows that the three-factor model is able to explain for returns reversal. After 24 months, an arbitrage strategy is unable to obtain statistically significant returns different from zero. An arbitrage strategy based on past SUE that holds stocks for 9 months into the test period generates positive CAR of 2.269% (15.13 t-statistic), against 3.104% unadjusted CAR (24.02 t-statistic). *See figure 13 annexed.*

Table 13 controls the CAR of relative strength portfolios based on earnings performance given by the SUE with the Carhart (1997) four-factor model. The additional momentum factor does not explain the continuation tendency in returns at short-term horizons. Up to 12 months after portfolio formation, past winning stock continue to generate superior abnormal returns when compared to the performance of past losing stocks. However, at longer horizons, the momentum factor suggested by Carhart (1997) displays a long-term reversal effect for strategies that holds stocks for 36 or more months into the test period. An arbitrage strategy that holds stocks for 60-month after portfolio formation is documented to generate statistically significant CAR of -3.094%, with 1% significance level (-6.37 t-statistic). *See figure 14 annexed.*

## 5.4. Multivariate analysis: Price and Earnings Momentum' tests

Previous results revealed the existence of return momentum and reversals in stock returns. Earnings momentum' tests revealed that building strategies based on fundamental information are useful in predicting future stock returns. In this section, we study the stock market reaction to the joint implications of fundamental information and past performance of prices. We focus our attention in the short-term horizon up to 12 months.

Table 14 show the results of double-sort procedures. This table present risk adjusted ACAR and CAR for portfolios ranked by two-way classifications with the Fama-French (1993) three-factor model. By analyzing this table, we can see a clear continuation pattern in stock returns classified as winners. Only the best performers realize statistically significant abnormal returns after portfolio formation at 1% significance level. In relation to the losers' segment of the results, they show normal performance as evidence of a mean reverting effect. Although, some strategies realize positive abnormal returns. Clearly, extreme past losers experience a mean reversion effect after portfolio formation. The existence of positive abnormal returns for losers' portfolios in some strategies may indicate that the market may overreact to pessimistic information related to earnings right after portfolio formation.

Since extreme past losers do not realize negative abnormal performance after portfolio formation, an arbitrage strategy does not compensate. Our results show that the most profitable multivariate strategy is investing only in past winners' stocks. An investor will benefit the most by taking long positions in 9-month/6-month strategies. This strategy yields a statistically significant ACAR of 1.137%, at 1% significance level (4.68 t-statistic). The second most profitable strategy is investing in the arbitrage portfolio following a 9-month/9-month strategy. This is the only strategy tested in that the arbitrage portfolio generates superior performance than the winner portfolio. This strategy yields a statistically significant ACAR of 0.992% (5.52 t-statistic), at 1% significance level.

Table 15 reports risk adjusted ACAR and CAR for portfolios ranked by two-way classifications with the Carhart (1997) four-factor model. Once controlling for momentum factor, stocks that are classified as 40% worst performers show normal performance, as they do not realize statistically significant returns different from zero. In relation to winning stocks, the top 30% best performers show a clear continuation pattern in returns, as they realize positive abnormal returns statistically significant at 1% significance level. Indeed, the most profitable strategy is to take long positions in the winner portfolio. Investing in winners' stocks from a 9-month/6-month and 9-month/9-month strategies yield a statistically significant ACAR of 1.162% (4.50 t-statistic) and 1.050% (4.87 t-statistic), respectively, with 1% statistically significance level.

#### 5.4.1. Robustness check

In this section, we test further robustness of the results for double-sort procedures. Specifically, we want to determine if momentum effect is robust across specific size-segments of the market capitalization spectrum and if it is pervasive over the time-period considered in this study.

#### 5.4.1.1. Size-effect

Table 16 presents risk adjusted ACAR and CAR for portfolios ranked by two-way classifications with the Carhart (1997) four-factor model by market capitalization size-segment (MCSS). The results confirm the continuation tendency found for past winners' stocks to keep winning at short horizons up to 9 months; and show that momentum returns are somewhat transversal regarding the size-segment of firms.

Nevertheless, the results reported suggest that momentum returns are mainly driven by stocks that belong to the medium market capitalization (MMC) and small market capitalization (SMC) size segments. Extreme winners' stocks from large market capitalization size-segment do not generate, on average, superior returns than the average market. As a result, the returns generated from a momentum arbitrage implemented with LMC stocks are not statistically different from zero.

#### 5.4.1.2. Time-effect

Table 17 presents risk adjusted ACAR and CAR for portfolios ranked by two-way classifications with the Carhart (1997) four-factor model across sub-periods (SP). The results confirm the continuation tendency found for past winning stocks to keep winning at short horizons up to 9 months; and show that momentum returns are pervasive over time.

Still, momentum returns in wining portfolios occur manly during the last 10 years (SP3). Buying past winners yields an ACAR of 1.3% per month for strategies that observe stocks during the prior 9 months and holds stocks for 6 to 9 months after portfolio formation. The returns of these strategies are statistically significant at 1% significance level. During SP1, that considers the period from January 1986 to March 1996, implementing an arbitrage strategy would generate an ACAR of 1.724% (3.54 t-statistic), the highest yield provided by an arbitrage portfolio reported in this study.

## 6. Conclusions

Financial literature has documented two broad anomalies over the last decades that have defied the tenets of market efficiency theory: the momentum and reversal effects. In this research work, we challenge the EMH of Fama (1970) in its weak-form by assessing if price and earnings momentum and reversals are robust in the UK stock market over December 1985 to June 2016; and whether these phenomena are related and can be explained by behavioral finance theory regarding the Underreaction and Overreaction Hypothesis.

Underlying the EMH is the notion that if any predictable patterns exist in returns, investors will quickly act to exploit them until the source of predictability is eliminated. However, our results indicate that the profits from momentum strategies have generated consistently superior returns as those achieved by the overall market for the last 31 years in the UK. Tests performed on momentum effect reveal that holding an arbitrage portfolio that takes long positions in the recent 10% best performers and short positions in the recent 10% worst performers over 3- to 12-months after portfolio formation captures the price momentum phenomena in time-series of prices.

Momentum can be largely attributed to extreme past winners' stocks. After controlling for risk using traditional multifactor models, extreme past winners' stocks exhibit steady positive abnormal returns and extreme past losers' stocks tend to exhibit normal performance. For instance, an arbitrage portfolio that forms portfolios based on prior 9-months' stock performance and holds them for equal period generates a statistically significant risk-adjusted ACAR with C4FM of 1.300%, at 1% significance level (19.45 t-statistic). This return' yield is largely attributed to the continuation pattern associated with past winners' stocks that generate an ACAR with C4FM of 1.284% (13.64 t-statistic). The portfolio of past losers exhibits normal performance (ACAR with C4FM of -0.016%; -0.17 t-statistic).

Traditional asset pricing models are ineffective in explaining momentum returns. Consistent with Liu, Norman and Xu (1999), controlling for systematic risk, size, and book-to-market ratio do not eliminate momentum profits in the UK, thus appearing to confirm the findings of Fama and French (1993, 1996) that momentum effect is robust to the Fama-French (1993) three-factor model. Momentum is also robust when controlling for the additional momentum factor proposed by Carhart (1997). As for the long-run returns, over horizons ranging 3- to 5-years, we find suggestions of negative serial correlations in returns similar to those found by DeBondt and Thaler (1985). Although, when controlling for risk, the Fama-French (1993) three-factor model is effective in explaining the reversal effect. Evidence provided is consistent with the concept that risk-based explanations and traditional asset pricing models cannot account for all the profits of the momentum anomaly (Jegadeesh and Titman, 2011); and contradicts the implications of EMH regarding the relation between risk and return (Fama, 1970).

Further analysis confirms the results of Chan, Jegadeesh and Lakonishok (1996) and Chen, Chen Hsin, and Lee (2015) that past returns and earnings surprises are related. Indeed, a substantial portion of the momentum effect is concentrated around the occurrence of unexpected earnings surprises.

Multivariate analysis performed point on a systematic drift of stock prices associated with the release of unexpected earnings surprises. This study point on the direction that momentum pattern is largely attributed to the interaction of price and favorable unexpected earnings surprises. For instance, following the same 9-month/9-month arbitrage strategy but now based mutually on price and SUE variables generates a yield of 0.928% (5.40 t-statistic) against the 1.300% (19.45 t-statistic) of univariate analysis based solely on prior performance of prices. This return yield is largely attributed to the continuation pattern associated with past winners' stocks that suffer from favorable earnings surprises that generate an ACAR with C4FM of 1.050% (4.87 t-statistic). The portfolio of past losers exhibits normal performance (ACAR with C4FM of 0.123%; 0.52 t-statistic).

Evidence provided reveals that investors systematically underreact to positive unexpected earnings surprises but are more sensible and accurate when revising their investments prospects in relation to negative earnings surprises. Multivariate analysis exposes a plausible underreaction effect to the release of favorable firm-specific information that is associated with the profitability of the momentum strategies. We bear the concept that investors tend to underweight positive earnings surprises and, consequently, that conservatism bias causes prices to systematically show a continuation pattern and origin momentum profit opportunities. This standpoint is supported on the Underreation Hypothesis of Barberies, Shleifer and Vishny (1998).

Additionally, robustness tests reveal that investors in large capitalization stocks in the UK react comparatively more efficiently to information contained in earnings surprises; and that momentum effect is mainly attributed to medium and small segments of the market capitalization. This is consistent with the financial theory regarding the influence of the liquidity effect and neglected firm effect in momentum effect.

Since transaction costs and limits to arbitrage are not considered, profit opportunities are not guaranteed in the "real world" by following similar investment strategies as the ones performed in this study. Although, we have made several contributions regarding the functioning of the UK stock market related to firm-specific information, which may be of special interest to technical analysts, portfolio managers and individual investors.

Overall, momentum effect is documented to be persistent and an exploitable anomaly in the UK from December 1985 to June 2016; is robust to risk-adjustments; and brought up (at least in part) by the presence of investors that systematically underreact to favorable and unexpected firm-specific information related to earnings.

*Table 2: Market-adjusted ACAR of j-month/k-month relative strength portfolios*

*This table reports the Market-adjusted ACAR of relative strength portfolios formed based on J-month past performance and held for K-months. The values of J and K are indicated in the first column and row, respectively. The stocks are ranked in ascending order after an observation period J and assigned into 10 equally weighted portfolios. The portfolio of stocks in the lowest past return decile is the P1, or loser Portfolio, being P10 the winner portfolio that comprehends the stocks in the highest return decile. The arbitrage portfolio measures the return difference between the winner and the loser portfolio. The sample period runs from December 1985 to June 2016. The coefficients reported are significant at 1 percent level (***), at 5 percent level (**) and at 10 percent level (*). The coefficients are in percentage (%).*

| Observations Period (J) | Portfolio (P) | Test Period (K) | | | |
|---|---|---|---|---|---|
| | | 3 | 6 | 9 | 12 |
| 3 | Loser | -0.411*** | -0.417*** | -0.379*** | -0.370*** |
| | | (-3.65) | (-5.25) | (-5.93) | (-6.48) |
| | Winner | 0.437*** | 0.395*** | 0.358*** | 0.383*** |
| | | (5.05) | (6.19) | (6.58) | (8.06) |
| | Arbitrage | 0.848*** | 0.811*** | 0.737*** | 0.753*** |
| | | (11.92) | (15.90) | (17.53) | (20.23) |
| 6 | Loser | -0.212 | -0.580*** | -0.499*** | -0.489*** |
| | | (-1.29) | (-4.78) | (-5.17) | (-5.71) |
| | Winner | 0.746*** | 0.367*** | 0.568*** | 0.363*** |
| | | (6.56) | (4.19) | (7.82) | (5.60) |
| | Arbitrage | 0.958*** | 0.947*** | 1.067*** | 0.852*** |
| | | (9.53) | (12.62) | (17.61) | (15.82) |
| 9 | Loser | -0.043 | -0.513*** | -0.667*** | -0.420*** |
| | | (-0.22) | (-3.50) | (-5.34) | (-4.08) |
| | Winner | 0.367*** | 0.440*** | 0.633*** | 0.490*** |
| | | (2.73) | (3.93) | (7.18) | (6.59) |
| | Arbitrage | 0.410*** | 0.953*** | 1.300*** | 0.910*** |
| | | (3.42) | (10.30) | (16.94) | (14.28) |
| 12 | Loser | 0.595** | 0.438** | -0.037 | -0.369*** |
| | | (2.56) | (2.56) | (-0.26) | (-2.77) |
| | Winner | 1.302*** | 0.669*** | 0.491*** | 0.223** |
| | | (7.98) | (5.83) | (4.84) | (2.34) |
| | Arbitrage | 0.707*** | 0.231** | 0.528*** | 0.592*** |
| | | (4.95) | (2.23) | (5.98) | (7.20) |

*Table 3: Market-adjusted ACAR of 9-month/k-month relative strength portfolios*

*This table reports the Market-adjusted ACAR per portfolio P of relative strength portfolios formed based on 9 -month past performance and held for K-months. The values K are indicated in the first row. The stocks are ranked in ascending order after an observation period J and assigned into 10 equally weighted portfolios. The portfolio of stocks in the lowest past return decile is the P1, or loser Portfolio, being P10 the winner portfolio that comprehends the stocks in the highest return decile. The arbitrage portfolio measures the return difference between the winner and the loser portfolio. The sample period runs from December 1985 to June 2016. The coefficients reported are significant at 1 percent level (***), at 5 percent level (**) and at 10 percent level (*). The coefficients are in percentage (%).*

| Portfolio (P) | Test Period (K) | | | |
|---|---|---|---|---|
| | 3 | 6 | 9 | 12 |
| Loser | -0.043 | $-0.513^{***}$ | $-0.667^{***}$ | $-0.420^{***}$ |
| | (-0.22) | (-3.50) | (-5.34) | (-4.08) |
| 2 | $0.293^{**}$ | -0.042 | -0.051 | 0.012 |
| | (2.07) | (-0.41) | (-0.57) | (0.16) |
| 3 | $0.266^{**}$ | 0.123 | 0.059 | $0.139^{**}$ |
| | (2.17) | (1.34) | (0.78) | (2.24) |
| 4 | $0.194^{*}$ | 0.074 | $0.115^{*}$ | $0.161^{***}$ |
| | (1.92) | (0.89) | (1.73) | (2.97) |
| 5 | $0.278^{***}$ | $0.138^{*}$ | $0.159^{**}$ | $0.172^{***}$ |
| | (3.09) | (1.78) | (2.42) | (2.97) |
| 6 | $0.211^{**}$ | 0.110 | $0.220^{***}$ | $0.247^{***}$ |
| | (2.25) | (1.50) | (3.60) | (4.70) |
| 7 | $0.283^{***}$ | $0.246^{***}$ | $0.284^{***}$ | $0.279^{***}$ |
| | (2.98) | (3.29) | (4.62) | (5.21) |
| 8 | $0.355^{***}$ | $0.271^{***}$ | $0.340^{***}$ | $0.319^{***}$ |
| | (3.31) | (3.06) | (4.67) | (5.15) |
| 9 | $0.344^{***}$ | $0.323^{***}$ | $0.452^{***}$ | $0.404^{***}$ |
| | (2.99) | (3.61) | (6.64) | (6.95) |
| Winner | $0.367^{***}$ | $0.440^{***}$ | $0.633^{***}$ | $0.490^{***}$ |
| | (2.73) | (3.93) | (7.18) | (6.59) |
| Arbitrage | $0.410^{***}$ | $0.953^{***}$ | $1.300^{***}$ | $0.910^{***}$ |
| | (3.42) | (10.30) | (16.94) | (14.28) |

*Table 4: FF3FM ACAR of j-month/k-month relative strength portfolios*

*This table reports the ACAR with Fama-French (1993) three-factor model of relative strength portfolios formed based on J-month past performance and held for K-months. The values of J and K are indicated in the first column and row, respectively. The stocks are ranked in ascending order after an observation period J and assigned into 10 equally weighted portfolios. The portfolio of stocks in the lowest past return decile is the P1, or loser Portfolio, being P10 the winner portfolio that comprehends the stocks in the highest return decile. The arbitrage portfolio measures the return difference between the winner and the loser portfolio. The sample period runs from December 1985 to June 2016. The coefficients reported are significant at 1 percent level (***), at 5 percent level (**) and at 10 percent level (*). The coefficients are in percentage (%).*

| Observation Period (J) | Position | Test Period (K) | | | |
|---|---|---|---|---|---|
| | | 3 | 6 | 9 | 12 |
| 3 | Loser | 0.369*** | 0.247*** | 0.161*** | 0.112** |
| | | (3.72) | (3.60) | (2.90) | (2.27) |
| | Winner | 0.708*** | 0.811*** | 0.816*** | 0.857*** |
| | | (7.71) | (12.58) | (15.42) | (18.64) |
| | Arbitrage | 0.340*** | 0.565*** | 0.655*** | 0.745*** |
| | | (5.03) | (11.98) | (17.09) | (22.06) |
| 6 | Loser | 0.451*** | 0.177* | 0.086 | 0.074 |
| | | (3.15) | (1.77) | (1.09) | (1.04) |
| | Winner | 0.748*** | 0.874*** | 0.946*** | 0.921*** |
| | | (5.95) | (9.81) | (13.04) | (14.06) |
| | Arbitrage | 0.297*** | 0.697*** | 0.860*** | 0.847*** |
| | | (3.12) | (10.38) | (16.01) | (17.54) |
| 9 | Loser | 0.261 | -0.006 | -0.143 | -0.027 |
| | | (1.44) | (-0.04) | (-1.39) | (-0.31) |
| | Winner | 0.932*** | 1.117*** | 1.099*** | 1.013*** |
| | | (6.29) | (10.12) | (12.30) | (13.41) |
| | Arbitrage | 0.671*** | 1.123*** | 1.242*** | 1.040*** |
| | | (5.70) | (13.48) | (18.15) | (17.84) |
| 12 | Loser | 0.697*** | 0.523*** | 0.081 | -0.017 |
| | | (3.10) | (3.36) | (0.66) | (-0.15) |
| | Winner | 0.767*** | 0.719*** | 0.756*** | 0.795*** |
| | | (4.36) | (5.99) | (7.39) | (8.46) |
| | Arbitrage | 0.070 | 0.196* | 0.675*** | 0.811*** |
| | | (0.49) | (1.98) | (8.48) | (11.07) |

*Table 5: FF3FM ACAR of 9-month/k-month relative strength portfolios*

*This table reports the ACAR with Fama-French (1993) three-factor model per portfolio P of relative strength portfolios formed based on 9 -month past performance and held for K-months. The values K are indicated in the first row. The stocks are ranked in ascending order after an observation period J and assigned into 10 equally weighted portfolios. The portfolio of stocks in the lowest past return decile is the P1, or loser Portfolio, being P10 the winner portfolio that comprehends the stocks in the highest return decile. The arbitrage portfolio measures the return difference between the winner and the loser portfolio. The sample period runs from December 1985 to June 2016. The coefficients reported are significant at 1 percent level (***), at 5 percent level (**) and at 10 percent level (*). The coefficients are in percentage (%).*

| Portfolio (P) | Test Period (K) | | | |
|---|---|---|---|---|
| | 3 | 6 | 9 | 12 |
| Loser | 0.261 | -0.006 | -0.143 | -0.027 |
| | (1.44) | (-0.04) | (-1.39) | (-0.31) |
| 2 | 0.152 | 0.029 | 0.064 | 0.144** |
| | (1.28) | (0.33) | (0.86) | (2.25) |
| 3 | 0.162* | 0.075 | 0.044 | 0.077 |
| | (1.70) | (1.06) | (0.73) | (1.46) |
| 4 | 0.269*** | 0.278*** | 0.254*** | 0.263*** |
| | (2.72) | (3.68) | (4.16) | (5.09) |
| 5 | 0.267*** | 0.203*** | 0.267*** | 0.271*** |
| | (3.17) | (3.34) | (4.97) | (5.71) |
| 6 | 0.384*** | 0.399*** | 0.395*** | 0.412*** |
| | (4.43) | (5.72) | (6.60) | (8.26) |
| 7 | 0.462*** | 0.485*** | 0.432*** | 0.400*** |
| | (5.00) | (7.25) | (7.69) | (7.59) |
| 8 | 0.517*** | 0.596*** | 0.507*** | 0.475*** |
| | (5.15) | (8.00) | (7.89) | (8.37) |
| 9 | 0.599*** | 0.759*** | 0.695*** | 0.677*** |
| | (5.05) | (8.59) | (9.54) | (10.73) |
| Winner | 0.932*** | 1.117*** | 1.099*** | 1.013*** |
| | (6.29) | (10.12) | (12.30) | (13.41) |
| Arbitrage | 0.671*** | 1.123*** | 1.242*** | 1.040*** |
| | (5.70) | (13.48) | (18.15) | (17.84) |

*Table 6: FF3FM ACAR of 9-month/9-month relative strength portfolios*

*This table reports the ACAR with Fama-French (1993) three-factor model per portfolio P of relative strength portfolios formed based on 9-month past performance and held for 9-months. The stocks are ranked in ascending order after an observation period J and assigned into 10 equally weighted portfolios. The portfolio of stocks in the lowest past return decile is the P1, or loser Portfolio, being P10 the winner portfolio that comprehends the stocks in the highest return decile. The arbitrage portfolio measures the return difference between the winner and the loser portfolio. The sample period runs from December 1985 to June 2016. The coefficients reported are significant at 1 percent level (***), at 5 percent level (**) and at 10 percent level (*). The coefficients are in percentage (%).*

| Portfolio (P) | Fama-French (1993) three-factor model | | | |
|---|---|---|---|---|
| | ACAR | β | γ | δ |
| Loser | -0.143 | $1.17^{***}$ | $0.90^{***}$ | $0.23^{***}$ |
| | (-1.39) | (67.85) | (34.51) | (7.85) |
| 2 | 0.064 | $1.04^{***}$ | $0.62^{***}$ | $0.11^{***}$ |
| | (0.86) | (71.49) | (29.33) | (5.24) |
| 3 | 0.044 | $1.00^{***}$ | $0.51^{***}$ | $0.09^{***}$ |
| | (0.73) | (77.60) | (28.51) | (4.95) |
| 4 | $0.254^{***}$ | $0.97^{***}$ | $0.45^{***}$ | $0.04^{***}$ |
| | (4.16) | (78.44) | (26.89) | (2.63) |
| 5 | $0.267^{***}$ | $0.98^{***}$ | $0.41^{***}$ | $0.04^{***}$ |
| | (4.97) | (81.84) | (24.35) | (2.77) |
| 6 | $0.395^{***}$ | $0.98^{***}$ | $0.46^{***}$ | $0.05^{***}$ |
| | (6.60) | (75.08) | (28.31) | (2.79) |
| 7 | $0.432^{***}$ | $0.93^{***}$ | $0.52^{***}$ | $0.05^{***}$ |
| | (7.69) | (70.12) | (28.20) | (2.61) |
| 8 | $0.507^{***}$ | $0.90^{***}$ | $0.55^{***}$ | $0.06^{***}$ |
| | (7.89) | (63.13) | (29.74) | (3.09) |
| 9 | $0.695^{***}$ | $0.96^{***}$ | $0.60^{***}$ | $0.04^{*}$ |
| | (9.54) | (60.33) | (30.91) | (1.76) |
| Winner | $1.099^{***}$ | $0.90^{***}$ | $0.78^{***}$ | $0.14^{***}$ |
| | (12.30) | (52.68) | (33.03) | (4.75) |
| Arbitrage | $1.242^{***}$ | $-0.28^{***}$ | $-0.11^{***}$ | $-0.08^{***}$ |
| | (18.15) | (-22.77) | (-6.50) | (-4.05) |

*Table 7: C4FM ACAR of 9-month/9-month relative strength portfolios*

*This table reports the ACAR with Carhart (1997) four-factor model per portfolio P of relative strength portfolios formed based on 9-month past performance and held for 9-months. The stocks are ranked in ascending order after an observation period J and assigned into 10 equally weighted portfolios. The portfolio of stocks in the lowest past return decile is the P1, or loser Portfolio, being P10 the winner portfolio that comprehends the stocks in the highest return decile. The arbitrage portfolio measures the return difference between the winner and the loser portfolio. The sample period runs from December 1985 to June 2016. The coefficients reported are significant at 1 percent level (***), at 5 percent level (**) and at 10 percent level (*). The coefficients are in percentage (%).*

| Portfolio (P) | Carhart (1997) four-factor model | | | | |
|---|---|---|---|---|---|
| | ACAR | β | γ | δ | λ |
| Loser | -0.016 | 1.14*** | 0.82*** | 0.16*** | -0.02 |
| | (-0.17) | (63.63) | (32.38) | (5.42) | (-1.16) |
| 2 | -0.018 | 1.03*** | 0.61*** | 0.13*** | 0.03** |
| | (-0.24) | (70.27) | (30.45) | (5.58) | (2.13) |
| 3 | 0.098*** | 1.01*** | 0.51*** | 0.09*** | 0.04*** |
| | (75.25) | (75.25) | (28.48) | (4.98) | (2.65) |
| 4 | 0.148*** | 1.00*** | 0.47*** | 0.05*** | 0.00 |
| | (2.63) | (79.13) | (27.07) | (2.62) | (-0.33) |
| 5 | 0.247*** | 0.98*** | 0.44*** | 0.05** | 0.01 |
| | (4.39) | (79.76) | (26.63) | (2.49) | (1.23) |
| 6 | 0.283*** | 0.96*** | 0.47*** | 0.03* | 0.01 |
| | (4.95) | (75.03) | (27.75) | (1.83) | (1.00) |
| 7 | 0.446*** | 0.93*** | 0.49*** | 0.01 | -0.03** |
| | (7.89) | (67.65) | (27.71) | (0.65) | (-1.96) |
| 8 | 0.528*** | 0.91*** | 0.55*** | 0.07*** | -0.02* |
| | (8.88) | (64.12) | (28.50) | (3.09) | (-1.67) |
| 9 | 0.705*** | 0.92*** | 0.60*** | 0.03 | -0.04** |
| | (9.93) | (58.02) | (29.62) | (1.09) | (-2.46) |
| Winner | 1.284*** | 0.92*** | 0.79*** | 0.10*** | -0.16*** |
| | (13.64) | (49.19) | (31.01) | (2.95) | (-7.40) |
| Arbitrage | 1.300*** | -0.22*** | -0.03 | -0.06*** | -0.14*** |
| | (19.45) | (-17.30) | (-1.41) | (-2.72) | (-9.72) |

*Table 8: Market-adjusted CAR of relative strength portfolios*

*This table reports the Market-adjusted CAR of relative strength portfolios formed based on J -month past performance of 24 and 36 months and held for K-months. The values of J and K are indicated in the first column and row, respectively. The stocks are ranked in ascending order after an observation period J and assigned into 10 equally weighted portfolios. The portfolio of stocks in the lowest past return decile is the P1, or loser Portfolio, being P10 the winner portfolio that comprehends the stocks in the highest return decile. The arbitrage portfolio measures the return difference between the loser and the winner portfolio. The sample period runs from December 1985 to June 2016. The coefficients reported are significant at 1 percent level (***), at 5 percent level (**) and at 10 percent level (*). The coefficients are in percentage (%).*

| Observation Period (J) | Portfolio (P) | Test Period (K) | | | | |
|---|---|---|---|---|---|---|
| | | 24 | 36 | 48 | 60 | 72 |
| 24 | Loser | 0.198 | 6.601* | 11.854*** | 15.604*** | 19.777*** |
| | | (0.07) | (1.90) | (3.05) | (3.75) | (4.31) |
| | Winner | 3.885* | -2.675 | -0.698 | -5.491 | -0.590 |
| | | (1.74) | (-0.81) | (-0.19) | (-1.32) | (-0.14) |
| | Arbitrage | -3.687** | 9.276*** | 12.552*** | 21.095*** | 20.367*** |
| | | (-1.99) | (3.86) | (4.75) | (7.16) | (6.54) |
| 36 | Loser | 1.482 | 7.402* | 16.943*** | 16.543*** | 28.906*** |
| | | (0.38) | (1.77) | (3.57) | (3.08) | (5.02) |
| | Winner | -14.456*** | -5.775 | -14.812*** | -20.801*** | -12.617** |
| | | (-3.92) | (-1.51) | (-3.32) | (-4.38) | (-2.55) |
| | Arbitrage | 15.938*** | 13.176*** | 31.754*** | 37.343*** | 41.523*** |
| | | (5.94) | (4.65) | (9.74) | (10.40) | (10.91) |

*Table 9: FF3FM CAR of relative strength portfolios*

*This table reports the CAR with Fama-French (1993) three-factor model of relative strength portfolios formed based on J -month past performance of 24 and 36 months and held for K-months. The values of J and K are indicated in the first column and row, respectively. The stocks are ranked in ascending order after an observation period J and assigned into 10 equally weighted portfolios. The portfolio of stocks in the lowest past return decile is the P1, or loser Portfolio, being P10 the winner portfolio that comprehends the stocks in the highest return decile. The arbitrage portfolio measures the return difference between the loser and the winner portfolio. The sample period runs from December 1985 to June 2016. The coefficients reported are significant at 1 percent level (***), at 5 percent level (**) and at 10 percent level (*). The coefficients are in percentage (%).*

| Observation Period (J) | Portfolio (P) | Test Period (K) | | | | | |
|---|---|---|---|---|---|---|---|
| | | 12 | 24 | 36 | 48 | 60 | 72 |
| 24 | Loser | -1.213 | 2.597 | 9.230*** | 16.725*** | 27.950*** | 33.602*** |
| | | (-0.66) | (0.92) | (2.70) | (4.19) | (6.09) | (6.81) |
| | Winner | 8.390*** | 15.504*** | 18.838*** | 21.194*** | 26.249*** | 37.448*** |
| | | (5.06) | (6.22) | (5.50) | (5.38) | (6.05) | (8.18) |
| | Arbitrage | -9.603*** | -12.906*** | -9.608*** | -4.470 | 1.700 | -3.846 |
| | | (-7.74) | (-6.83) | (-3.97) | (-1.59) | (0.54) | (-1.14) |
| 36 | Loser | -6.690*** | 3.008 | 6.837* | 20.784*** | 28.069*** | 32.384*** |
| | | (-2.94) | (0.86) | (1.69) | (4.27) | (4.94) | (5.26) |
| | Winner | 11.761*** | 15.617*** | 21.104*** | 23.750*** | 27.711*** | 34.688*** |
| | | (5.73) | (4.80) | (5.51) | (4.77) | (5.48) | (6.04) |
| | Arbitrage | -18.451*** | -12.609*** | -14.266*** | -2.966 | 0.358 | -2.304 |
| | | (-12.03) | (-5.26) | (-5.12) | (-0.85) | (0.09) | (-0.55) |

*Table 10: C4FM CAR of relative strength portfolios*

*This table reports the CAR with Carhart (1997) four-factor model of relative strength portfolios formed based on J - month past performance of 36 months and held for K-months. The values of J and K are indicated in the first column and row, respectively. The stocks are ranked in ascending order after an observation period J and assigned into 10 equally weighted portfolios. The portfolio of stocks in the lowest past return decile is the P1, or loser Portfolio, being P10 the winner portfolio that comprehends the stocks in the highest return decile. The arbitrage portfolio measures the return difference between the loser and the winner portfolio. The sample period runs from December 1985 to June 2016. The coefficients reported are significant at 1 percent level (***), at 5 percent level (**) and at 10 percent level (*). The coefficients are in percentage (%).*

| Observation Period (J) | Portfolio (P) | Test Period (K) | | | | | |
|---|---|---|---|---|---|---|---|
| | | 12 | 24 | 36 | 48 | 60 | 72 |
| 36 | Loser | -2.667 | 7.477** | 13.089*** | 26.736*** | 37.558*** | 42.027*** |
| | | (-1.33) | (2.27) | (3.31) | (5.34) | (6.68) | (7.05) |
| | Winner | 11.750*** | 17.235*** | 23.465*** | 25.137*** | 27.382*** | 31.969*** |
| | | (5.86) | (5.43) | (6.14) | (5.26) | (5.62) | (6.00) |
| | Arbitrage | -14.417*** | -9.758*** | -10.376*** | 1.599 | 10.176*** | 10.058** |
| | | (-10.16) | (-4.27) | (-3.77) | (0.46) | (2.73) | (2.51) |

*Table 11: Market-adjusted CAR of relative strength portfolios based on SUE*

*This table reports the Market-adjusted CAR of relative strength portfolios based on SUE and held for K months. The values of K are indicated in the first row. Stocks are ranked each month into one of ten individual portfolios of stocks based on SUE and held for K months. All stocks are equally-weighted in a portfolio. Each portfolio and the values of K-months after portfolio formation are indicated in the first column and row, respectively. The portfolio of stocks in the lowest past SUE decile is the P1, or loser Portfolio, being P10 the winner portfolio that comprehends the stocks in the highest SUE decile. The arbitrage portfolio measures the return difference between the winner and the loser portfolio. The sample period runs from December 1985 to June 2016. The coefficients reported are significant at 1 percent level (***), at 5 percent level (**) and at 10 percent level (*). The coefficients are in percentage (%).*

| Portfolio (P) | Test Period (K) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 3 | 6 | 9 | 12 | 15 | 18 | 21 | 24 | 36 | 48 | 60 |
| Loser | -0.632*** | -0.783*** | -0.861*** | -0.716*** | -0.627*** | -0.225*** | 0.116** | 0.944 | 4.915*** | 7.777*** | 9.386*** |
| | (-5.07) | (-4.99) | (-4.87) | (-4.27) | (-3.93) | (-2.70) | (-1.96) | (-0.36) | (5.51) | (8.11) | (8.10) |
| Winner | 0.949*** | 1.713*** | 2.243*** | 2.766*** | 3.087*** | 3.438*** | 3.708*** | 4.086*** | 4.993*** | 5.470*** | 6.263*** |
| | (9.22) | (12.14) | (13.63) | (14.51) | (14.45) | (14.69) | (14.50) | (14.75) | (14.81) | (13.76) | (13.17) |
| Arbitrage | 1.581*** | 2.496*** | 3.104*** | 3.482*** | 3.714*** | 3.664*** | 3.593*** | 3.142*** | 0.078*** | -2.307*** | -3.124*** |
| | (19.06) | (22.40) | (24.02) | (24.24) | (23.90) | (22.40) | (21.29) | (19.37) | (11.32) | (6.55) | (5.68) |

*Table 12: FF3FM CAR of relative strength portfolios based on SUE*

*This table reports the CAR with Fama-French (1993) three-factor model of relative strength portfolios based on SUE and held for K months. The values of K are indicated in the first row. Stocks are ranked each month into one of ten individual portfolios of stocks based on SUE and held for K months. All stocks are equally-weighted in a portfolio. Each portfolio and the values of K-months after portfolio formation are indicated in the first column and row, respectively. The portfolio of stocks in the lowest past SUE decile is the P1, or loser Portfolio, being P10 the winner portfolio that comprehends the stocks in the highest SUE decile. The arbitrage portfolio measures the return difference between the winner and the loser portfolio. The sample period runs from December 1985 to June 2016. The coefficients reported are significant at 1 percent level (***), at 5 percent level (**) and at 10 percent level (*). The coefficients are in percentage (%).*

| Portfolio (P) | Test Period (K) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 3 | 6 | 9 | 12 | 15 | 18 | 21 | 24 | 36 | 48 | 60 |
| Loser | 0.344** | 1.060*** | 1.716*** | 2.596*** | 3.441*** | 4.594*** | 5.657*** | 7.102*** | 13.226*** | 17.609*** | 21.716*** |
| | (2.53) | (5.54) | (7.27) | (9.28) | (10.74) | (12.84) | (14.42) | (16.85) | (25.09) | (27.68) | (29.51) |
| Winner | 1.473*** | 2.856*** | 3.985*** | 5.124*** | 6.148*** | 7.329*** | 8.351*** | 9.562*** | 13.678*** | 17.621*** | 21.595*** |
| | (14.40) | (19.58) | (21.70) | (23.36) | (24.24) | (25.88) | (26.39) | (27.67) | (29.97) | (32.29) | (34.39) |
| Arbitrage | 1.128*** | 1.796*** | 2.269*** | 2.528*** | 2.707*** | 2.735*** | 2.695*** | 2.460*** | 0.452 | 0.012 | -0.122 |
| | (13.20) | (14.88) | (15.13) | (14.18) | (13.21) | (11.96) | (10.66) | (9.00) | (1.29) | (0.03) | (-0.25) |

*Table 13: C4FM CAR of relative strength portfolios based on SUE*

*This table reports the CAR with Carhart (1997) four-factor model of relative strength portfolios based on SUE and held for K months. The values of K are indicated in the first row. Stocks are ranked each month into one of ten individual portfolios of stocks based on SUE and held for K months. All stocks are equally-weighted in a portfolio. Each portfolio and the values of K-months after portfolio formation are indicated in the first column and row, respectively. The portfolio of stocks in the lowest past SUE decile is the P1, or loser Portfolio, being P10 the winner portfolio that comprehends the stocks in the highest SUE decile. The arbitrage portfolio measures the return difference between the winner and the loser portfolio. The sample period runs from December 1985 to June 2016. The coefficients reported are significant at 1 percent level (***), at 5 percent level (**) and at 10 percent level (*). The coefficients are in percentage (%).*

| Portfolio (P) | Test Period (k) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 3 | 6 | 9 | 12 | 15 | 18 | 21 | 24 | 36 | 48 | 60 |
| Loser | 0.561*** | 1.387*** | 2.176*** | 3.154*** | 4.243*** | 5.708*** | 7.151*** | 8.972*** | 15.644*** | 20.276*** | 24.952*** |
| | (4.27) | (7.50) | (9.52) | (11.66) | (13.60) | (16.23) | (18.31) | (21.13) | (28.83) | (31.30) | (33.51) |
| Winner | 1.407*** | 2.724*** | 3.811*** | 4.909*** | 5.864*** | 6.985*** | 7.977*** | 9.166*** | 13.440*** | 17.846*** | 21.859*** |
| | (14.05) | (18.89) | (20.89) | (22.55) | (23.42) | (25.00) | (25.73) | (27.06) | (29.85) | (33.24) | (35.32) |
| Arbitrage | 0.846*** | 1.337*** | 1.635*** | 1.755*** | 1.621*** | 1.277*** | 0.827*** | 0.194 | -2.204*** | -2.430*** | -3.094*** |
| | (10.21) | (11.37) | (11.15) | (10.08) | (8.08) | (5.67) | (3.31) | (0.71) | (-6.23) | (-5.76) | (-6.37) |

*Table 14: FF3FM ACAR and CAR of two-way relative strength portfolios*

*This table reports the ACAR and CAR with Fama-French (1993) three-factor model of relative strength portfolios based cumulatively on SUE and prior 9-month performance and held for K months. The values of K are indicated in the second column. Stocks are ranked each month into one of ten individual portfolios of stocks based on SUE and held for K months. All stocks are equally-weighted in a portfolio. The values of K-months after portfolio formation are indicated in the second column and each portfolio is indicated in the first row. The portfolio of stocks in the lowest past classification decile is the P1, or loser Portfolio, being P10 the winner portfolio that comprehends the stocks in the highest classification decile. The arbitrage portfolio measures the return difference between the winner and the loser portfolio. The sample period runs from December 1985 to June 2016. The coefficients reported are significant at 1 percent level (***), at 5 percent level (**) and at 10 percent level (*). The coefficients are in percentage (%).*

| Panel | Test Period (K) | Portfolio (P) Loser | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Winner | Arbitrage |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a) ACAR | 3 | 0.847* | 0.128 | 0.118 | 0.851** | 0.003 | 0.583** | 0.346 | 0.436* | 0.494* | 0.723** | -0.124 |
| | | (1.75) | (0.39) | (0.47) | (1.97) | (0.01) | (2.56) | (1.35) | (1.67) | (1.65) | (2.19) | (-0.38) |
| | 6 | 0.265 | -0.224 | 0.103 | 0.960*** | 0.193 | 0.309 | 0.498*** | 0.392 | 0.766*** | 1.137*** | 0.873*** |
| | | (0.77) | (-0.83) | (0.56) | (3.01) | (0.96) | (1.57) | (2.69) | (1.60) | (3.56) | (4.68) | (3.77) |
| | 9 | -0.077 | -0.018 | 0.066 | 0.507** | 0.305* | 0.061 | 0.508*** | 0.476** | 0.992*** | 0.915*** | 0.992*** |
| | | (-0.29) | (-0.08) | (0.34) | (2.07) | (1.75) | (0.33) | (3.32) | (2.33) | (5.37) | (4.53) | (5.52) |
| | 12 | 0.213 | 0.062 | 0.033 | 0.393** | 0.415** | 0.160 | 0.371*** | 0.476*** | 0.961*** | 0.847*** | 0.634*** |
| | | (0.95) | (0.30) | (0.24) | (2.06) | (2.49) | (0.94) | (2.85) | (2.83) | (5.91) | (4.49) | (4.03) |
| b) CAR | 3 | 2.540* | 0.385 | 0.354 | 2.552** | 0.010 | 1.749** | 1.039 | 1.308* | 1.482* | 2.168** | -0.372 |
| | | (1.75) | (0.39) | (0.47) | (1.97) | (0.01) | (2.56) | (1.35) | (1.67) | (1.65) | (2.19) | (-0.38) |
| | 6 | 1.588 | -1.344 | 0.617 | 5.760*** | 1.157 | 1.855 | 2.990*** | 2.355 | 4.595*** | 6.823*** | 5.236*** |
| | | (0.77) | (-0.83) | (0.56) | (3.01) | (0.96) | (1.57) | (2.69) | (1.60) | (3.56) | (4.68) | (3.77) |
| | 9 | -0.692 | -0.162 | 0.590 | 4.563** | 2.746* | 0.553 | 4.568*** | 4.283** | 8.928*** | 8.238*** | 8.929*** |
| | | (-0.29) | (-0.08) | (0.34) | (2.07) | (1.75) | (0.33) | (3.32) | (2.33) | (5.37) | (4.53) | (5.52) |
| | 12 | 2.553 | 0.745 | 0.397 | 4.716** | 4.985** | 1.919 | 4.449*** | 5.708*** | 11.531*** | 10.160*** | 7.607*** |
| | | (0.95) | (0.30) | (0.24) | (2.06) | (2.49) | (0.94) | (2.85) | (2.83) | (5.91) | (4.49) | (4.03) |

*Table 15: C4FM ACAR and CAR of two-way relative strength portfolios*

*This table reports the ACAR and CAR with Carhart (1997) four-factor model of relative strength portfolios based cumulatively on SUE and prior 9-month performance and held for K months. The values of K are indicated in the second column. Stocks are ranked each month into one of ten individual portfolios using double-sort procedures based on SUE and prior 9-month return, and held for K months. All stocks are equally-weighted in a portfolio. The values of K-months after portfolio formation are indicated in the second column and each portfolio is indicated in the first row. The portfolio of stocks in the lowest past classification decile is the P1, or loser Portfolio, being P10 the winner portfolio that comprehends the stocks in the highest classification decile. The arbitrage portfolio measures the return difference between the winner and the loser portfolio. The sample period runs from December 1985 to June 2016. The coefficients reported are significant at 1 percent level (***), at 5 percent level (**) and at 10 percent level (*). The coefficients are in percentage (%).*

| | | Portfolio (P) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel | Test Period (K) | Loser | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Winner | Arbitrage |
| a) ACAR | 3 | 0.589 | -0.039 | 0.397 | 0.007 | 0.137 | 0.423$^{*}$ | 0.238 | 0.206 | 0.516$^{*}$ | 0.976$^{***}$ | 0.387 |
| | | (1.41) | (-0.13) | (1.43) | (0.02) | (0.40) | (1.82) | (1.02) | (0.69) | (1.93) | (2.96) | (1.31) |
| | 6 | 0.409 | -0.115 | 0.121 | 0.451$^{*}$ | 0.474$^{*}$ | 0.342$^{**}$ | 0.464$^{***}$ | 0.622$^{***}$ | 0.598$^{***}$ | 1.162$^{***}$ | 0.752$^{***}$ |
| | | (1.32) | (-0.42) | (0.58) | (1.87) | (1.93) | (2.13) | (3.18) | (3.04) | (2.78) | (4.50) | (3.41) |
| | 9 | 0.123 | -0.095 | -0.084 | 0.356 | 0.610$^{***}$ | 0.168 | 0.597$^{***}$ | 0.658$^{***}$ | 0.711$^{***}$ | 1.050$^{***}$ | 0.928$^{***}$ |
| | | (0.52) | (-0.40) | (-0.52) | (1.52) | (3.13) | (1.09) | (4.61) | (4.11) | (4.13) | (4.87) | (5.40) |
| | 12 | 0.216 | 0.021 | -0.160 | 0.357$^{*}$ | 0.475$^{***}$ | 0.257$^{*}$ | 0.413$^{***}$ | 0.608$^{***}$ | 0.625$^{***}$ | 0.967$^{***}$ | 0.751$^{***}$ |
| | | (1.07) | (0.10) | (-0.99) | (1.76) | (2.85) | (1.82) | (3.30) | (4.43) | (4.26) | (4.86) | (5.05) |
| b) CAR | 3 | 1.766 | -0.118 | 1.192 | 0.022 | 0.410 | 1.269$^{*}$ | 0.714 | 0.618 | 1.547$^{*}$ | 2.927$^{***}$ | 1.160 |
| | | (1.41) | (-0.13) | (1.43) | (0.02) | (0.40) | (1.82) | (1.02) | (0.69) | (1.93) | (2.96) | (1.31) |
| | 6 | 2.455 | -0.687 | 0.729 | 2.705$^{*}$ | 2.846$^{*}$ | 2.053$^{**}$ | 2.786$^{***}$ | 3.729$^{***}$ | 3.585$^{***}$ | 6.970$^{***}$ | 4.514$^{***}$ |
| | | (1.32) | (-0.42) | (0.58) | (1.87) | (1.93) | (2.13) | (3.18) | (3.04) | (2.78) | (4.50) | (3.41) |
| | 9 | 1.103 | -0.852 | -0.757 | 3.200 | 5.488$^{***}$ | 1.509 | 5.376$^{***}$ | 5.920$^{***}$ | 6.396$^{***}$ | 9.452$^{***}$ | 8.348$^{***}$ |
| | | (0.52) | (-0.40) | (-0.52) | (1.52) | (3.13) | (1.09) | (4.61) | (4.11) | (4.13) | (4.87) | (5.40) |
| | 12 | 2.591 | 0.249 | -1.925 | 4.281$^{*}$ | 5.695$^{***}$ | 3.088$^{*}$ | 4.954$^{***}$ | 7.295$^{***}$ | 7.502$^{***}$ | 11.602$^{***}$ | 9.011$^{***}$ |
| | | (1.07) | (0.10) | (-0.99 | (1.76) | (2.85) | (1.82) | (3.30) | (4.43) | (4.26) | (4.86) | (5.05) |

*Table 16: C4FM ACAR and CAR of optimal two-way relative strength portfolios by MCSS*

*This table reports the ACAR and CAR with Carhart (1997) four-factor model by market capitalization size-segment (MCSS) of relative strength portfolios based cumulatively on SUE and prior 9-month performance and held for K months. The size-segment is indicated in the second column and the values of K are indicated in the third column. Stocks are ranked each month into one of ten individual portfolios using double-sort procedures based on SUE and prior 9-month return. All stocks are equally-weighted in a portfolio. The MCSS and values of K-months are indicated in the second and third column, respectively, and each portfolio is indicated in the first row. The portfolio of stocks in the lowest past classification decile is the P1, or loser Portfolio, being P10 the winner portfolio that comprehends the stocks in the highest classification decile. The arbitrage portfolio measures the return difference between the winner and the loser portfolio. The optimal strategy measures the return difference between the winners and the losers' portfolios indicated in the right section of this table. The sample period runs from December 1985 to June 2016. The coefficients reported are significant at 1 percent level (***), at 5 percent level (**) and at 10 percent level (*). The coefficients are in percentage (%).*

| Panel | Ranked by: PRIOR RETURN SUE | | Portfolio (P) Loser | 1 2 | 1 3 | 10 8 | 10 9 | Winner | Arbitrage |
|---|---|---|---|---|---|---|---|---|---|
| a) ACAR | LMC | 6 | 1.277 | 1.117$^{*}$ | 0.750 | 1.708$^{***}$ | 1.459$^{***}$ | 0.534 | -0.743 |
| | | | (1.40) | (1.81) | (0.95) | (3.77) | (3.36) | (1.43) | (-1.42) |
| | | 9 | 0.046 | 0.953$^{*}$ | 0.729 | 1.414$^{***}$ | 1.757$^{***}$ | 0.652$^{*}$ | 0.606 |
| | | | (0.06) | (1.94) | (1.15) | (3.14) | (4.56) | (1.95) | (1.48) |
| | MMC | 6 | 0.143 | 0.325 | -0.112 | 1.406$^{***}$ | 1.568$^{***}$ | 1.352$^{***}$ | 1.209$^{***}$ |
| | | | (0.34) | (0.76) | (-0.25) | (3.92) | (3.57) | (3.75) | (4.05) |
| | | 9 | 0.146 | 0.456 | -0.683$^{*}$ | 1.491$^{***}$ | 1.701$^{***}$ | 1.184$^{***}$ | 1.038$^{***}$ |
| | | | (0.46) | (1.28) | (-1.77) | (4.45) | (6.30) | (3.89) | (4.47) |
| | SMC | 6 | 0.467 | 0.527 | 0.425 | 1.506$^{**}$ | 1.473$^{**}$ | 1.306$^{**}$ | 0.839$^{**}$ |
| | | | (0.87) | (1.09) | (0.69) | (2.42) | (2.52) | (2.14) | (2.00) |
| | | 9 | 0.114 | 0.549 | 0.358 | 1.239$^{**}$ | 1.114$^{**}$ | 1.122$^{**}$ | 1.008$^{***}$ |
| | | | (0.28) | (1.47) | (0.62) | (2.01) | (2.20) | (2.25) | (3.07) |
| b) CAR | LMC | 6 | 7.662 | 6.703$^{*}$ | 4.503 | 10.250$^{***}$ | 8.756$^{***}$ | 3.203 | -4.459 |
| | | | (1.40) | (1.81) | (0.95) | (3.77) | (3.36) | (1.43) | (-1.42) |
| | | 9 | 0.417 | 8.573$^{*}$ | 6.557 | 12.726$^{***}$ | 15.813$^{***}$ | 5.872$^{*}$ | 5.455 |
| | | | (0.06) | (1.94) | (1.15) | (3.14) | (4.56) | (1.95) | (1.48) |
| | MMC | 6 | 0.858 | 1.947 | -0.671 | 8.435$^{***}$ | 9.406$^{***}$ | 8.113$^{***}$ | 7.255$^{***}$ |
| | | | (0.34) | (0.76) | (-0.25) | (3.92) | (3.57) | (3.75) | (4.05) |
| | | 9 | 1.313 | 4.106 | -6.147$^{*}$ | 13.423$^{***}$ | 15.308$^{***}$ | 10.657$^{***}$ | 9.344$^{***}$ |
| | | | (0.46) | (1.28) | (-1.77) | (4.45) | (6.30) | (3.89) | (4.47) |
| | SMC | 6 | 2.804 | 3.164 | 2.552 | 9.038$^{**}$ | 8.836$^{**}$ | 7.837$^{**}$ | 5.033$^{**}$ |
| | | | (0.87) | (1.09) | (0.69) | (2.42) | (2.52) | (2.14) | (2.00) |
| | | 9 | 1.030 | 4.945 | 3.221 | 11.147$^{**}$ | 10.028$^{**}$ | 10.102$^{**}$ | 9.072$^{***}$ |
| | | | (0.28) | (1.47) | (0.62) | (2.01) | (2.20) | (2.25) | (3.07) |

*Table 17: C4FM ACAR and CAR of optimal two-way relative strength portfolios by SP*

*This table reports the ACAR and CAR with Carhart (1997) four-factor model of relative strength portfolios segmented by sub-periods (SP) based cumulatively on SUE and past 9-month performance and held for K months. The sub-period is indicated in the second column and the values of K are indicated in the third column. Stocks are ranked each month into one of ten individual portfolios using double-sort procedures based on SUE and prior 9-month return. All stocks are equally-weighted in a portfolio. The SP and values of K-months are indicated in the second and third column, respectively, and each portfolio is indicated in the first row. The portfolio of stocks in the lowest past classification decile is the P1, or loser Portfolio, being P10 the winner portfolio that comprehends the stocks in the highest classification decile. The arbitrage portfolio measures the return difference between the winner and the loser portfolio. The optimal strategy measures the return difference between the winners and the losers' portfolios indicated in the right section of this table. The sample period runs from December 1985 to June 2016. The coefficients reported are significant at 1 percent level (***), at 5 percent level (**) and at 10 percent level (*). The coefficients are in percentage (%).*

| Panel | Ranked by: PRIOR RETURN SUE | | Portfolio (P) Loser | 1<br>2 | 1<br>3 | 10<br>8 | 10<br>9 | Winner | Arbitrage |
|---|---|---|---|---|---|---|---|---|---|
| a) ACAR | SP1 | 6 | -0.606 | 0.042 | -0.048 | 1.160$^{**}$ | 1.307$^{*}$ | 1.117$^{**}$ | 1.724$^{***}$ |
| | | | (-1.00) | (0.06) | (-0.06) | (2.49) | (1.91) | (1.98) | (3.54) |
| | | 9 | -0.381 | 0.072 | 0.312 | 1.094$^{**}$ | 0.844 | 0.890$^{*}$ | 1.271$^{***}$ |
| | | | (-0.72) | (0.11) | (0.43) | (2.02) | (1.60) | (1.73) | (3.00) |
| | SP2 | 6 | 0.446 | -0.081 | 0.377 | 2.241$^{***}$ | 1.830$^{***}$ | 0.664 | 0.218 |
| | | | (0.95) | (-0.16) | (0.74) | (3.47) | (2.97) | (1.42) | (0.62) |
| | | 9 | 0.132 | 0.371 | 0.192 | 2.223$^{***}$ | 1.579$^{***}$ | 0.349 | 0.217 |
| | | | (0.31) | (0.89) | (0.37) | (3.94) | (3.48) | (0.90) | (0.69) |
| | SP3 | 6 | 0.862 | 1.075$^{**}$ | 0.057 | 1.458$^{***}$ | 1.287$^{***}$ | 1.314$^{***}$ | 0.452 |
| | | | (1.50) | (2.43) | (0.10) | (3.49) | (3.03) | (3.44) | (1.21) |
| | | 9 | 0.324 | 0.876$^{**}$ | -0.542 | 1.298$^{***}$ | 1.653$^{***}$ | 1.309$^{***}$ | 0.985$^{***}$ |
| | | | (0.79) | (2.52) | (-1.06) | (3.06) | (5.38) | (4.10) | (3.55) |
| b) CAR | SP1 | 6 | -3.638 | 0.251 | -0.290 | 6.962$^{**}$ | 7.844$^{**}$ | 6.704$^{**}$ | 10.341$^{***}$ |
| | | | (-1.00) | (0.06) | (-0.06) | (2.49) | (1.91) | (1.98) | (3.54) |
| | | 9 | -3.433 | 0.647 | 2.810 | 9.845$^{**}$ | 7.595$^{***}$ | 8.008$^{*}$ | 11.441$^{***}$ |
| | | | (-0.72) | (0.11) | (0.43) | (2.02) | (1.60) | (1.73) | (3.00) |
| | SP2 | 6 | 2.675 | -0.485 | 2.261 | 13.444$^{***}$ | 10.979$^{***}$ | 3.984 | 1.308 |
| | | | (0.95) | (-0.16) | (0.74) | (3.47) | (2.97) | (1.42) | (0.62) |
| | | 9 | 1.184 | 3.337 | 1.728 | 20.003$^{***}$ | 14.208$^{***}$ | 3.138 | 1.954 |
| | | | (0.31) | (0.89) | (0.37) | (3.94) | (3.48) | (0.90) | (0.69) |
| | SP3 | 6 | 5.171 | 6.450$^{**}$ | 0.339 | 8.749$^{***}$ | 7.724$^{***}$ | 7.882$^{***}$ | 2.712 |
| | | | (1.50) | (2.43) | (0.10) | (3.49) | (3.03) | (3.44) | (1.21) |
| | | 9 | 2.920 | 7.881$^{**}$ | -4.882 | 11.684$^{***}$ | 14.875$^{***}$ | 11.781$^{***}$ | 8.861$^{***}$ |
| | | | (0.79) | (2.52) | (-1.06) | (3.06) | (5.38) | (4.10) | (3.55) |

## 7. References


Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of financial Economics, 17*(2), 223-249.

Amihud, Y., & Mendelson, H. (1991). *Liquidity, maturity, and the yields on US Treasury securities. The Journal of Finance, 46*(4), 1411-1425.

Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2013). Cognitive dissonance, sentiment, and momentum. *Journal of Financial and Quantitative Analysis, 48*(01), 245-275.

Arbel, A., & Strebel, P. (1983). Pay attention to neglected firms!. *The Journal of Portfolio Management, 9*(2), 37-42.

Asness, C. S., Liew, J. M., & Stevens, R. L. (1997). Parallels between the cross-sectional predictability of stock and country returns. *The Journal of Portfolio Management, 23*(3), 79-87.

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum everywhere. *The Journal of Finance, 68*(3), 929-985.

Ball, R., & Brown, P. (1968). An empirical evaluation of accounting income numbers. *Journal of accounting research*, 159-178.

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. *Handbook of the Economics of Finance, 1*, 1053-1128.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of financial economics, 49*(3), 307-343.

Bernard, V. L., & Thomas, J. K. (1989). Post-earnings-announcement drift: delayed price response or risk premium?. *Journal of Accounting research*, 1-36.

Bhushan, R. (1994). An informational efficiency perspective on the post-earnings announcement drift. *Journal of Accounting and Economics, 18*(1), 45-65.

Black, F. (1986). Noise. *The journal of finance, 41*(3), 528-543.

Booth, G. G., Fung, H. G., & Leung, W. K. (2016). A risk-return explanation of the momentum-reversal "anomaly". *Journal* of Empirical Finance, *35*, 68-77.

Bodie, Z., Kane, A., & Marcus, A.J., (2011). *Investments, 9e*. New York, NY: McGraw-Hill/Irwin.

Campbell, K., & Limmack, R. J. (1997). Long-term over-reaction in the UK stock market and size adjustments. *Applied Financial Economics, 7*(5), 537-548.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance, 52*(1), 57-82.

Chan, L. K., Jegadeesh, N., & Lakonishok, J. (1996). Momentum strategies. *The Journal of Finance, 51*(5), 1681-1713.

Chen, H. Y., Chen, S. S., Hsin, C. W., & Lee, C. F. (2015). Does revenue momentum drive or ride earnings or price momentum?. In Handbook of Financial Econometrics and Statistics (pp. 2217-2261). Springer New York.

Chopra, N., Lakonishok, J., & Ritter, J. R. (1992). Measuring abnormal performance: do stocks overreact?. *Journal of financial Economics, 31*(2), 235-268.

Chordia, T., & Shivakumar, L. (2006). Earnings and price momentum. *Journal of financial economics, 80*(3), 627-656.

Chui, A. C., Wei, K. C. J., & Titman, S. (2000). Momentum, legal systems and ownership structure: An analysis of Asian stock markets. Working paper.

Clare, A., & Thomas, S. (1995). The overreaction hypothesis and the UK stockmarket. *Journal of Business Finance & Accounting, 22*(7), 961-973.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *The Journal of Finance, 53*(6), 1839-1885.

De Bondt, W. F., & Thaler, R. H. (1985). Does the stock market overreact?. *The Journal of finance, 40*(3), 793-805.

De Bondt, W. F., & Thaler, R. H. (1987). Further evidence on investor overreaction and stock market seasonality. *Journal of finance, 42*(3), 557-581.

Dissanaike, G. (1997). Do stock market investors overreact?. *Journal of Business Finance & Accounting, 24(*1), 27-50.

Erb, C. B., & Harvey, C. R. (2006). The strategic and tactical value of commodity futures. *Financial Analysts Journal, 62*(2), 69-97.

Fama, E. F. (1965). The behavior of stock-market prices. *The journal of Business, 38*(1), 34-105.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance, 25(*2), 383-417.

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of financial economics, 49*(3), 283-306.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics, 33*(1), 3-56.

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The journal of finance, 51*(1), 55-84.

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The adjustment of stock prices to new information. *International economic review, 10*(1), 1-21.

Freeman, R. N., & Tse, S. (1989). The multiperiod information content of accounting earnings: Confirmations and contradictions of previous earnings reports. *Journal of Accounting Research*, 49-79.

George, T. J., & Hwang, C. Y. (2004). The 52- week high and momentum investing. *The Journal of Finance, 59*(5), 2145-2176.

Griffin, J. M., Ji, X., & Martin, J. S. (2003). Momentum investing and business cycle risk: Evidence from pole to pole. *The Journal of Finance, 58*(6), 2515-2547.

Grundy, B. D., & Martin, J. S. M. (2001). Understanding the nature of the risks and the source of the rewards to momentum investing. *Review of Financial studies, 14*(1), 29-78.

Haugen, R. A., & Baker, N. L. (1996). Commonality in the determinants of expected stock returns. *Journal of Financial Economics, 41*(3), 401-439.

Hong, D., Lee, C., & Swaminathan, B. (2003). Earnings momentum in international markets. Working paper.

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance, 54*(6), 2143-2184.

Israel, R., & Moskowitz, T. J. (2013). The role of shorting, firm size, and time on market anomalies. *Journal of Financial Economics, 108*(2), 275-301.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance, 48*(1), 65-91.

Jegadeesh, N., & Titman, S. (2001). Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of finance, 56*(2), 699-720.

Jegadeesh, N., & Titman, S. (2011). Momentum. *Annu. Rev. Financ. Econ., 3*(1), 493-509.

Jensen, M. C. (1968). The performance of mutual funds in the period 1945–1964. *The Journal of finance, 23*(2), 389-416.

Kahneman, D., & Tversky, A. (1982). On the study of statistical intuitions. *Cognition, 11*(2), 123-141.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The review of economics and statistics*, 13-37.

Lui, W., Strong, N., & Xu, X. (1999). The profitability of momentum investing. *Journal of Business Finance & Accounting, 26*(9- 10), 1043-1091.

Malkiel, B. G. (2003). The EMH and its critics. *The Journal of Economic Perspectives, 17*(1), 59-82.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *The journal of finance, 42*(3), 483-510.

Moskowitz, T. J., & Grinblatt, M. (1999). Do industries explain momentum?. *The Journal of Finance, 54*(4), 1249-1290.

Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics, 104*(2), 228-250.

Novy-Marx, R. (2012). Is momentum really momentum?. *Journal of Financial Economics, 103*(3), 429-453.

Pástor, Ľ., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political economy, 111*(3), 642-685.

Rouwenhorst, K. G. (1998). International momentum strategies. *The Journal of Finance, 53*(1), 267-284.

Rouwenhorst, K. G. (1999). Local return factors and turnover in emerging stock markets. *The journal of finance, 54*(4), 1439-1464.

Shiller, R. J. (1987). Investor behavior in the October 1987 stock market crash: Survey evidence.

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *The Journal of Economic Perspectives, 17*(1), 83-104.

Smith, J., & Yadav, S. (1996). A comparison of alternative covariance matrices for models with over-lapping observations. *Journal of International Money and Finance, 15*(5), 813-823.

Spyrou, S.I., Kassimatis, K., Galariotis, E.C., (2007). Overreaction, underreaction & efficient reaction: UK evidence. *Applied Financial Economics, 17*, 221–235.

Tversky, A., & Kahneman, D. (1975). Judgment under uncertainty: Heuristics and biases. In Utility, probability, and human decision making (pp. 141-162). Springer Netherlands.

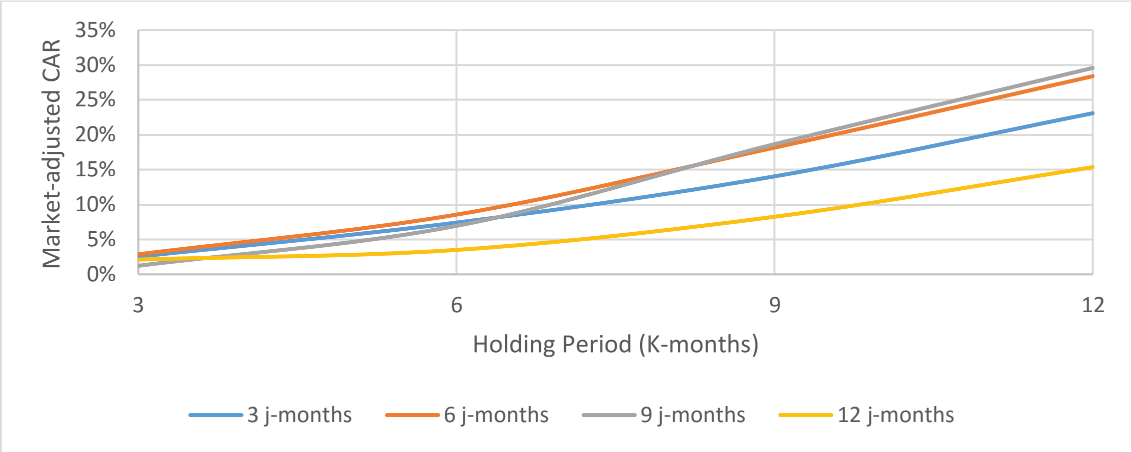
Zarowin, P. (1990). Size, seasonality, and stock market overreaction. *Journal of Financial and Quantitative analysis, 25*(01), 113-125.

Zarowin, P., (1989). Size short-run stock market overreaction: evidence of size and seasonality effects. *Journal of Portfolio Management Spring*, 26–29.

Zhao, S., Tong, Y., Wang, Z., & Tan, S. (2016). Identifying Key Drivers of Return Reversal with Dynamical Bayesian Factor Graph. PloS one, 11(11), e0167050.

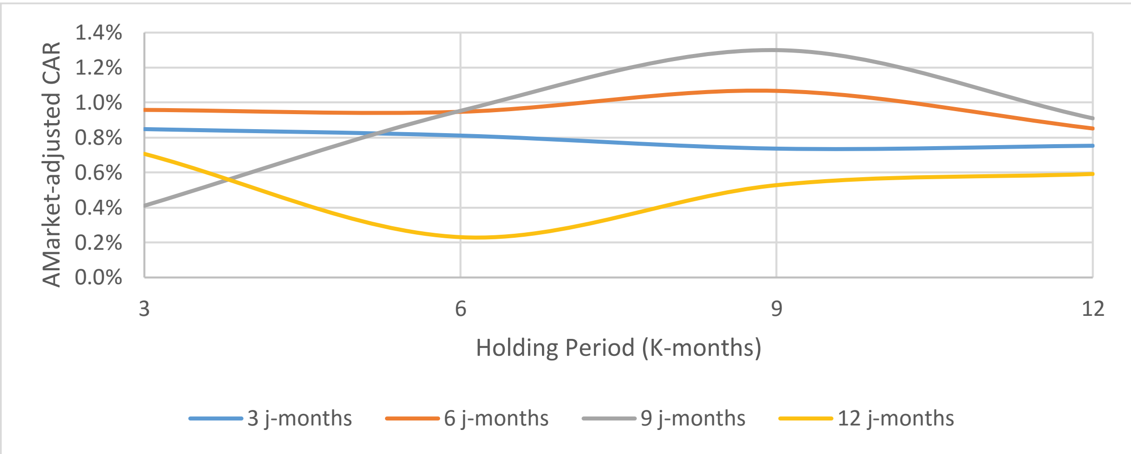
# ANNEXES

*Figure 1: Market-adjusted CAR of arbitrage portfolios for j-month/k-month strategies*



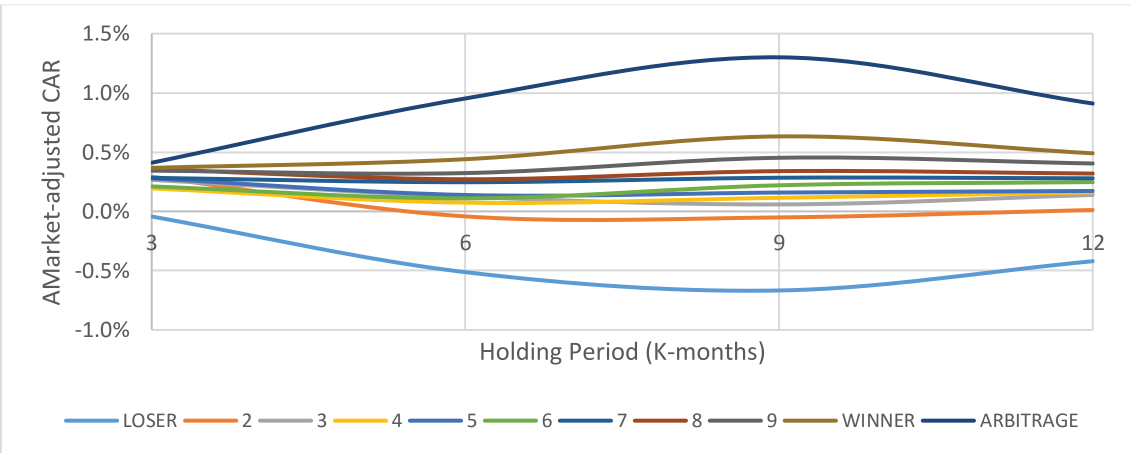

*Note: with reference to table 2*

*Figure 2: Market-adjusted ACAR of arbitrage portfolios for j-month/k-month strategies*



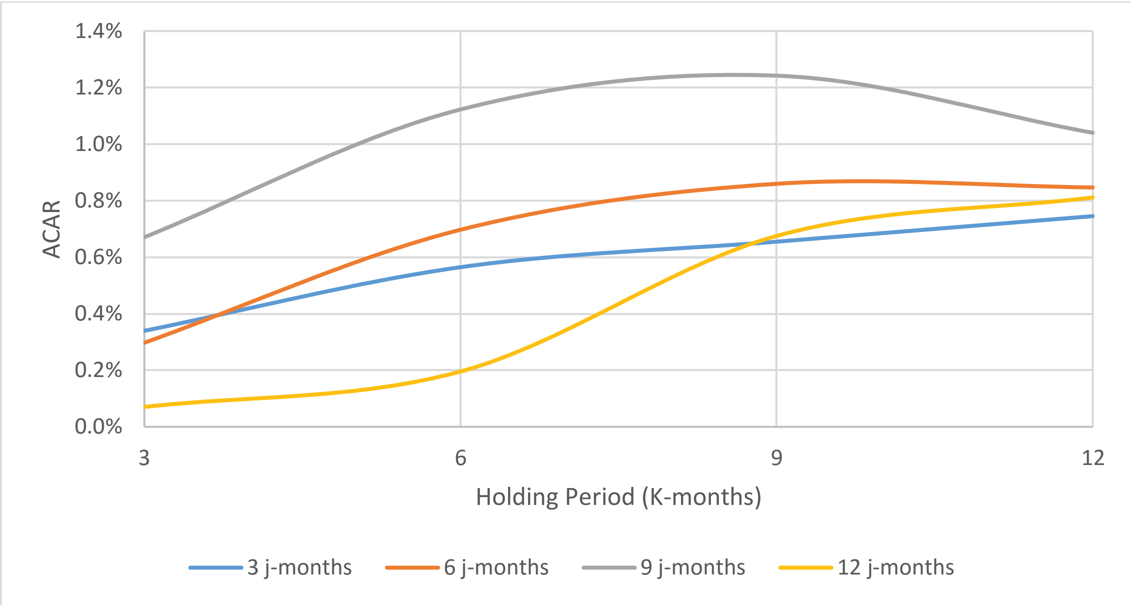

*Note: with reference to table 2*

*Figure 3: Market-adjusted ACAR per portfolio for 9-month/k-month strategies*



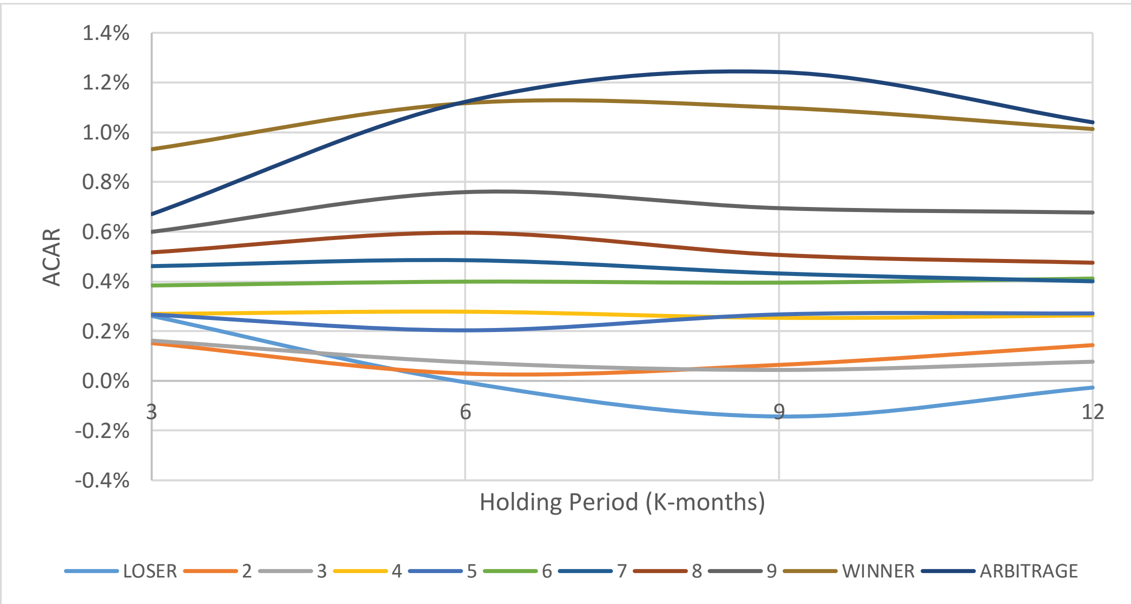

*Note: with reference to table 3*

*Figure 4: FF3FM ACAR of arbitrage portfolios for j-month/k-month strategies*



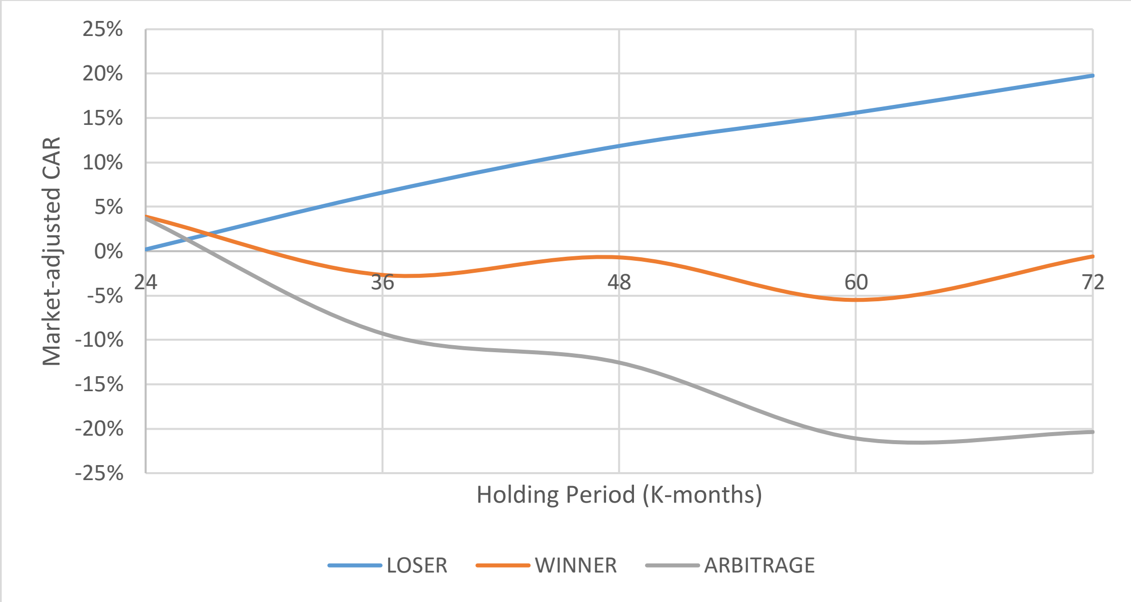

*Note: with reference to table 4*

*Figure 5: FF3FM ACAR per portfolio for 9-month/k-month strategies*



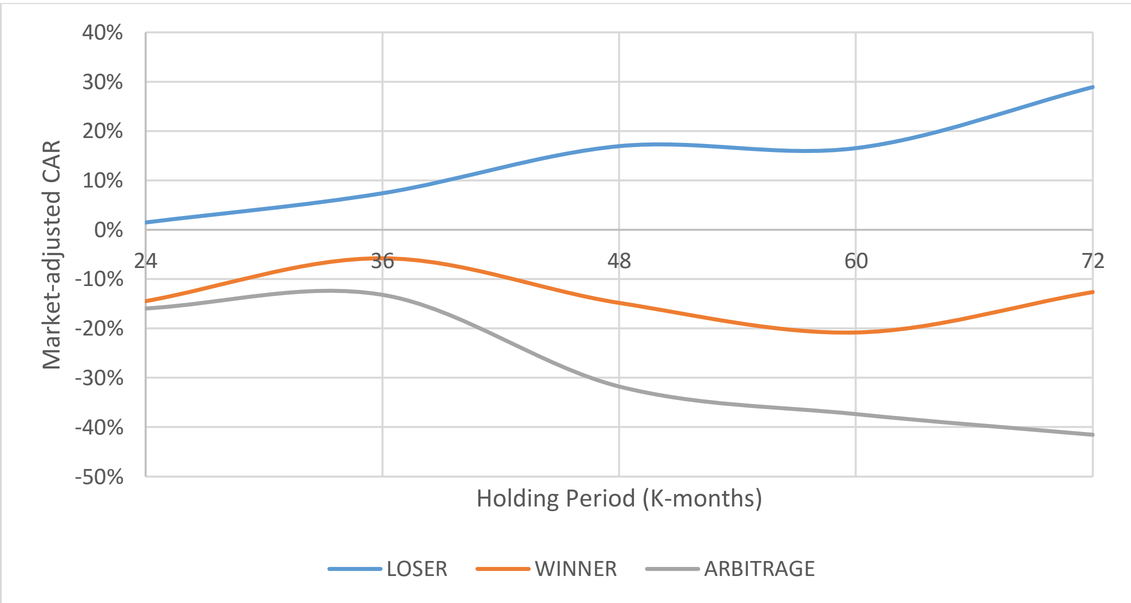

*Note: with reference to table 5*

*Figure 6: Market-adjusted CAR of the winner, loser and arbitrage portfolios for value strength portfolios based on past 24 months' return and hold 72 months up into the test period*



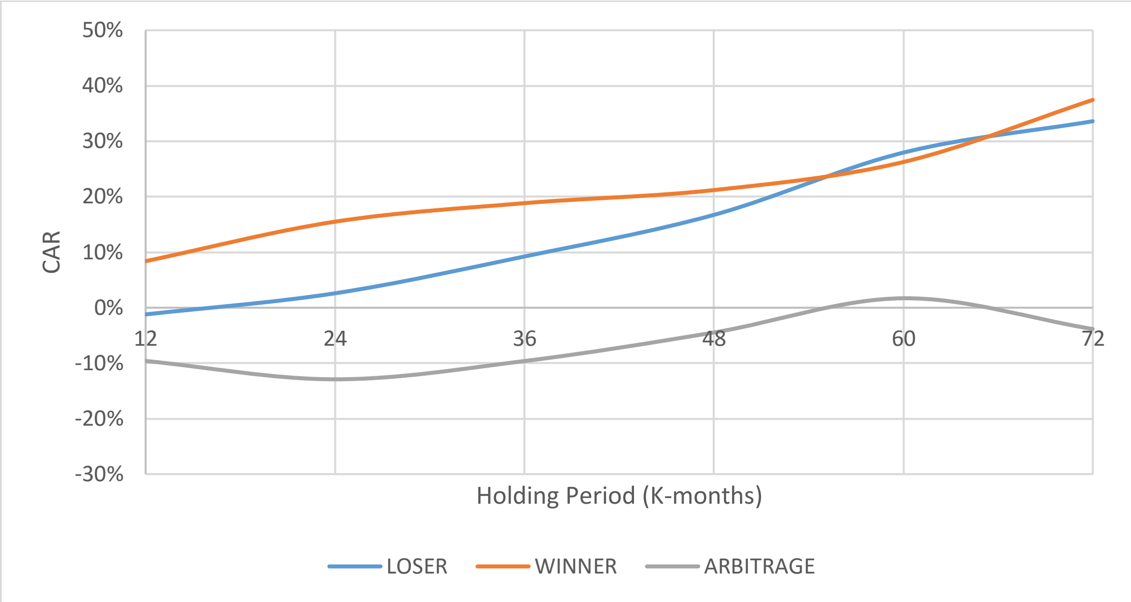

*Note: with reference to table 8*

*Figure 7: Market-adjusted CAR of the winner, loser and arbitrage portfolios for value strength portfolios based on past 36 months' return and hold 72 months up into the test period*



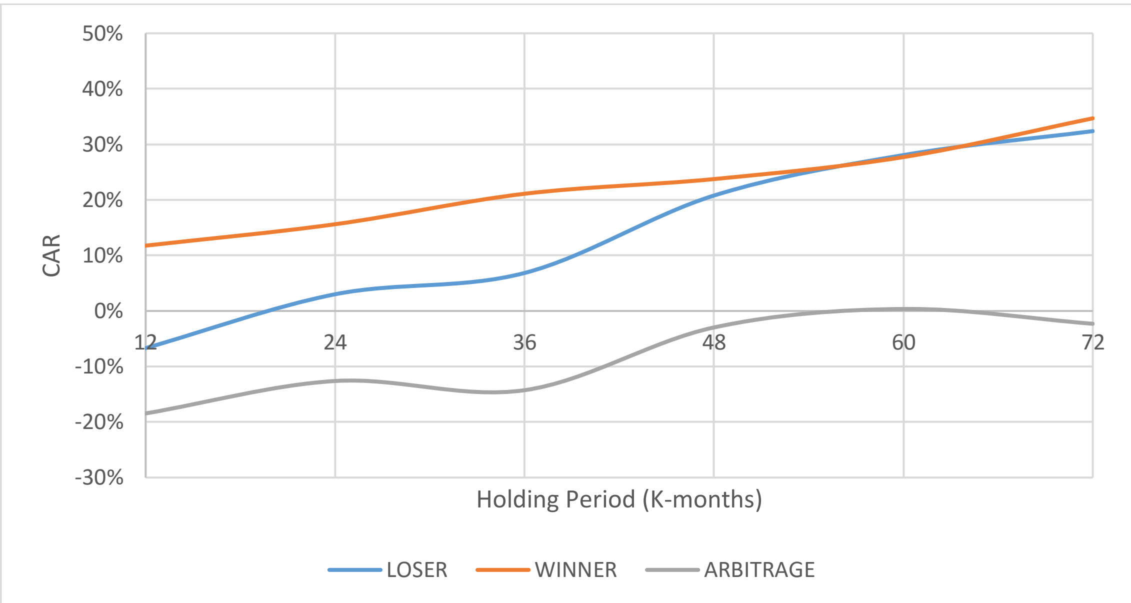

*Note: with reference to table 8*

*Figure 8: FF3FM CAR of the winner, loser and arbitrage portfolios for value strength portfolios based on past 24 months' return and hold 72 months up into the test period*



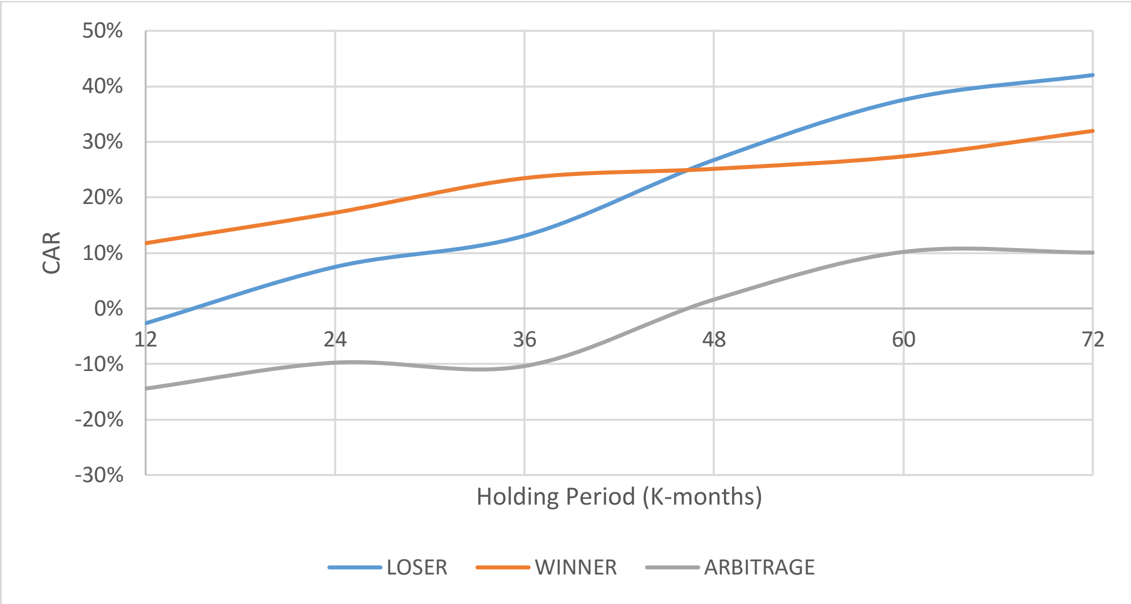

*Note: with reference to table 9*

*Figure 9: FF3FM CAR of the winner, loser and arbitrage portfolios for value strength portfolios based on past 36 months' return and hold 72 months up into the test period*



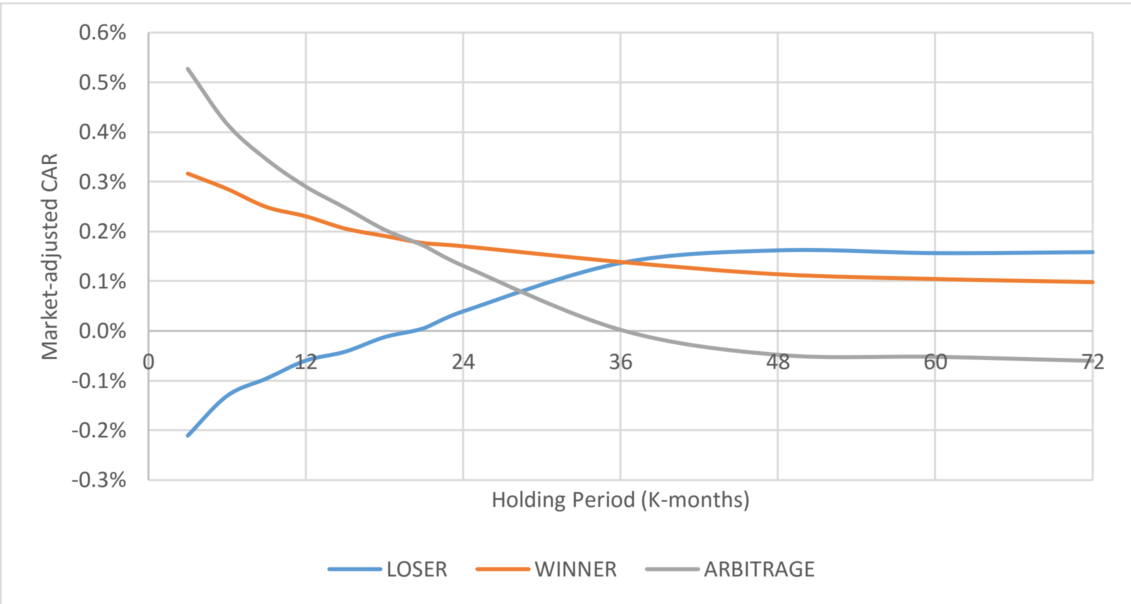

*Note: with reference to table 9*

*Figure 10: CH4FM CAR of the winner, loser and arbitrage portfolios for value strength portfolios based on past 36 months' return and hold 72 months up into the test period*



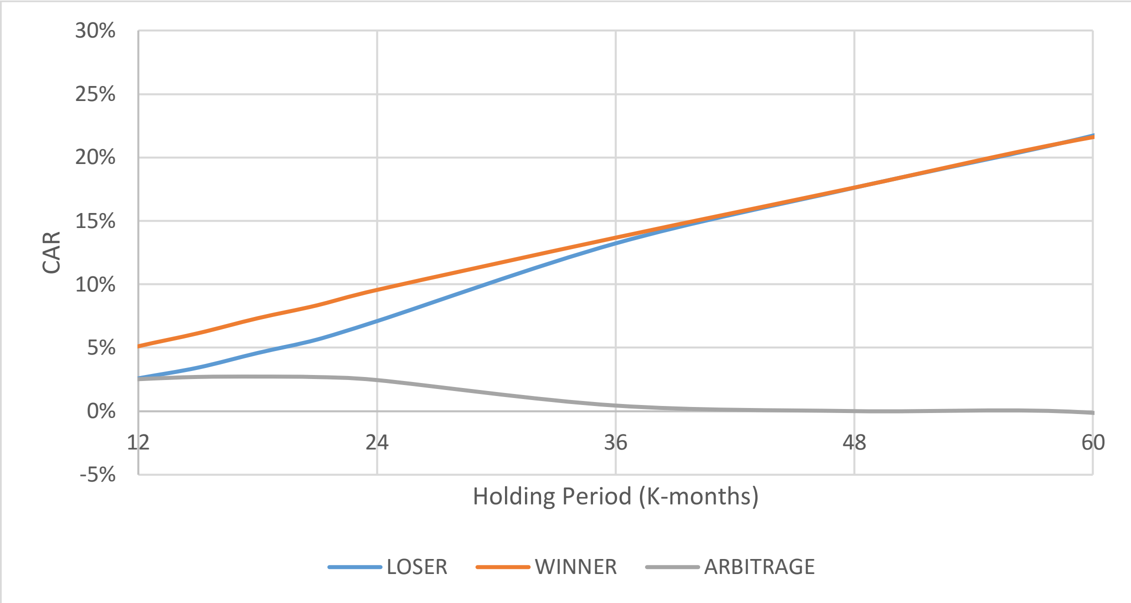

*Note: with reference to table 10*

*Figure 11: Market-adjusted CAR of winner, loser and arbitrage portfolios based on SUE*



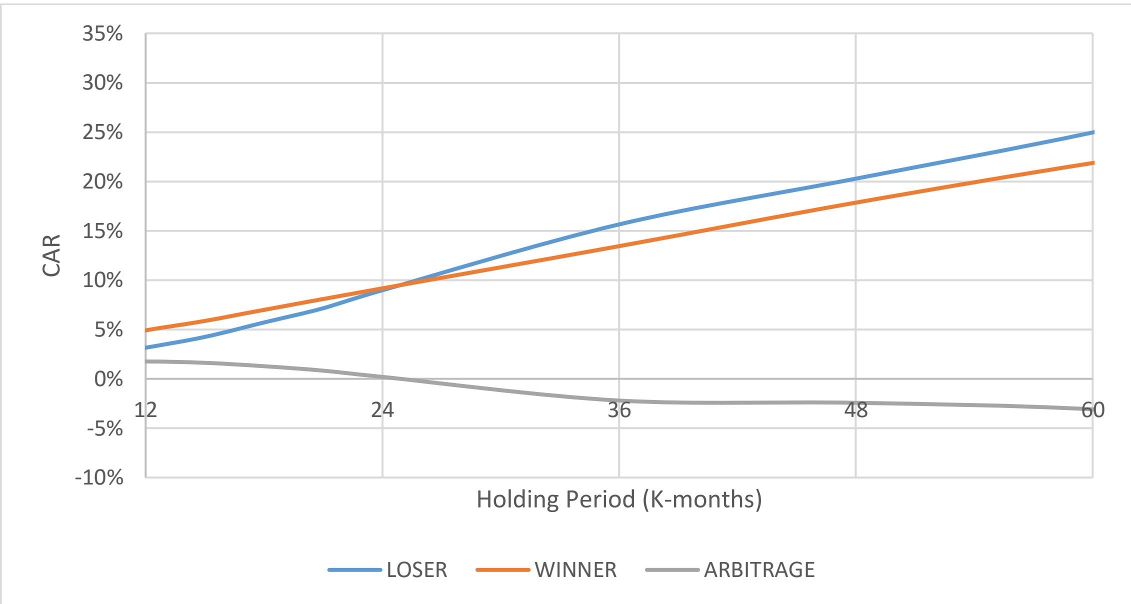

*Note: with reference to table 11*

*Figure 12: FF3FM CAR of winner, loser and arbitrage portfolios based on SUE*




*Note: with reference to table 12*

*Figure 13: CH4FM CAR of winner, loser and arbitrage portfolios based on SUE*




*Note: with reference to table 13*