Testing the Long-Term Profitability of the Short-Term Reversal Strategy

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Abstract

The purpose of this investigation was to test the theoretical possibility of an investor earning a positive cash return from the activities of the stock market despite effectively holding no position at all in said market.

The sample data were the daily returns for the shares of the 780 companies listed on the NASDAQ and the New York Stock Exchange ("NYSE"), which fell within the top 500 listed companies by market capitalisation between 1 January 2005 and 31 December 2017. The reversal strategy's performance was evaluated using portfolios constructed as quantiles of 100 or 500 shares, respectively, where the investor had the option of implementing the reversal strategy immediately after an information-gathering period closed or a day thereafter. The time intervals used were 1 January 2005 to 29 September 2008 (the day the Dow Jones Industrial Average crashed by 777.68 points), 29 September 2008 to 31 December 2017 and 1 January 2005 to 31 December 2017.

Of the 1000 portfolios tested in each time interval, at least 416 had positive average returns in every time interval. Of the portfolios that had positive average returns over the time intervals, at least 66 had statistically significant average returns in every time interval. The best-performing portfolio for the entire sample period was a combination of the best-performing pre-crash and post-crash portfolios – an investor who held that portfolio realised a cumulative return of approximately $61.39 for every $1 invested.

The conclusion was that it was theoretically possible for an investor to earn a positive cash return from the market's activities despite effectively holding no position at all in the market. Consequently, it was concluded that the strong form of Fama's (1970) Efficient Market Hypothesis was disproved. Future research should include out-of-sample tests, tests that include restrictions on short selling and tests that consider the impact of trading costs on portfolio performance, to render the conclusions of this investigation more practically applicable to investors.

Key Words

Costless Portfolio; Zero-Investment Portfolio; Risk-Return Trade-Off; Efficient Market Hypothesis; Reversal Strategy

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Chapter 1: Introduction

The purpose of this investigation is to test the long-term profitability of the short-term reversal strategy to ascertain whether an investor who had constructed a costless long-short portfolio and implemented a reversal strategy could over the long-run have succeeded in accruing statistically significant positive cash returns from a synthetic zero position in the market.

To test the long-term profitability of the short-term reversal strategy, analyses will be conducted of the performances of 1000 costless portfolios that have been constructed using the top 500 shares by market capitalisation listed on the New York Stock Exchange and the NASDAQ over the period from 1 January 2005 to 31 December 2017, as listed on the Standard and Poor's 500 Index ("the S & P 500"). The results obtained therefrom will allow a determination of whether or not it was theoretically possible for an investor to derive a positive cash return from the activities of the stock market, while effectively holding no position in the market at all, over the period from 1 January 2005 to 31 December 2017.

The word "effectively" is of importance. The investor in question would be holding a *synthetic* zero position in the market, a long-short portfolio composed of equal numbers of long and short positions, weighted in such a way that the net value of the portfolio would equal zero. Were the question to do with an *actual* zero position in the market, the answer would be a definitive "no", for the simple reason that said investor would not have any money invested in the market.

But the investor in this case *would* have money in the market, which would effectively have been borrowed. The investor would construct a universe of stocks that was a subsample of the stocks listed on the exchanges to which he or she would have access. He or she would enter short positions with respect to shares that had relatively outperformed in the sample and would enter long positions with respect to shares that had relatively underperformed in the sample. The weightings of the positions would be such that the total portfolio value (the sum of the components) would equal zero; the funds raised from the weighted short positions would then be exhausted financing the long positions completely.

The research question to which this investigation seeks an answer is the following: "Could an investor who had constructed a costless long-short portfolio and implemented a reversal strategy have succeeded over the long-run in accruing statistically significant positive cash returns from a synthetic zero position in the market?" This question is of interest because the convention in investment is to construct a portfolio composed entirely of long positions and to weight those long positions in such a way as to obtain the desired market exposure (in the manner of an index fund, for example).

The investigation's purpose becomes of interest because a positive answer to the research question (that is, a "Yes" to the question, "Could an investor who had constructed a costless long-short portfolio and implemented a reversal strategy have succeeded over the long-run in accruing statistically significant positive cash returns from a synthetic zero position in the market?") not only provides disproof of Eugene Fama's (1970) Efficient Market Hypothesis, but also opens the door for exploration of a new form of investment, one with lower-than-average risk and higher-than-average returns compared to conventional, risk-bearing investment strategies. The Efficient Market Hypothesis, in its strongest form, argues that a security's price reflects all public and private information about it, which implies that no investor can consistently outperform the market. The modern portfolio theory introduced by Markowitz (1952) holds as a central principle the idea of a risk-return trade-off: an investor will always prefer a portfolio that yields a higher expected return, for a given level of risk, but an investor must take on some risk in order to receive some returns.

The long-run implementation of the short-run reversal strategy is in a sense a test of modern portfolio theory. Modern portfolio theory holds as one of its fundamental principles the idea that it is impossible for an investor to generate a positive cash return from a net zero position in the market. If the evidence obtained from this investigation yields the answer that it is possible to have a synthetic zero position in the market and derive profits therefrom, then that answer will serve as a contradiction to established financial theory because it will indicate that it is indeed possible to generate risk-free profits from market participation, in direct opposition to the Efficient Markets Hypothesis.

If it is proven possible for an investor to assemble a long-short portfolio that ultimately costs him or her nothing and derive a positive return from what is essentially a net zero position, then Fama's (1970) argument fails because the investor will have succeeded in earning a significant positive cash return from the market using a portfolio assembled on the basis of public information available (the use of private information ordinarily entails insider trading, which is illegal under many jurisdictions). Disproof of the dominant theories will allow practitioners and investors to explore the possibility of building practically achievable costless portfolios with which to accomplish the use of the reversal strategy over a consistently long period of time, which will allow investors to take on less risk for more and more consistent returns – an improvement of the current status quo on two fronts.

Chapter 2: Literature Review

2.1: Introduction

Chapter 2 contains the literature review, which will be segmented into two parts. Section 2.2 contains prior literature, specifically synopses of the conclusions arrived at by financial authorities who conducted investigations into various aspects of the reversal strategy's performance and have come over time to be the leading authorities on the subject. Section 2.3 contains arguments based on the literature, in support of further development of theory and practice associated with the topics of this investigation.

2.2: Prior Literature (Findings and Argumentation by Leading Authorities)

2.2.1: Jegadeesh (1990)

Jegadeesh (1990) tested for significant serial correlation in stock returns using data from the Center for Research in Security Prices for the period 1929-1982.

Once said significant serial correlations were identified, data from 1934 to 1987 were used to test for and identify highly significant abnormal returns, obtained from portfolios constructed in such a way as to presumably take advantage of the predicted returns of stocks.

Possible explanations given included size-based risk adjustments (tests performed failed to yield significant results, thus indicating that much of the empirical regularity remained unexplained), time-varying market risk (it was mentioned here that because the composition of the portfolios varied, the betas of the portfolios varied as well and that if one could determine how the betas varied with time, one could also determine the predicted abnormal returns; subsequent tests did not yield significant results, thus indicating that time-varying market risk failed to explain the empirical regularity) as well as bid-ask spreads and thin trading (security prices impart a bias to the expected returns because they fluctuate between the bid and ask prices; repetitions of the earlier tests excluding the last trading day failed to yield significantly different results).

It was postulated that alternative asset pricing model specifications that allowed for more general variation in security risk premia could explain the results that were obtained. It was then concluded that there existed strong evidence of predictability in stock returns, thus allowing the reliable rejection of the random walk hypothesis.

2.2.2: Lehmann (1990)

Lehmann (1990) studied market efficiency by testing the profits of costless portfolios consisting of short positions in stocks that recently outperformed the market and long positions in stocks that recently underperformed the market.

Equity securities listed on the New York and American Stock Exchanges were used because daily return data from 1962 to 1990 were available from the CRSP for those securities. It was determined that the portfolio weight for each security would be proportional to the out- or underperformance of the security vis-à-vis the equally weighted portfolio of all included securities. A week was held to be sufficiently short for the local martingale model[1] to apply while the strategy's horizon was set to twenty-six weeks.

All securities listed on the above exchanges in a given week and in the k weeks beforehand were included in the portfolio strategy, with the size of each investment being proportional to each security's return in week k less that of the equally weighted portfolio of all included securities. The investments were weighted such that the strategy was costless. A result of the portfolio weights was that the profits

[1] A martingale is a stochastic process such that, at any point in time, the conditional expected value of the process, given all the previous values, is simply equal to the value of the process at that point in time. (Hazewinkel, 2001).

yielded were the difference in returns between a long-only portfolio and a short-only portfolio, therefore they were measured in percentage points per week. The product of each security's weight and its return *k* weeks later would yield its portfolio profits for the week. Repetition of the process for all the weeks in the investment horizon yielded the strategy's profits for the entire period.

A major problem that arose with using weekly security returns to detect for market inefficiency as the author did was that there were predictable fluctuations in measured security returns that were entirely unrelated to market inefficiency in that 80% of the price movements over successive transactions were between the bid and ask prices, which led to pronounced negative serial correlation even in daily returns. A problem with the CRSP data was that it only listed closing prices, with no regard for bid prices, offer prices or bid-offer spreads. The above effects made the one-week strategy look more profitable than it really was – for example, stocks that sold at the bid price on a Tuesday would move to the offer price on the following Tuesday roughly half of the time, thus yielding an apparent profit on the short position in that stock. Some mitigating factors that the author mentioned included considering that the biases were only serious problems for portfolios with one-week lags and computing the portfolio weights using their four-day returns from Wednesday to Monday, thus reducing the bias by reducing the correlation between portfolio weights and subsequent returns' measurement error. It was noted that said elimination of Tuesday's returns was conservative in that it removed both the "useful" (bid-to-bid) and "corrupted" (bid-to-ask or ask-to-bid) returns.

The issue of transaction costs was also raised. The strategy ordinarily required upwards of 2,000 transactions per week, which would raise transaction costs and, thus, reduce profits from the implementation. However, it was unclear which transaction costs were relevant because an investor treating the implementation of the strategy as a marginal change to an existing portfolio would be expected to face lower transaction costs. Furthermore, the strategy could be modified to reduce the frequency of trading.

Statistical tests were then performed to evaluate the profitability of the costless portfolio strategy. It was found that the two one-week portfolios earned positive profits for each of the 49 twenty-six-week periods, the 98 quarterly observations and the 24 annual observations. The two-week portfolio earned positive profits in each of the six-month periods but failed to survive the inclusion of transaction costs. There was also little persistence in the return reversal effect. The efficient markets hypothesis ignoring market frictions was therefore rejected. The winner and loser portfolios (the short and long positions) had weekly average returns within an order of magnitude of their standard deviations, implying that they greatly exceeded their corresponding sample variances. The large negative correlations between the long and short positions in the loser and winner portfolios caused the resulting costless portfolios to have mean profits approximately equal to their standard deviations. Mean profits were positive in each six-month period and were more than three times larger than their standard deviations.

In conclusion, the efficient markets hypothesis was rejected. It was claimed that the costless portfolio yielded positive returns in approximately 90% of the weeks of the study and, if viewed in six-month periods, in each of the 49 periods covered by the data. The measured arbitrage profits thusly obtained persist after corrections for mismeasurement of security returns as well as for the factoring in of plausible transaction costs. The costless portfolios were constructed using modest positions in securities, reducing the likelihood of major market impact and resultant price movements (unless the securities involved were illiquid.) The return reversals obtained likely reflected short-term imbalances in the liquidity market, which market makers were remedying by serving as intermediaries between patient and impatient traders. The "little persistence" in return reversal effects gave rise to two potential responses: that one could claim equity markets are on average efficient over longer periods, e.g. a month, or that the tests used had low power and that additional evidence of market inefficiency was required.

2.2.3: Jegadeesh and Titman (1993)

Jegadeesh and Titman (1993) constructed 16 strategies, with holding periods of one, two, three or four quarters and formation periods of one, two, three or four quarters (the returns of the preceding one, two, three or four quarters were used as criteria for stock selection). Stocks for each portfolio were divided into deciles; overlapping periods were used, to increase the power of the tests.

Using daily returns data drawn from the Center for Research in Security Prices for the years 1965 to 1989, the reversal strategies were then tested. The costless portfolios all yielded positive returns, each of which (except for the three-month/three-month strategy, which did not skip a week) were statistically significant; the most successful strategy was the 12-month/three-month strategy, which yielded 1.31% per month.

Emphasis was then placed on the six-month/six-month strategy and an attempt was made to identify the sources of the profits. A one-factor model was constructed, then portfolio betas, 6-month serial covariance and lead-lag effects were tested. It was found that the betas of extreme past returns exceeded the betas of the full sample. It was also found that, because the betas of past winners were higher than those of past losers, the costless portfolios had negative betas. It was inferred from the evidence that market risk did not explain the profits. Tests of 6-month serial covariance determined that it was negative, thus eliminating it as a possible cause.

Evidence was found that suggested stock underreactions to firm-specific information were causing the profits, but said evidence was also consistent with an alternative model featuring lead-lag effects of factors on stocks. But tests that were conducted yielded evidence that the postulated lead-lag effects were not important sources of relative strength profits.

Subsequently, profitability was tested based on size and beta by using three size-oriented and three beta-based subsamples. The subsample with the largest firms yielded lower results than the other size-based subsamples. Evidence implied that cross-sectional differences in systematic risk within the sample did not explain performance and that profits were due to serial correlation in firm-specific returns. Evidence also suggested that the profits observed were due to buy-side performance (the long positions) rather than sell-side performance (the short positions).

Tests conducted in different sub-periods found that reversal strategies generally underperformed in January and were low in August, but outperformed in April, November and December, thus exhibiting a sort of seasonality. When assessing portfolio performance in event time, the cumulative returns exhibited an inverted U shape, which authors had initially been thought to be due to a high initial risk followed by a decline in risk, but risk increased over that period. It was found that earnings announcements caused momentum, with winner portfolios significantly outperforming loser portfolios (by at least 0.7% on average) for the first six months after an earnings announcement, then underperforming eight to 12 months later.

It was concluded that costless winner-minus-loser portfolios realised significant abnormal returns over their sample period and that the reversals observed in the sample data indicated that a more sophisticated model of investor behaviour was needed.

2.2.4: Mei and Gao (1995)

Mei and Gao (1995) studied return reversals in 132 real estate securities traded on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX). Daily returns for those securities were extracted using the CRSP tape from 2 July 1962 to 31 December 1990. Lehmann's (1990) methodology was applied to their analysis. Return reversals observed were first documented. Thereafter, an arbitrage portfolio was constructed to test for arbitrage profits and, consequently, market efficiency.

It was found that the arbitrage portfolio's profits significantly exceeded zero for all period lengths and time horizons, but the degree of profitability differed between cases. If a six-month or one-year trading period were used to evaluate the portfolio, the trading week yielded the best results (semi-annual returns of 30.77 cents and annual returns of 62.2 cents on a costless portfolio with $1 in each long and short position) – this result was in keeping with Lehmann's (1990) original result (using a calendar week) and implied that it takes approximately a week for the market to realise return reversals, a finding consistent with French and Roll's variance ratio test result, which stated that stocks had strong negative autocorrelations for time horizons beyond one week.

To test the consistency of the strategy, separate sub-analyses of their data were conducted for the 1960s, '70s and '80s. While all semi-annual and annual returns were positive for all three decades, returns declined as time progressed. The decline was attributed to active arbitraging in the market during the 1980s.

It was found that the shorter the lag time, the better the results of the portfolio were. For lags larger than four trading weeks, portfolios constructed using that data yielded negative results, a finding similar to Lehmann's result (1990) that a portfolio wherein the weights were based on information about the most recent period's returns was the most profitable. Results indicated that the return reversal effect was most prominent at weekly intervals.

The arbitrage portfolio ordinarily yielded statistically significant abnormal profits exceeding what would otherwise be obtained but said abnormal profits disappeared once transaction costs were considered and, in fact, the arbitrage portfolio yielded returns significantly lower than the non-arbitrage portfolio.

It was concluded that although there existed some statistically significant return reversals in exchange traded real estate securities, which could lead to economically significant trading profits if trading costs could be somehow avoided, the consideration of the implicit bid-ask spread and the deduction of the trading costs effectively eliminated the trading profits, proving the efficiency of the real estate market in that one could not profit from return reversal arbitrage. It was also recommended that long-term real estate security managers reduce their acquisition costs by purchasing a few days after a weekly rally and selling a few days after a weekly downturn – the caveat attached was that, while that rule would not guarantee investment savings or gains in each transaction, it ought in the long run to increase portfolio performance.

2.2.5: Keim and Madhavan (1997)

Keim and Madhavan (1997) examined the magnitude and determinants of transaction costs for a sample of institutional traders with different investment styles.

It was first noted that investment performance reflected a portfolio manager's investment strategy and the trading costs associated therewith. The components of the investment strategy included the selection of shares to be traded and the timing of the trades. It was also noted that trading costs were able to markedly reduce the notional return to an investment strategy. From those observations came the argument that there was great interest in assessing the magnitude of trading costs. A corollary to the argument was the fact that, because trading costs could vary substantially across trading styles, any analyses to be conducted had to be in relation to the investment strategy used.

It was noted that differences in investment style caused substantially different demands for immediacy of trade and it was speculated that resulting differences in order submission strategies probably caused differences in trading costs. It was also speculated that the magnitude of trading costs could be influenced by the market on which a stock traded. It was noted, though, that while small retail traders were price takers, large institutional traders typically negotiated prices directly with dealers. Thus, the institutional traders possibly avoided the collusion among dealers that served to widen quoted bid-ask spreads. It was argued that comparisons of costs across markets could also shed light on broader

questions regarding the relative merits of alternative trading designs, particularly regarding the mechanisms that different markets use to conduct trades (auction mechanisms, such as were used in the exchanges, or dealer markets, such as was then used by NASDAQ). It was put forward that trading costs had two major components: explicit costs (largely commission costs) and implicit costs (primarily the price impact of a trade). It was also put forward that examination of both components jointly was of great importance because of the possibility that they were systematically related.
The data used for the analysis were data on then recent equity transactions by 21 institutional traders, which amounted to \$83 billion. The data covered more than 62,000 equity orders, each of which typically resulted in multiple trades, placed by institutions that differed in their investment objectives and trading styles. Focus was placed on institutional investors because they accounted for a significant proportion of equity ownership and trading volume. The data were deemed unique in that they provided a complete record of all individual trades generated by a specific indicated desire to trade, which was important because an order for a certain number of shares might have resulted in several distinct trades spanning many different and not necessarily adjacent days. The data allowed for the measurement of the total costs associated with a particular strategy involving multiple trades as opposed to the costs of an individual trade. The data also included information about whether the initiated trade was a purchase or sale. In particular, the institutions in the sample indicated, at a particular date, a specific desire to initiate a programme to purchase or sell stated quantities of shares of a stock to adjust their portfolio composition. A trader who approached the market intending to purchase shares would receive a different response compared to one who sought to sell shares, so it was an important distinction to be made. Most trades in the sample, both unweighted and weighted by the value of the trade, were executed using market orders, so the classification was held to closely resemble one based on whether immediacy was demanded or supplied.

The findings of the investigation were the following. Transaction costs were substantial. Both explicit and implicit trading costs were positively related to measures of trade difficulty. Trades in NASDAQ stocks were generally more expensive than comparable trades in equity-listed stocks, particularly for buyer-initiated shares. Purchases were generally more costly than equivalent sales, especially in small stocks. Substantial variation in trading costs across institutions was documented – said variation reflected differences in investment style and trade difficulty. However, even within a particular investment style, there were considerable differences in the costs faced by various institutions, which it was speculated possibly arose from differences in trading skill. Some institutions in the sample had significant positive excess costs that could not be explained by their order characteristics or the stocks that they traded.

2.2.6: Jegadeesh and Titman (2011)

Jegadeesh and Titman (2011) reviewed the then-existing literature regarding momentum and momentum strategies. Jegadeesh's (1990) and Lehmann's (1990) original finding that losers over the preceding one week to one month outperformed winners over the following one week to one month was cited, as was Jegadeesh and Titman's (1993) work, specifically the findings of seasonality in portfolio performance and the finding that when strategies skipped a week between the formation period and the holding period, they generated higher and more significant returns.

Chui, Titman and Wei (2010) was also covered. Chui, Titman and Wei had investigated the profitability of momentum strategies in international markets. It was found that different cultures exhibited momentum differently, with more individualistic cultures weighted more highly information that they came by on their own as opposed to more collectivist cultures, wherein the opposite happened. It was also found that momentum strategies were less popular in more collectivist cultures.

2.2.7: De Groot, Huij and Zhou (2012)

De Groot, Huij and Zhou (2012) investigated the impact of trading costs on short-term reversal investment strategies. Following reference to earlier work on the topic by various authors, it was argued that the noted impact of trading costs on reversal profits was largely attributable to excessive trading in small-cap stocks. When stocks were ranked according to past returns, the most volatile stocks were most likely to be in the extreme quantiles and they were typically the stocks with the smallest market capitalisations. Consequently, a long-short portfolio using stocks in the extreme quantiles would contain them, which would raise trading costs because those stocks were generally the costliest to trade and the raised trading costs could eliminate reversal profits. Three hypotheses were tested: that the reported impact of trading costs on reversal profits was largely attributable to excessive trading in small-cap stocks and reducing the universe to large-cap stocks would significantly reduce costs; that trading costs could be further reduced by implementing a more sophisticated portfolio construction algorithm; and that trading costs affected European markets more strongly because of lower liquidity.

The American stock data comprised the 1,500 largest stocks in the Citigroup US Broad Market Index (BMI) from January 1990 to December 2009, without micro-cap stocks to ensure their findings were free of market microstructure concerns. The European stock data comprised return data for the largest 1000 stocks in the Citigroup European Broad Market Index from January 1995 to December 2009 – the trading cost model that was used, provided by Nomura Securities, was not accurately calibrated to estimate trading costs for European stocks before 1995. The FactSet Global Prices database provided daily stock returns (including dividends), market capitalisation and price volumes.

Nomura's researchers provided aggregated data in the form of average trading costs for decile portfolios of S&P 1500 stocks sorted by quarterly dollar volume from January 1990 to December 2009. That allowed trading cost estimates for a specific stock's trading cost estimate using the stock's volume rank at a point in time. Other assumptions were that trades closed within 24 hours and that trade sizes were $1,000,000 by the end of 2009. Trade sizes were deflated by 10% per annum. It was argued that the assumption about the sizes ensured that any effects they documented could be exploited by a sizeable strategy.

The same trade sizes were used in the Keim and Madhavan (1997) model to estimate trading costs as in the Nomura model. For the sample, it was found that the cost estimates closely matched Keim and Madhavan's (1997). It was found that the most liquid stocks with the largest trading volumes had negative cost estimates and the number of stocks with negative estimates increased over time. Keim and Madhavan's (1997) model yielded negative cost estimates for nearly half the stocks in the 2007 sample. Nomura's cost estimates for S&P1500 stocks were up to six times larger than Keim and Madhavan's (1997).

The differences in cost estimates provided by the models became more extreme once considerations were restricted to the 500 largest stocks in the sample. Keim and Madhavan's (1997) were very low and, in many cases, even negative, with many years in the sample period featuring entirely negative estimates. Nomura's estimates were substantially higher. Keim and Madhavan's (1997) model gave average one-way trading costs of 0.04% for the top 50 stocks; Nomura's model gave average one-way trading costs of 0.06% for the bottom 50. Some reasons for the differences in cost estimates were postulated. Nomura's model imposed a quadratic relationship on trading volume and transaction costs, which made cost estimates positive even for the most liquid stocks; Keim and Madhavan's (1997) model imposed a logarithmic relationship, which made cost estimates for some of the most liquid stocks to be negative. Keim and Madhavan's model used a constant negative coefficient for market capitalisation, but the average market capitalisation of the sample increased over time, so the cost estimates declined. It was admitted that scaling techniques had not been applied to prior trading costs – if previous trading costs had been inflated, as was done in the literature, larger cost reductions would have been observed. Nomura's model was periodically recalibrated and so was able to adjust to changing market conditions within the sample.

The Keim and Madhavan (1997) trading cost model was used to estimate net reversal profits for the first analysis. Keim and Madhavan [1997] modelled trading costs using the following equation: $C_i = \beta_0 + \beta_1 D_i^{NASDAQ} + \beta_2 Trsize_i + \beta_3 Logmcap_i + \beta_4 \frac{1}{P_i} + \beta_5 D_i^{TECH} + \beta_6 D_i^{INDEX} + \epsilon_i$, where for order i, C_i was the total cost in percentage form, D_i^{NASDAQ} was a dummy variable equal to one if the stock traded was listed on NASDAQ and zero otherwise, $Trsize_i$ was the ratio of the order value to the traded stock's market capitalisation, P_i was the price of the traded stock, D_i^{TECH} was a dummy variable for technical managers, D_i^{INDEX} was a dummy variable for index managers and ϵ_i was the error term.

A problem that was noted with the model was that its coefficients were estimated over the period January 1991 to March 1993 – it was wondered if the estimates obtained were more accurate over recent periods, given the changes in the markets since that period. It was also noted that increased trading volumes over time, increased competition among stockbrokers and technological advancements might have had significant impacts upon bid-ask spreads, market impact costs and commissions. To mitigate against the potential adverse effects of their observations, trading cost estimates for stocks that were within the S&P 1500 index over the sample period were obtained from Nomura. Nomura's trading cost model was calibrated quarterly from 1995 to 2009. The estimated broker commissions were 0.05% per trade in the 1990s and 0.03% in the early 2000s.

The belief was expressed that, due to the observations above, the Keim and Madhavan (1997) model's trading cost estimates were to be cautiously interpreted. It was acknowledged that said model was probably optimally specified for its initial purpose (describing in-sample relations between trading costs and stock characteristics). It was deemed desirable that Nomura's model had been calibrated using European trade data from 1995 to 2009, which allowed investigations of reversal profits and trading costs within those markets.

It was stated that, to the best of the authors' knowledge, their research was the first to investigate trading cost impact on reversal profits in European equity markets and give a comprehensive overview of trading costs impact on said profits. It was expected that European trading costs would exceed US costs due to the European markets' comparative illiquidity. Comparisons of the trading cost estimates for the 1500 largest US stocks with those of the 1000 largest European stocks, all provided by Nomura, yielded results that matched expectations.

Reversal profits were first analysed across different market cap segments. Reversal profits were evaluated for the 1500, 500 and 100 largest US stocks. It was hypothesised that the reported impact of trading costs on reversal profits was mostly due to excessive trading in small-cap stocks and that restricting the stock universe to large-cap stocks would significantly reduce trading costs. Portfolios were constructed by daily sorting all available stocks into mutually exclusive quintile portfolios based on the preceding five trading days' results, assigning equal weights to each stock. The portfolios held long positions in the 20% of stocks in each portfolio with lowest returns and short positions in the 20% of stocks with highest returns, based on the previous week's performance. A day was skipped between ranking and construction to avoid bid-ask bounces. Portfolios were rebalanced daily. Gross and net returns of the long portfolio, the short portfolio and the long-short portfolio less the equally-weighted quintile portfolio return were calculated. Net returns for each stock at each point in time using the trading cost estimates mentioned earlier were also calculated, with the "conservative" restriction that all estimates were non-negative.

The strategy was first considered using the 1500 stocks. A reversal strategy such as the one outlined in the last paragraph yielded gross returns of 0.617% per week and a weekly turnover of 677%, with an average holding period of fewer than three days. However, trading costs (using Nomura's as well as Keim and Madhavan's [1997] estimates) eliminated returns entirely, leading to net losses of -1.037% and -0.661%, respectively.

There was a highly nonlinear relationship between market capitalisation or trading volume and trading costs such that the smallest and least liquid stocks were the most expensive to trade – disproportionately so, especially because their higher volatility gave them the highest probability of falling within the extreme quintiles when stocks were ranked on past returns, thus implying that long-short portfolios were typically invested in the most expensive stocks. It was noted that while some studies reported stronger anomalies among small-cap stocks, there was room to wonder if the potentially higher returns yielded by small-cap stocks compensated for their higher trading costs.

The reversal strategies for the largest 500 and 100 stocks outperformed the strategy for the largest 1500 stocks, both in terms of gross return and in terms of cost-adjusted net returns under the Nomura and Keim and Madhavan (1997) models. The results indicated that reversal profits appeared to be highest among the largest stocks. The results also demonstrated that small-cap stocks' higher trading costs outweighed their potentially higher returns. It was written that the finding that investors could use reversal strategies to earn themselves significant net weekly returns upwards of 0.3% was a serious challenge to rational asset pricing models and had important implications for reversal strategies' practical implementation. It was concluded that the key lesson was that investors seeking to earn superior returns through reversal trading were more likely to realise their objectives by trading in liquid stocks with low transaction costs.

The conventional reversal portfolio construction method was cited as a reason for the importance of trading costs. It was written that the conventional method was sub-optimal when evaluating a real-live investment strategy and considering trading costs, as it would only benefit the holder if trading costs were less than the expected return differential. It was argued that a portfolio construction method that directly sold stocks that were no longer relative losers and bought back stocks that were no longer relative winners, would cause excessive transaction costs and generate excessive turnover. Lowering the rebalancing frequency exposed one to the risk of holding stocks that had already reverted. In response, it was suggested that the portfolio be rebalanced stock by stock when a stock was at least among the top 50% of winning or losing stocks based on past return, at which point said stock would be replaced by the stock with the lowest or highest past-week return at that time, which had not yet been included in the portfolio. It was argued that this "smart" approach would have a substantially lower turnover than the "standard" approach and would have the same number of stocks, just with flexible holding periods.

The reversal strategy was re-tested using the same stocks, but with the modified approach. With the 1500-stock reversal strategy, weekly turnover reduced from 677% to 325%, with an effective holding period per stock of approximately six days. Keim and Madhavan's (1997) trading cost estimate was 0.61%; Nomura's was 0.28%. For the 500-stock and 100-stock reversal strategies, weekly turnovers were 326% and 337%, respectively. While gross returns were marginally lower than under the "standard" model, the "smart" model yielded higher net returns for all strategies using both cost models. All net returns proved to be highly significant statistically and economically.

Reversal profits in European markets were then evaluated. Quintile portfolios were then constructed for the 1000, 600 and 100 largest European stocks to calculate long-short reversal portfolio returns. Only the Nomura estimates were used; both the conventional and modified methods were applied. The European results displayed the same characteristics as the US results: the modified method yielded better results across all portfolios; the fewer the stocks in the portfolio, the better the strategy performed; the conventional method yielded net losses, but the modified method yielded net profits. Trading costs did, however, have a larger impact in Europe than in the US, because Europe's stock market was less liquid than the US's.

Follow-up analyses were then performed. At first, the conventional model was applied but with rebalancing every five days. Applied to the US stocks as mentioned above, weekly turnover decreased to 306%, 310% and 315% for the top 1500, 500 and 100 US stocks, respectively. The decrease in weekly turnover did decrease trading costs, but gross returns also declined. While the 500-stock and 100-stock reversal strategies yielded net returns, the 1500-stock strategy yielded a net loss due to a 0.205% decline in gross returns due to the change in rebalancing frequency. The order of magnitude of the net reversal profits did not change.

Two subperiod analyses were then performed. The first pertained to the period January 2000 to December 2009; the second to the period January 2002 to December 2007 (after the dotcom bubble burst and before the subprime bubble burst). The conjecture for the first analysis was that the decimalisation of the quotation system and the increase in stock trading volumes had affected reversal profits, and that – in keeping with Low's (2004) Adaptive Market Hypothesis that the public dissemination of an anomaly might affect its probability – increased investment activities by professional investors after publications about the reversal effect in the late 1990s had arbitraged away much of reversal strategies' anomalous profits.

For the first analysis, the "smart" strategy's net profitability was largely constant, with net returns ranging from -0.279% (1500 stocks) to 0.59% (100 stocks). For the second analysis, net profits ranged from -0.178% (1500 stocks) to 0.348% (100 stocks). There were concerns that the cost estimates underestimated in-crisis costs and overstated reversal profits. It was concluded that reversal profits were constant over time and rather profitable during non-crisis periods.

The findings were then tested for robustness to the choice of trade rule. They evaluated reversal profits for the 500 largest US stocks that sold stocks once their rank in past-week return exceeded the 30^{th}, 40^{th}, 60^{th}, 70^{th} and 80^{th} percentiles, with purchases taking place at the corresponding opposite percentiles. The best results were achieved under the 70/30 rule (0.353% weekly net returns.) Reversal profits were highly significant statistically and economically for all trade rules. It was concluded that their findings were robust with respect to trade rules.

Gross and net returns of the "smart" long-short reversal portfolios for the largest 1500, 500 and 100 US stocks were regressed on the Fama-French risk factors for market, size and value. In all cases, the Fama-French risk factors had very little explanatory power, with the highest adjusted-R^2 observed having been 5%. It was concluded that reversal profits were unrelated to common risk factor exposures.

It was argued that the findings had critical implications for explanations in the literature of reversal anomalies. Short-term reversals were generally held to be evidence of a shortage of sufficient market liquidity to offset price effects arising from unexpected purchase and sale pressures and that market makers set their prices partly to control their inventories. In following the liquidity explanation, reversals should have diminished over time as market liquidity increased. Also, reversal effects should have been stronger for small-cap stocks, which had higher turnovers, than for large-cap stocks, that had generally lower turnovers. However, their findings refuted the liquidity explanation. Lo and Mackinlay (1990) as well as Boudoukh, Richardson and Whitelaw (1994) noted that nonsynchronous trading contributed to contrarian profits. Their explanation assumed the gradual diffusion of information in financial markets and that large-cap stocks reacted faster to information than small-cap stocks because they had greater analyst coverage. The findings, however, refuted that explanation as well. Only the behavioural explanation suggested in the literature, that market prices tend to overreact to information in the short run, was not refuted by the findings.

It was ultimately concluded that the earlier finding that trading costs rendered reversal strategies unprofitable was largely due to excessive trading in small-cap stocks. A more sophisticated portfolio construction method and restriction of the stock universe to large-cap stocks would reduce trading costs significantly and generally result in statistically and economically significant net returns.

2.2.8: Booth, Fung and Leung (2016)

Booth, Fung and Leung (2016) investigated the nature of the momentum reversals exhibited by American stock returns from 1962 to 2013. It was first contended that momentum-reversal as a phenomenon could be explained using the traditional risk-return paradigm. It was argued that the earlier supposition was supported by the notion that large institutional traders preferred to take large positions in large-company stocks because small-company stocks often suffered from such things as short-selling restrictions, a lack of market depth and information asymmetries.

The data used were stock price, return, institutional trading and volume data from the AMEX, NASDAQ, NYSE and NYSE Arca from January 1962 to December 2013. The institutional trading data were obtained from Thomson Reuter, Institutional Trading (13F); the other data were obtained from the CRSP. The monthly return and the market capitalisation of each stock on the last day of each month in the data sample were retrieved. For each quarter after 1980, data concerning institutional investors' holdings, shares outstanding at the end of each quarter and institutional trading volumes. A double-sort procedure was implemented, sorting into quintiles first by returns, then by market capitalisation. The procedure was also conducted in reverse, to test for the impact of the sorting order on the results.

The quintile with the largest stocks became the "big" quintile and the one with the smallest became the "small" quintile. The stock with the highest returns in each quintile became the "winner"; the one with the lowest became the "loser". The authors created six long-short portfolios:

1. a long position in the losing big portfolio with a short position in the losing small portfolio;
2. a long position in the winning big portfolio with a short position in the winning small portfolio;
3. a long position in the winning small portfolio with a short position in the losing small portfolio;
4. a long position in the winning big portfolio with a short position in the losing small portfolio;
5. a long position in the winning small portfolio with a short position in the losing big portfolio;
6. and a long position in the winning big portfolio with a short position in the losing big portfolio.

The continuously compounded cumulative mean returns of the loser/big-loser/small strategy were all negative and statistically significant for all the holding periods following portfolio formation, suggesting that shorting the smallest firms would incur short- and long-term losses. The market capitalisations of the long portfolios economically and statistically exceeded those of the short portfolios, which implied that there was a small-firm effect that dominated the momentum effect. Institutional investors were found to largely invest in large firms and not necessarily trade in accordance with recent momentum. The performance results of the winner/big-winner/small portfolio demonstrated that there was a small-firm effect at work and the short portfolio's returns dominated those of the long portfolio. But over various holding periods, the winner/big-winner/small strategy yielded statistically significant negative cumulative returns.

The winner/small-loser/small strategy also exhibited evidence of the small-firm effect dominating the momentum effect (the long portfolio's market capitalisation exceeded the short portfolio's), implying there were significant positive returns to be yielded by the reverse strategy.

The winner/big-loser/small strategy yielded significant negative returns for all periods. The results were consistent and significant in the short- and long-term, implying there were significant positive returns to be yielded by the reverse strategy.

The winner/small-loser/big portfolio had a significantly larger short portfolio than long portfolio. All cumulative returns were positive and significant, due to the combined positive effects of momentum and size benefiting performance. Institutional investors appeared to invest significantly more in the long position than in the short position.

The winner/big-loser/big strategy was free of any small-firm effects. Returns within one year were positive and significant. The positive initial price momentum effect explained reasonably well the return behaviours exhibited because of the absence of small-firm effects. Once again, institutional investors preferred to invest in large firms.

It was concluded that size effects appeared to dominate price momentum effects in strategy performance. If the short portfolio had the smaller stocks, then the cumulative returns of the portfolio would be consistently negative and significant. When the long portfolio has the smallest firms, overall returns were positive with no price reversals. In a strategic portfolio built using long positions in large stocks that previously outperformed and short positions in small stocks that previously underperformed, significant short- and long-term price reversals presented themselves and the long portfolio underperformed the short portfolio. Small-capitalisation stocks outperformed large-capitalisation stocks. Furthermore, institutional investors preferred to invest in large firms regardless of various winner-loser strategic combinations – the result differed with previous findings that institutional investors preferred trading with momentum. The "momentum-price reversal anomaly" arose from the small-firm effect dominating the price reversal effect.

2.2.9: Andrei and Cujean (2017)

Andrei and Cujean (2017) proposed a joint theory to explain momentum and reversals. The theory was based on a rational-expectations framework, with several conditions set in place to better define their work and a specific concentration upon word-of-mouth communication, with the necessary condition that the marketplace contained both momentum and contrarian traders. The necessary conditions for momentum and reversal to occur were then laid out, specifically the role of word-of-mouth communication in propagating rumours that would cause a disjuncture between a security's price and its underlying fundamentals, that would later be corrected by agents in the economy through either investing in or disinvesting out of the security as required by the correction of their expectations to match reality. It was also proved that, even though the model's initial setup was static, it also extended to a dynamic setup. Furthermore, it was proved that it was impossible to eliminate momentum or reversals even for a hypothetical large, unconstrained risk-neutral arbitrageur for the simple reason that said person would still have to consider his or her unfavourable impact upon the security being traded. (Many sales would lower the security's price; many purchases would raise it.)

2.2.10: Rinne and Suominen (2017)

Rinne and Suominen (2017) studied a pair trading strategy that used short-term market return reversals. The criteria applied were that the stocks were listed on the New York Stock Exchange, were priced at or above \$5 at the end of the year in which the portfolio was formed, that the market capitalisation of the stocks exceeded the 10th percentile of NYSE stocks at the end of that year and that the stocks had a complete return history for that year. The top 20 stocks (or 100, in some cases) that had the highest weekly return correlation with each other were selected; pairs representing different share classes of the same company were excluded. Robustness was also tested for – the procedure was repeated using only stocks whose market capitalisations exceeded the 70th percentile of NYSE stocks.

Expected five-day excess returns were obtained via regression on the previous 20 days of daily excess returns to obtain estimates of the stocks' return reversal patterns; estimates of the pairs' return reversal patterns were obtained via regressing the pairs' expected five-day daily returns on the previous five days of daily returns. An assumption was added to the analysis: the investor would only implement such a strategy if the pairs' expected returns exceeded some minimum required return ("trigger limit"), which would suffice to cover professional traders' expected transaction costs for short-term long-short positions.

Two strategies were considered – one wherein the positions were closed after five days and one where the positions were closed during a seven-day window beginning three days after implementation, on the first day in which the expected five-day return became negative. Details were not given regarding the first strategy. The second strategy yielded average returns per trade between 1% and 1.8%, depending on the sample size and trigger limit. Concentration on fewer pairs yielded higher returns. Usage of more pairs yielded reduced volatility. The strategy proved to be robust when only large-cap stocks were used. It was argued that the results proved that the type of pair trading under consideration was profitable during the sample period (January 1987 to December 2011), because the return estimates used exceeded the reasonable estimates of transaction costs faced by professional traders in such positions. The last test was for robust performance given standard risk factors. The pair trading returns of the top 100 pairs with a bi-directional trigger limit of 0.5% were considered. The average daily return was 0.1%; the Carhart (1997) four-factor alpha was 0.09%, which turned out to be highly statistically significant. The results proved that standard risk factors did not drive the performance of the pair trading strategy.

The authors also used Finnish data in their analysis. They analysed all the trades on the Helsinki Stock Exchange for UPM Kymmene and Stora Enso between 1987 and 2003, as well as their official opening prices, closing prices and equity book values. Two regressions were conducted on the pair, one using returns derived from closing prices and the other from returns up to three hours before close of business. Results indicated that reversals were greatest on Mondays, Tuesdays and Fridays. The authors argued the Friday reversals were to be expected because the market makers had to bear more risk on any positions they held over the weekend due to the release of information over the weekend. Results indicated that there were significant return reversals in both regressions, affording traders the possibility to execute profitable pair trades on the days with the highest expected pair trading returns.

Two strategies were considered, with the details having been as was stated two paragraphs above. Returns ranged between 1.46% for a 0.5% bi-directional trigger limit and 2.37% for a 1% bi-directional trigger limit. (A 0.5% bi-directional trigger limit, for example, implied the following: the share in question was sold if its expected return exceeded 0.5% and it was bought if its expected return was less than -0.5%). Brokerage firms incurred transaction costs lower than 0.4% in the trade. Transaction costs did increase with the size of the transaction, but the authors found that 1% remained reasonable. Increasing the threshold increased the returns per trade, although total returns decreased due to the reduction of viable trades. The above return estimates per transaction corresponded to annualised return estimates ranging between 113% and 238%.

From the Finnish data, the conclusion was drawn that some financial institutions systematically exploited pair trading opportunities, earning substantial profits as compensation for providing liquidity to the market. Days with the highest expected trading returns had abnormally high trading volumes. The Finnish return data also indicated that return volatility could be as low as 4.2% with trading returns being as high as 2.4%. It must be noted that the results decayed towards the end of the sample period, which corresponded with the introduction of statistical arbitraging and other quantitative techniques.

2.2.11: Zhang, Wang, Wang, Xing and Lei (2018)

Zhang, Wang, Wang, Xing and Lei (2018) examined the impact of historical performance on present stock returns and constructed a modified Carhart (1997) model to capture said impact.

[In the journal article *On Persistence in Mutual Fund Performance*, Carhart (1997) constructed models of performance measurement based on the Capital Asset Pricing Model, Fama and French's (1993) three-factor model and a model he had produced in an earlier paper (Carhart, 1995). The CAPM-based model had the following equation: $r_{i,t} = \alpha_{i,T} + \beta_{i,T} VWRF_t + e_{i,t}$. The three-factor model had the following equation: $r_{i,t} = \alpha_{i,T} + b_{i,T} RMRF_t + s_{i,T} SMB_t + h_{i,T} HML_t + e_{i,t}$. The four-factor model had the following equation: $r_{i,t} = \alpha_{i,T} + b_{i,T} RMRF_t + s_{i,T} SMB_t + h_{i,T} HML_t + p_{i,T} PR1YR_t + e_{i,t}$. For the equations, the variables were defined thusly. The return on an portfolio in excess of the one-month T-bill return was denoted using $r_{i,t}$. VWRF was the excess return on the CRSP value-weighted portfolio of all NYSE, AMEX and NASDAQ stocks. RMRF was the excess return on a value-weighted aggregate market proxy. SMB, HML and PR1YR were returns on value-weighted, zero-investment and factor-mimicking portfolios for size, book-to-market equity and one-year momentum in stock returns. The unexplained out- or underperformance of the portfolio was denoted using $\alpha_{i,T}$. The error term of the model was $e_{i,t}$.]

The sample consisted of A-shares (shares available for domestic investors) listed on the Shanghai and Shenzhen Stock Exchanges from January 1992 to December 2015. (The sample period for the regression only begins in January 2007, however.) Weekly stock returns of SHSE and SZSE A-shares in the SinoFin economic and financial database were included. The first six months of returns for each stock were excluded, to exclude initial price anomalies caused by an IPO (initial public offering). Stocks with negative net asset values per share were excluded. Weekly stock returns, adjusted for dividends, were selected on Wednesdays.

Portfolios were formed by sorting the sample firms on prior J days' returns, with return breakpoints being the 30th and 70th of the prior J days' performance. Formation periods (the observation periods –

the firms' performances over the observation periods directly influence the compositions of the portfolios) and holding periods were 1, 2, 3, 4, 6, 9 and 12 days, including 49 J-K strategies (the strategies are based on J-day returns and held for K days). Daily, weekly and monthly returns were winsorised each day, week and month at the 0.5% and 99.5% levels. Momentum factors were constructed with a 1-week holding period and a formation period ranging from 1 to 250 weeks. The high trading frequency and low bid-ask spreads led the authors to not include lags between holding and formation weeks. Returns of individual stocks over the past J days were calculated in each week of sample intervals – the winners and losers were defined as the top and bottom 30% of performance in a formation period, respectively.

In the sample of winner-minus-loser strategies with no lags, stock returns did reverse. The effect was especially significant in the short- and long-term. A portfolio with a 1-week formation period yielded an average return of -0.52. Market risk dominated in China, so homogeneous movements followed, and it was therefore uncommon for individual stocks to perform markedly differently from the market. Stocks also exhibited some degree of mean reversion following a large positive or negative event.

The return to the momentum strategy for the preceding 2-week formation period was positive, which probably reflected "short term overreaction by overreaction" rather than investor under-reaction. It was claimed that no middle-term momentum effect existed and that the middle-term reversal effect was insignificant.

Average returns to winner-minus-loser strategies over the 60-week formation period were significantly negative, suggesting a significantly long-term reversal effect. A long-term reversal phenomenon was more pronounced around the three-year formation period. Returns to winner-minus-loser strategies with formation periods longer than three years were less pronounced, yet still significantly negative.

Volatilities of loser-minus-winner strategies with no lags from past 1-week to 250-week formation periods from 1997 to 2015, were stationary at around 0.02. Portfolio Sharpe ratios were higher in the short term than in other periods. It was argued that it was thus more valuable in China to invest based on short- and long-term past performance.

Between 1997 and 2005, 30- to 60-week formation periods yielded few instances of the momentum effect in the middle term. From 2006 to 2015, winner-minus-loser portfolios yielded significantly negative returns; the momentum effect did not present. The returns to the portfolios without lags illustrated that the average weekly returns of 250 strategies changed between 1997 and 2005, from -0.31% to 0.14%. The average returns between 2006 and 2015 were generally lower than those of the preceding period. If lags were included between 1997 and 2005, a momentum effect was observed in a few weeks, while portfolio returns experienced reversals during the 2006-2015 period (the 2-1 strategy excepted.) A possible explanation given was that people's incomes increased between 2006 and 2015 and the Internet expanded, while investors remained irrational and sensitive to market movements and increasingly speculative trading increased the reversal effect.

Considering the lag-less momentum strategies, winner-minus-loser portfolios all yielded negative returns in bull markets, with a stronger reversal effect in bull markets than in bear markets. There were a few occasions of the momentum effect in the bear market period. In bull markets, investors were more willing to trade stocks – the resultant fast-in-fast-out trading amplified reversal effects.

Fama-Macbeth two-step regressions were conducted to test short- and long-term reversal effects, with independent variables being winsorised weekly at the top and bottom 0.5%. Regressions of individual stock returns on past 1-week returns, with controls for size, book-to-market ratios, price-to-earnings ratios, turnover and beta included. Each year was divided into two six-month periods – market capitalisations, book values and price-earnings ratios were uploaded periodically. Market capitalisations and book-to-market ratios were updated annually in May because Chinese company results were released annually on 30 April. To eliminate positive skewness, authors used the natural logarithms of market capitalisation, book-to-market ratios, price-to-earnings ratios and turnover were used in the regressions. Individual stock betas were estimated using previous 2-year weekly returns in each period – if fewer than 50 weeks of data were available, they were recorded as missing.

Individual stock returns in one week had very significant negative correlations with individual stock returns in the following week, especially when the regression was controlled for other factors (*t=-7.35* vs *t=-9.96*). the coefficient for 1997-2005 was smaller than that for 2006-2015, with the latter period having a stronger reversal effect. Returns were more significantly negatively autocorrelated in the bear market over a one-week period than in the bull market. When 52-week Fama-MacBeth regressions were constructed, it was found that the 52-week prior returns had weak predictive power and varied over the sample, thus leading to the conclusion that the classic momentum factor did not work well, and more bespoke modelling was required to better describe the Chinese stock market.

Time series regressions were then constructed using weekly return data from January 1997 to December 2015. The market portfolio yielded an average weekly excess return (equally-weighted A-share weekly returns above the risk-free interest rate) of 0.23%. The weekly average return to buying small-cap and selling large-cap stocks was 0.24%. HML yielded a statistically insignificant return of 0.01%. Selling a high price-to-earnings ratio portfolio and buying a low price-to-earnings ratio portfolio yielded 0.19% in weekly excess return. A super-short-term reversal effect was found – the 1-week winner-minus-loser portfolio yielded an average weekly return of -0.52%, which was highly significant.

Factor spanning tests were also conducted, regressing one factor on the other four in the time series regression. Mr (excess market portfolio return) and HML regressions yielded insignificant results. Market risk was found to play a key role in explaining the excess returns of Chinese stocks. RMRf accounted for more than 80% of the portfolio returns in the regression results. The HML factor appeared to be redundant for explaining stock returns, as implied by the insignificant results from its factor spanning test. The price-to-earnings ratio proved to be more appropriate for representing business growth than the book-to-market ratio in China. A pervasive reversal effect also led to the selection of the short-term reversal factor instead of the one-year momentum factor.

Weekly excess portfolio returns were sorted using past one-week performance. There appeared to be a negative relationship between past performance and current returns. Stocks in the lowest decile yielded average returns from 1-week formation portfolios of 0.4%; stocks in the highest decile, -0.25%. From 1997 to 2005, the inter-decile spread was 0.18%, which was statistically insignificant. From 2006 to 2015, the inter-decile spread was 1.12%, which was highly significant. The bull market yielded an inter-decile spread of 0.86%; the bear market, 0.83%. There existed a tail-rising phenomenon in Decile One for both the bull market and bear market portfolios, illustrating that investors seemingly preferred to follow whatever trend presented (i.e. in bull markets, investor behaviour at the tails implied an inclination to be bullish and in bear markets, investor behaviour at the tails implied an inclination to be bearish). The arrival of important information made some stocks likely to show significant short-term momentum effects.

Time-series regressions on the pricing factors were conducted. CAPM had an average explanatory power of 85.6%, indicating the dominance of market risk in the Chinese stock market. Alphas decreased monotonically throughout the sample, from 0.238 in the lowest decile to -0.382 in the highest. Portfolios with poorer past performance exhibited higher expected returns. The inter-decile spread had an alpha of 0.621, significantly positive. CAPM was unable to capture reversal effects. The inter-decile spread had a higher alpha to CAPM during the 2006-2015 period than during the 1997-2005 period; said alpha for the inter-decile spread was higher in the bull market than in the bear market. In the latter period, the reversal effect was more pronounced in the bull market after market risk adjustments.

The alpha for the inter-decile spread to CAPM+WML1 was -0.025, significantly smaller than that of CAPM. CAPM+WML1 had an average explanatory power of 88.6%, with WML1 contributing nearly 3%. Chinese stocks generally lack individuating characteristics due to the pronounced systemic risk present. Rather than basing investment decisions on company performance and characteristics, investors preferred to trade according to policy-orientation and market information. Positive or negative signals would cause short-term investor overreactions, followed by corrections once the true nature of underlying market movements was realised. Consequently, reversals would occur.

Modified Fama-French three-factor regressions were then conducted. 10 portfolios had an average explanatory power of 91.1%, 5.5% more than CAPM. The "interceptions" decreased monotonically, however, from 0.127 in the first decile to -0.428 in the last. The short-term reversal effect could not be captured by fundamental information, as the significant positivity of the gaps demonstrated. When a one-week momentum factor was incorporated, the average R^2 for the ten portfolios was 93.6% and the alpha for the inter-decile spread was a statistically insignificant -0.018. The marginal contribution WML1 made to the three-factor model was found to be significant and assistive in explaining portfolio returns.

It was then questioned whether the proposed modified Carhart (1997) model explained the impact of the long-term reversal effect, to which effect 10 portfolios sorted by their performance over the preceding 156 weeks were constructed, with Decile One denoting the portfolio with the poorest returns. The inter-decile spread to the CAPM had an alpha of 0.298, which was statistically significant. Consistent with other market risk-adjusted regressions for one-week portfolio returns, any existent reversal effects were stronger in the latter period and in the bull market.

Though WML1 contributed marginally to CAPM's explanatory power, it did capture the reversal effect. Inter-decile spreads to the three-factor model had an alpha of 0.117; the average explanatory power for the ten portfolios was 92.7%. A modified Fama-French three-factor model was able to partially capture the long-term reversal effect, which indicated that long-term performance might partially depend upon a firm's fundamental information.

Semi-partial correlation coefficient squares were also looked at for ten portfolios with a one-week formation period. (Semi-partial correlation coefficients measured the independent impact of explanatory variables after excluding collinearity in a linear regression; semi-partial correlation coefficient squares reflected the independent weight of the explanatory variables in explaining the dependent variable). The market risk factor had the highest explanatory power regarding portfolio returns; the book-to-market ratio had the lowest. WML1 had an average explanatory power of 2.71% and only marginally explained stock returns. Chinese stock investors seemed to prefer short-term speculation rather than long-term growth.

Portfolio returns were regressed on their proposed four-factor model, to test if it could effectively explain the anomalies. 10 portfolios were divided based on size, price-earnings ratios, book-to-market ratios and weekly turnover. Results from the F-tests performed indicated that size, price-earnings ratio and book-to-market effects could be well explained by the model, which could not explain trading volumes.

The model was also tested out-of-sample. 10 portfolios were formed from the stocks, based on the preceding week's returns, sizes, price-to-earnings ratios and returns on equity. A rolling 51-week time series regression slope was used – 50 weeks to calculate the coefficients; one week to forecast. Root mean square errors of the difference between real and predicted portfolio returns from 1998 to 2015 were reported. The proposed model yielded smaller root mean square errors than CAPM and the Fama-French three-factor model, suggesting that the proposed model had a better pricing fit. The proposed model worked better than the Fama-French and CAPM models for portfolios based on the preceding week's returns and price-earnings ratios. The Fama-French model worked better for portfolios based on size and returns on equity. The models' pricing and forecasting ability generally depended on the criterion used to arrange the stocks into portfolios. The short-term reversal effect for their proposed model was emphasised. The price-earnings ratio was used, rather than the book-to-market ratio. For the Fama-French model, the focus was on pricing factors concerning fundamental information. It was also noted that size and return on equity had a significantly positive correlation in China.

Time-series regressions for value-weighted portfolios with holding period returns were conducted. The reversal strategies with a one-week formation period could gain weekly average profits of 0.441%. Super-short-term and long-term reversal effects were still significant. The CAPM and Fama-French three-factor models were unable to explain the difference in average returns across stocks with different short-term past performances. WML1 was able to explain the short-term reversal effect – it contributed 3% to the explanatory power of CAPM and the modified three-factor Fama-French model. The modified FF+WML1, by contrast, was able to capture the super-short-term and long-term reversal effects. Reversal effects were less pronounced in value-weighted portfolios than in equally-weighted portfolios because large-cap stocks had heavier weights.

Chinese stocks exhibited a significant reversal effect, rather than the middle-term momentum effect observed in the American stock market. One-month reversal factors were therefore constructed instead of the Carhart (1997) one-year momentum factor. It was shown that the reversal effect was pronounced for monthly data and could not be captured by the CAPM and three-factor models.

Firm size was controlled for in an investigation of reversal strategy returns. Stocks were sorted according to their market capitalisation in the last period and divided into three groups based on size, namely the top and bottom 30%, and the middle 40%. Each subsample contained 10 portfolios sorted by past performance. Reversals in middle- and small-cap stocks were stronger than in large-cap stocks. Prices changed dramatically in China, especially for small firms. Small-cap stocks showed larger reversal effects because they were more vulnerable to large capital movements.

The stocks in the sample were divided into the top 30%, middle 40% and bottom 30% according to turnover, which were then used to measure trading volume. 10 portfolios were constructed in each group, sorted by past performance. In the portfolios with one-week formation periods, the inter-decile spread in the high trading volume group was 0.545, significantly higher than in the middle (0.395) and low trading volume groups (0.214). In high trading volume subsamples, WML1 contributed 2.3% to the explanatory power of the Fama-French three-factor model. Recent high trading volume made prices very volatile. Stock returns were highly and significantly correlated to historical returns – more aggressive trading activity intensified the link.

Prices were more likely to bias the market in the case of high-beta stocks, so the overreaction would cause a reversal. Given Chinese stocks' general lack of individuating characteristics, beta represented the investors' sensitivity to past information. It was theorised that an increase in beta would intensify the reversals. Stocks were sorted by their betas into three subsamples (top 30%, middle 40% and bottom 30%). In one-week formation portfolios, the inter-decile spread for the high-beta portfolios was 0.783, larger than in the middle-beta (0.693) and low-beta (0.440) groups. The more volatile the market was, the stronger the reversal effect observed.

It was concluded that selling outperforming stocks and buying underperforming ones could indeed generate "riskless" profits. A reversal strategy built using one-week formation portfolios yielded 0.52% in riskless profits, more than yielded by any other strategy. Heavy policy intervention and irrational investment made it difficult for high-quality stocks to distinguish themselves from the rest, so stock return movements were likely to be "choppy". Short-term reversals reflected investors' sensitivity to information and tendency to follow the trend; long-term reversals were due to mean reversion that took place once investors had accumulated enough information to see that they had initially overreacted. Most Chinese media coverage tended to recommend stocks with low price-to-earnings ratios and retail investors had little interest in business growth. They argued finally that, for Chinese stock markets to develop soundly, it was essential to strengthen the market function to encourage investment in high-quality stocks while improving information efficiency and individual investor education.

2.3: Literature Review (Arguments in Support of Further Research)

In *Portfolio Selection*, Harry Markowitz (1952) first introduced the ideas of the efficient frontier and the risk-return trade-off to the world of finance. He argued that each investor would assemble for him- or herself a portfolio that minimised the expected risk to which the capital would be exposed and maximised the expected return on that capital. He further argued that the optimal portfolio for such an investor would fall upon the efficient frontier and that each investor, being subject to the risk-return trade-off, would prefer a portfolio with a higher expected return and a lower expected risk, subject to the investor's investing specifications and constraints. The efficient frontier is the set of all possible long-only portfolios that maximise the expected return, for a given amount of risk taken on by the investor. The risk-return trade-off is the consequent idea that for one to assemble a portfolio with a high expected return, one must be willing to face high expected risk.

From Markowitz's work, and the work of later authors, came the idea in modern portfolio theory that an investor had to be involved in the market's activities to receive a return on the market's activities, i.e. one had to have a position in the market to derive any benefit from the market and in the absence of any such position, one could not derive any benefit from the market.

In *Efficient Capital Markets: A Review of Theory and Empirical Work*, Eugene Fama (1970) first outlined the three forms of what has come to be known as the Efficient Market Hypothesis. The weak form argued that all historical information regarding a security was included in its current price, implying that security prices followed random walks because it was impossible for anyone to earn abnormal profits from using past prices to predict future ones (i.e. through technical analysis). The semi-strong form argued that a security's price contained all available public information about that security and, furthermore, adjusted rapidly to any new information that arose, thus eliminating the possibility of using either fundamental or technical analysis to earn abnormal profits. The strong form argued, finally, that a security's price reflected all public and private information pertaining to that security, which implied that no investor could consistently outperform the market.

The semi-strong form of the Efficient Market Hypothesis argued against the existence of momentum and reversal events in security prices, as momentum implied a measure of predictive power in past prices and reversals implied that not all public information about a security was factored into its price. Momentum allowed the possibility of an investor examining past prices, assembling a portfolio of stocks and then disinvesting from that portfolio at a later stage, such that whatever underlying trend implied by the past prices would have been maximally utilised as a source of abnormal profits (subject to the usual bounds upon human knowledge such as non-omniscience and non-precognition, which would produce an imperfect result). Reversals allowed the possibility of an investor constructing a portfolio in such a way as to use currently available public information to take contrarian bets regarding the subsequent movements of various securities, then consistently profiting therefrom, thus outperforming the market.

The strong form of the Efficient Market Hypothesis entailed the arguments of the semi-strong form. It also implied the impossibility of generating a significant positive cash return from the market's activities by means of holding a synthetic zero position, because holding a synthetic zero position was logically equivalent to having no net position in the market at all and (in concurrence with Markowitz [1952]) if one was effectively taking on zero risk, then one should expect zero returns. To obtain a positive cash return from a synthetic zero position would be to effectively outperform the market for the simple reason that any return derived from the market would have had a certain level of risk that said investor would have had to take, but the holder of the synthetic zero position would have effectively taken on no risk at all.

The ideas contained in Fama (1970), while initially of theoretical interest to financial professionals as indicative of a reality contrary to what they sought to produce daily through active investing, only gained traction among members of the public in recent times. The Efficient Market Hypothesis gained popularity in recent years after the crash of the US markets on 29 September 2008, with proponents of the Efficient Markets Hypothesis originating index tracker funds to facilitate the practice of passive investing and notable figures such as Warren Buffett publicly advocating index funds as an investment vehicle.

(In 2007, Warren Buffett made a $1,000,000 bet with Protégé Partners that an index fund would outperform a collection of hedge funds over a ten-year period. He proceeded to win the bet on 29 December 2017 [Protégé Partner's basket of hedge funds yielded 2.2% on average per annum; the S&P 500 yielded 7.1% per annum] and donated his winnings to the Omaha, Nebraska-based affiliate of Girls Inc., a charity that provides after-school care and summer programmes for girls aged 5 to 18 [Price, 2017]. In an interview with CNBC's *On the Money*, Warren Buffett also said, "Consistently buy an S&P 500 low-cost index fund. I think it's the thing that makes the most sense practically all of the time" [Martin, 2018].)

Return reversals were best defined as reversals in the trend of the movements of the price of a tradeable asset. For example, suppose that a given tradeable asset had been falling in price over a given number of days. Suppose that said asset's price rose on a given day and continued to rise for a given number of days. The event of the trend in the returns to the holder changing direction from negative to positive, would be a return reversal.

Return reversals were not a new phenomenon in finance. One of the earliest observations of return reversals in markets was by Niederhoffer and Osborne (1966), who sought to discover laws of price fluctuations in the stock market through examination of the correspondence between ticker price movements and the predictions of the random walk hypothesis. They analysed the complete set of ticker prices for six of the first seven stocks in the Dow Jones Industrial Average for the trading days of October 1964. They concluded the following:

1. That there existed a general tendency for price reversals between trades;
2. That reversals were relatively more concentrated at integer prices (in US Dollars) where "stable slow-moving participants offer to buy and sell";
3. That there was a concentration of particular types of reversals just above and below integer prices;
4. That fast-moving competitors who were aware of the behaviours of the slower-moving market participants would be in a good position to enter positions at suitable non-integer prices so as to set themselves up to profit off the reversal trade that would follow;
5. And that after two or more price changes in the same direction, the probability of the price trend continuing in a given direction after those changes exceeded the probability of a price trend continuing in a given direction after two or more changes in opposite directions.

Authors who investigated the profitability of the return reversal strategy as implemented using costless portfolios generally agreed that successful implementation could indeed produce significant positive cash returns from what would essentially be a net zero position in the market.

Jegadeesh (1990) tested for significant serial correlation in stock returns using data from the Center for Research in Security Prices for the period 1929-1982. Following his finding said significant serial correlations, he used data from 1934 to 1987 to test for and identify highly significant abnormal returns, obtained from portfolios constructed in such a way as to presumably take advantage of the predicted returns of stocks.

Lehmann (1990) made a significant contribution to the study of reversals as a canonically "anomalous" financial phenomenon. Lehmann (1990) studied market efficiency by testing the profits of costless portfolios consisting of short positions in stocks that recently outperformed the market and long positions in stocks that recently underperformed the market, using daily return data from 1962 to 1990 for equity securities listed on the New York and American Stock Exchanges. He found that the costless portfolio yielded positive returns in approximately 90% of the weeks of the study and, if viewed in six-month periods, in each of the 49 periods covered by the data. He also found that the measured arbitrage profits thusly obtained persisted after corrections for mismeasurement of security returns as well as for the factoring in of plausible transaction costs. He noted that there was "little persistence" in return reversal effects, which he argued gave rise to two potential responses: that one could claim equity markets are on average efficient over longer periods, e.g. a month, or that the tests used had low power and that additional evidence of market inefficiency was required.

Subsequent to the work of Jegadeesh (1990) and Lehmann (1990), investigations by other authors, such as Jegadeesh and Titman (1993), Mei and Gao (1995), Booth, Fung and Leung (2016), Rinne and Suominen (2017) and Zhang *et al.* (2018), provided further evidence that the profitability of the return reversal strategy was not a glitch observed only by Jegadeesh (1990) and Lehmann (1990) but was indeed a consistent and long-lasting financial occurrence, not just in the American stock market but also in the stock markets of other countries, such as Finland (Rinne and Suominen, 2017), China (Zhang et al., 2018), Tunisia (Boussaidi, 2017), Turkey (Bildik and Gülay, 2007) and Japan (Gunaratne and Yonesawa, 1997). Evidence of reversals was also found in non-equity financial markets such as fixed income (Khang and King, 2004). The authors agreed with Jegadeesh (1990) and Lehmann's (1990) conclusions that there was sufficient evidence to reject the Efficient Market Hypothesis.

De Groot, Huij and Zhou (2012) looked into the seemingly high trading costs involved in the implementation of the costless return reversal strategy – they found that the high trading costs came about due to excessive trading in small-cap stocks and that restriction of one's universe to large-cap stocks would serve to reduce trading costs and increase trading profits even with an investor using the most elementary methodology available for the purpose. They also demonstrated that implementing a modified, smarter methodology maximised one's abnormal profits from the strategy's implementation.

Andrei and Cujean (2017) produced a mathematical model demonstrating the link between momentum and reversals and the necessary conditions for either phenomenon to arise; furthermore, they proved that all persons in the market would experience momentum and reversal effects in their portfolios, even hypothetical large, unconstrained risk-neutral arbitrageurs, for the simple reason that said persons would still have to consider his or her unfavourable impact upon the security being traded (an example of diminishing marginal utility in action, many sales would lower a security's price and many purchases would raise it for the simple reason that there would only be so many shares available for purchase or sale at a given price before one would have to trade at the next applicable price to satisfy one's orders).

In conclusion, what the literature has indicated is that, rather than being anomalies unexplainable by rational finance, momentum, reversals and their related strategies are well documented and well researched financial phenomena that an investor is likely still able to exploit today. There is concurrence among some authors that it is theoretically possible to construct a synthetic zero position in the market, which generates significant positive cash returns. However, many practitioners and scholars of modern finance continue to believe that the Efficient Market Hypothesis holds.

If it is conclusively proven that it is possible to generate significant positive cash returns from holding a net zero position in a given market, there are significant ramifications for financial theory and practice.

Markowitz (1952) argued that it should be impossible for an investor to construct a zero-investment portfolio that then proceeds to generate positive cash returns for that investor, because an investor must take on some form of actual risk to realise an actual return. If an investor succeeded in constructing a zero-cost portfolio that proceeded to generate significant positive cash returns, then said investor would have succeeded in deriving positive benefits from market activities despite effectively holding a net zero position in the market and thus being practically uninvolved in the market's activities. Proof of the possibility of generating a significant positive cash return from a net zero position will necessitate re-examination of the efficient frontier concept and, by extension, of modern portfolio theory as investors will now have the option of constructing portfolios with effectively zero cost and minimum risk, which will allow for more investment opportunities and will require the development of new supporting literature to guide investors, practitioners and academics alike.

Fama (1970) argued that it was impossible for any investor to construct a portfolio that outperformed the market over a given period, because share prices reflected all public and private information about those shares, thus implying the impossibility of extracting any trading advantage for oneself by any direct action that one could take with the information at one's disposal. By extension, for an investor's portfolio to outperform the market over a given period, said investor would have to essentially be lucky and it is only to said investor's luck that such success would be attributable. If an investor succeeded in using public information and insights drawn therefrom to construct a zero-cost portfolio that proceeded to outperform the market, then said investor would have succeeded in disproving the Efficient Markets Hypothesis because said investor would have taken active measures to apply public information to his or her trading and derived tangible benefits therefrom, thereby obtaining success that would only be *partially* attributable to luck, unlike in the case where the Efficient Markets Hypothesis is true and the investor's success is *solely* attributable to luck. While this would be unlikely to dissuade passive investors from continuing to invest passively, this would serve as solid evidence in favour of active investing, which has suffered a loss of esteem in the years following the onset of the Great Recession.

More evidence is needed of the pervasiveness of the momentum-reversal phenomenon. Most studies thereof predate the crash of 29 September 2008, so a study spanning that day is required to investigate if the profitability of the costless reversal strategy that was observed in US markets before the crash is also observable after the crash, in which period one would expect different investor behaviour because of the general increase in risk aversion that would have followed the major losses incurred by numerous investors in the global markets, especially the US stock market – the largest stock market on the planet, where the losses occurred first and were most psychologically scarring. Evidence of continued profitability will serve to provide conclusive proof that the observations of prior authors regarding the failure of the Efficient Market Hypothesis were not just a pre-crash phenomenon but represent a continuing trend to be taken note of and capitalised upon post-crash.

Once said evidence is obtained, there will then be room for practitioners to use the theoretical proof as a basis for a new form of investing, one which entails no risk and yet generates high rewards – portfolios, in other words, with infinite or almost infinite Sharpe (1966) ratios. Said portfolios will have their constraints, naturally – the costless portfolios imply the use of short sales, so margin requirements and borrowing costs will be imposed on the holders of the synthetic zero positions by the actual owners of the stocks that are being sold short; furthermore, different jurisdictions have different legal restrictions and requirements that apply to financial markets, specifically to short sales, with which all involved parties must comply. But the existence of the empirical possibility will avail opportunities for profit, which will be pursued by investors and practitioners, thus finally leading to the conclusive disproof of the Efficient Market Hypothesis.

Chapter 3: Hypotheses, Data and Methodology

3.1: Hypotheses

For each of the 1000 costless long-short portfolios that will be analysed as part of this investigation, the null and alternative hypotheses were the following.

1. The null hypothesis (H_0) was that the average cash return from the long-short portfolio, irrespective of formation and holding periods, was zero.

2. The alternative hypothesis (H_1) was that the average cash return from the long-short portfolio, irrespective of formation and holding periods, was larger or smaller than zero.

The reasons why the benchmark against which the average cash returns of the long-short portfolios were tested, was zero were the following.

The long-short portfolios that were tested were constructed in such a way as to be synthetic zero positions in the market. They had no net position in the market at all. Consequently, to test the performance of the synthetic zero positions for statistical significance, their performance had to be compared to that of an actual zero position. Testing the performance of the zero-cost long-short portfolios against a long position-only benchmark (such as the cash yield over a period of a market index) would have been inappropriate because such a comparison would have been of two different things and such an "apples and pears" scenario could not be expected to yield meaningful insights.

US inflation would likewise have been an inappropriate benchmark against which to test the performance of the zero-cost long-short portfolios. Inflation measures the rate at which one's money loses real purchasing power. It is consequently a benchmark suitable for a long-only portfolio because it measures the decline in real value of money that one holds. The long-short portfolios in this investigation were constructed and rebalanced in such a way as to have no net position in the market at all. Testing their performance against inflation would have been inappropriate because such a comparison would have compared "apples and pears" and such comparisons could not be expected to yield meaningful insights. Note that while the long-short portfolios in this investigation were constructed and rebalanced in such a way as to have no cash holding remaining after rebalancing, in reality a cash holding would arise after rebalancing. That cash holding would likely be held in a return-yielding vehicle for the duration of the holding period of the portfolio, after which it would grow or shrink in size depending upon the performance of the long-short portfolio over the preceding holding period. This cash holding, adjusting as it would over holding periods, would keep up with inflation and one would be able to use inflation as a benchmark against which to test its performance.

3.2: Data

The sample data were the daily returns for the shares of the 780 companies listed on the NASDAQ and the New York Stock Exchange ("NYSE"), which fell within the top 500 listed companies by market capitalisation between 1 January 2005 and 31 December 2017, as listed on the Standard and Poor's 500 Index ("the S & P 500"). The S & P 500 was rebalanced approximately every three months – if a company met the criteria for S & P 500 listing in any of the quarters within the sample period, then it was included in the investigation. The list of companies was compiled using Bloomberg. The data for said companies were obtained from the archives of the NASDAQ and the New York Stock Exchange using Eikon. The full list of companies included in the sample is given in Appendix 1.

The top 500 shares were chosen for their size and liquidity, in keeping with observations by De Groot, Huij and Zhou (2012) about the adverse effects upon reversal strategy profitability of excessive trading in small-cap stocks. The New York Stock Exchange and NASDAQ are the largest and second-largest markets in the world, by total capitalisation. Their collected top 500 stocks were therefore highly likely to be sufficiently liquid for inclusion in a reversal strategy, which should reduce trading costs. Said companies' stocks would also have been included in the Standard & Poor's 500 Index ("the S & P 500") in that period (the S & P 500 shares are the shares of the companies listed on either the NASDAQ or the NYSE, whose market capitalisations place them within the top 500 most valuable companies in the USA). Consequently, the investigation would also have yielded useful insight about whether an investor could have earned a significant positive cash return from investing using the S & P 500 stocks, which surpassed the return yielded by the S & P 500 and yet had less risk involved. Given the size of the US stock markets, numerous reversal events were also expected.

The sample period was from 1 January 2005 to 31 December 2017. This period allowed analysis of the reversal strategy's profitability before, during and after the bursting of the subprime mortgage bubble, which is marked by the decline of the Dow Jones Industrial Average by 777.68 points on 29 September 2008 (Twin, 2008). This period also allowed testing of the reversal strategy's long-term profitability, which will be of some interest to investors seeking a stable, consistent means whereby they can consistently outperform the market.

3.3: Methodology

The methodology applied was as follows.

The shares were ranked in descending order of performance per period. Sub-samples of 100 and 500 shares were selected. Once selected, the sub-samples of shares were divided into twentieths. Reversal portfolios were constructed therefrom through the combination of twentieths, using a method hereinafter referred to as the extreme quantiles method.

The extreme quantiles method took into consideration how far apart the twentieths were from each other. Each reversal portfolio consisted of equally weighted long positions in the shares of the k^{th}-worst-performing twentieth and equally weighted short positions in the shares of the k^{th}-best-performing twentieth, where the twentieths were chosen in such a way as to be equidistant from the median of the sub-sample and k was a whole number between one and ten. For example, reversal portfolio one consisted of equally weighted long positions in the worst-performing twentieth and equally weighted short positions in the best-performing twentieth; reversal portfolio two consisted of equally weighted long positions in the second-worst twentieth and equally weighted short positions in the second-best twentieth; reversal portfolio three consisted of equally weighted long positions in the third-worst twentieth and equally weighted short positions in the third-best twentieth, etc. The combination of a long position in a relatively underperforming twentieth and a short position in a relatively outperforming twentieth provided a zero-cost reversal portfolio.

The portfolios created using the above methods were run over three time periods: the period between 1 January 2005 and 26 September 2008 (the pre-crash period), the period from 29 September 2008 to 31 December 2017 (the post-crash period) and the period between 1 January 2005 and 31 December 2017 (the entire sample period). The reason for the splits was to assess the profitability of the short-term reversal strategy if consistently applied before 29 September 2008, after 29 September 2008 and over the entire sample period. (On 29 September 2008, the Dow Jones Industrial Average lost 777.68 points, the largest one-day point drop in its history. The Standard and Poor's 500 Index lost 8.8% of its value that day and the NASDAQ Composite Index's value fell by 9.1%. Said declines generally served as confirmation of the bursting of the subprime mortgage bubble that had previously dominated American and global markets. One would expect investor behaviour before and after the crash to differ significantly [Twin, 2008].)

The long-short positions to be constructed were costless (i.e. the long positions were financed entirely by the short positions). The zero net position thus ensured the creation of the synthetic zero positions in the market that were used to test the null hypothesis for each portfolio.

The formation period was the period over which the shares' returns were calculated. The shares were ranked based upon those returns and the portfolios were constructed accordingly thereafter, using the methods detailed above. The holding period was the period over which the portfolio was held before the investor rebalanced it and drew his or her cash return. The possible formation and holding periods were one calendar day, seven calendar days, fourteen calendar days, twenty-one calendar days and twenty-eight calendar days. There were therefore twenty-five cases to be considered in this investigation.

Two analyses were conducted. The first was conducted on the basis that the investor observed the desired data at the end of the formation period and implemented the reversal strategy immediately thereafter. The second analysis was run on the basis that the investor skipped a day before implementing the reversal strategy. The two analyses' results would provide information regarding if the profitability of the reversal strategy was influenced in any way by the investor's speed of implementation.

There were therefore 1000 costless long-short portfolios and 3000 t-statistics that were analysed in this investigation.

The underpinning assumptions of this investigation were that the investor was able to purchase and sell as many shares as were necessary at exactly the closing price for the day of trade, that the weightings of the shares in the reversal portfolios and their constituent twentieths were always equal and that the investor was always able to balance the net position of the portfolio prior to implementation.

The two-sample t-test for samples of unequal size with unequal variances (Welch, 1947) was used to test the null hypothesis. The formula for the t-statistic was given by the following equation (Equation 1):

$$t = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{\frac{{s_1}^2}{N_1} + \frac{{s_2}^2}{N_2}}} \tag{1}$$

$\overline{X_1}$ and $\overline{X_2}$ were the first and second sample means.
${s_1}^2$ and ${s_2}^2$ were the first and second sample variances.
N_1 and N_2 were the first and second sample sizes.

The hypotheses for the t-tests were as follows.

1. The null hypothesis (H_0) was that the first and second sample means were equal in size.

2. The alternative hypothesis (H_1) was that the first and second sample means differed in size.

Two-sample t-tests for samples of unequal size with unequal variances were used to test the null hypothesis, because the true average cash returns of the reversal portfolios, which were to be estimated in this investigation, were assumed to be normally distributed. Statistical theory dictated that, where a sample with a given number of observations was drawn from a normal distribution, the sample mean would follow a t-distribution with degrees of freedom equal to the sample size less 1. The zero position in the market had no shares at all and therefore had no variance.

Chapter 4: Results

1000 costless portfolios were constructed for 25 different formation and holding period combinations. Two-sided T-tests were conducted on the portfolios to test the significance of their performances over three time periods: the period before 29 September 2008, the period from 29 September 2008 onwards and the entire sample period. The chosen one-sided level of significance for the T-tests was 5% (0.05) - a test result was only deemed statistically significant if its p-value was less than 5%. The contents of this chapter serve to illustrate the key findings from the investigation.

The key for the tables below is as follows (Appendix 2).

"Extreme" indicates that the portfolio in question was constructed using the extreme quantiles method.

"100" or "500" indicates that the portfolio was constructed as a quantile of 100 or 500 shares, respectively.

"Run Immediately" or "Run" indicates that the investor implemented the reversal strategy immediately after the designated formation period closed.

"Skip a Day" or "Run Skip" indicates that the investor waited a day after the designated formation period closed before implementing the reversal strategy.

"Portfolio *k*" indicates that the portfolio was constructed using Quantile *k*, which consisted of equally weighted long positions in the twentieth of the shares in the sub-sample at position 21-*k* and equally weighted short positions in the twentieth of the shares at position *k*.

The shorthand notation for naming the 25 cases analysed gives the formation period first, followed by the holding period, joined by a hyphen.

"D" indicates a period of one calendar day.

"D7" indicates a period of seven calendar days.

"D14" indicates a period of fourteen calendar days.

"D21" indicates a period of twenty-one calendar days.

"D28" indicates a period of twenty-eight calendar days.

For example, "D14-D21" indicates that the formation period for the portfolio was fourteen calendar days and that the holding period was twenty-one days.

Table 2 details the worst-performing portfolios for each of the four types of reversal portfolio, before the crash on 29 September 2008.

The Worst-Performing Portfolios for Each of the Four Types of Reversal Portfolio, Before the Crash				
	Extreme 100		Extreme 500	
Run Immediately	Case	D-D7	Case	D-D7
	Portfolio	1	Portfolio	1
	Days	246.00	Days	246.00
	Total	-11775.9037%	Total	-44453.4144%
	Mean	-47.8695%	Mean	-180.7049%
	Std. Error	65.6837%	Std. Error	154.0127%
	t-statistic	-11.43060707	t-statistic	-18.40268329
	p-value	7.80927E-25	p-value	2.19375E-48
Skip a Day	Case	D14-D21	Case	D14-D7
	Portfolio	1	Portfolio	1
	Days	81.00	Days	244.00
	Total	-1111.2783%	Total	-13745.7875%
	Mean	-13.7195%	Mean	-56.3352%
	Std. Error	42.2388%	Std. Error	99.2545%
	t-statistic	-2.923270078	t-statistic	-8.865934034
	p-value	0.002251394	p-value	8.31298E-17

Table 2: the worst-performing portfolios for each of the four types of reversal portfolio, before the crash on 29 September 2008.

If the investor implemented the reversal strategy immediately, the D-D7 combination generally exhibited the worst performance for quantiles of both 100 and 500 shares. If the investor skipped a day before implementation, the worst performance was exhibited by portfolios with 14 calendar day formation periods, though the holding periods differed (21 calendar days, for 100 stocks and 7 calendar days for 500 stocks). The worst-performing pre-crash portfolio was Extreme 500 D-D7 Run (Portfolio 1) – the investor would have lost on average approximately 1.81 US cents a day or $444.53 over the 246 weeks of implementation.

Table 3 details the worst-performing portfolios, that had the most statistically significant results, before the crash on 29 September 2008.

The Worst-Performing Portfolios, With the Most Significant Results, Before the Crash					
	Extreme 100			Extreme 500	
Run Immediately	Case	D-D7		Case	D-D7
	Portfolio	1		Portfolio	1
	Days	246.00		Days	246.00
	Total	-14928.1689%		Total	-44453.4144%
	Mean	-60.6836%		Mean	-180.7049%
	Std. Error	66.5347%		Std. Error	154.0127%
	t-statistic	-14.305097		t-statistic	-18.40268329
	p-value	1.87124E-34		p-value	2.19375E-48
Skip a Day	Case	D21-D21		Case	D14-D7
	Portfolio	3		Portfolio	1
	Days	81.00		Days	244.00
	Total	-925.0378%		Total	-13745.7875%
	Mean	-11.4202%		Mean	-56.3352%
	Std. Error	37.8846%		Std. Error	99.2545%
	t-statistic	-2.713030622		t-statistic	-8.865934034
	p-value	0.004080468		p-value	8.31298E-17

Table 3: the worst-performing portfolios, that had the most statistically significant results, before the crash on 29 September 2008.

If the investor implemented the reversal strategy immediately, the D-D7 combination generally yielded the most significant results for quantiles of both 100 and 500 shares. If the investor skipped a day before implementation, the most significant results were yielded by two portfolios, one with a 21 calendar day formation period and the other with a 14 calendar day formation period. The worst-performing pre-crash portfolio with the most significant results was Extreme 500 D-D7 Run (Portfolio 1) – the p-value of that portfolio was insignificantly different from zero to 47 decimal places.

Table 4 details the worst-performing portfolios for each of the four types of reversal portfolio, after the crash on 29 September 2008.

The Worst-Performing Portfolios for Each of the Four Types of Reversal Portfolio, After the Crash					
	Extreme 100			Extreme 500	
Run Immediately	Case	D-D7		Case	D-D7
	Portfolio	1		Portfolio	1
	Days	431.00		Days	431.00
	Total	-15333.7487%		Total	-54018.6032%
	Mean	-35.5771%		Mean	-125.3332%
	Std. Error	33.7992%		Std. Error	69.7328%
	t-statistic	-21.85259461		t-statistic	-37.31366049
	p-value	4.75829E-72		p-value	3.1917E-137
Skip a Day	Case	D28-D28		Case	D14-D7
	Portfolio	2		Portfolio	1
	Days	121.00		Days	430.00
	Total	-1224.4862%		Total	-18450.8607%
	Mean	-10.1197%		Mean	-42.9090%
	Std. Error	41.9465%		Std. Error	59.6356%
	t-statistic	-2.653785615		t-statistic	-14.92026887
	p-value	0.00451889		p-value	3.77409E-41

Table 4: the worst-performing portfolios for each of the four types of reversal portfolio, after the crash.

If the investor implemented the reversal strategy immediately, the D-D7 combination generally exhibited the worst performance for quantiles of both 100 and 500 shares. If the investor skipped a day before implementation, the worst performance was exhibited by portfolios with 28 calendar day formation and holding periods (for 100 stocks) as well as 14 calendar day formation periods and 7 calendar day holding periods (for 500 stocks). The worst-performing post-crash portfolio was Extreme 500 D-D7 Run (Portfolio 1) – the investor would have lost on average approximately 1.25 US cents a day or $540.19 over the 431 weeks of implementation.

Table 5 details the worst-performing portfolios, that had the most statistically significant results, after the crash on 29 September 2008.

The Most Underperforming Portfolios, With the Most Significant Results, After the Crash					
	Extreme 100			Extreme 500	
Run Immediately	Case	D-D7		Case	D-D7
	Portfolio	1		Portfolio	1
	Days	431.00		Days	431.00
	Total	-19344.0546%		Total	-54018.6032%
	Mean	-44.8818%		Mean	-125.3332%
	Std. Error	34.6854%		Std. Error	69.7328%
	t-statistic	-26.86347693		t-statistic	-37.31366049
	p-value	2.49416E-94		p-value	3.1917E-137
Skip a Day	Case	D14-D7		Case	D14-D7
	Portfolio	1		Portfolio	1
	Days	430.00		Days	430.00
	Total	-1219.2740%		Total	-18450.8607%
	Mean	-2.8355%		Mean	-42.9090%
	Std. Error	13.9088%		Std. Error	59.6356%
	t-statistic	-4.227441845		t-statistic	-14.92026887
	p-value	1.44508E-05		p-value	3.77409E-41

Table 5: the worst-performing portfolios, that had the most statistically significant results, after the crash on 29 September 2008.

If the investor implemented the reversal strategy immediately, the D-D7 combination generally yielded the most significant results for quantiles of both 100 and 500 shares. If the investor skipped a day before implementation, the D14-D7 combination generally yielded the most significant results for quantiles of both 100 and 500 shares. The worst-performing post-crash portfolio with the most significant results was Extreme 500 D-D7 Run (Portfolio 1) – the p-value of that portfolio was insignificantly different from zero to 136 decimal places.

Table 6 details the worst-performing portfolios for each of the four types of reversal portfolio, for the entire sample period.

The Worst-Performing Portfolios for Each of the Four Types of Reversal Portfolio, for the Entire Sample Period					
	Extreme 100			Extreme 500	
Run Immediately	Case	D-D7		Case	D-D7
	Portfolio	1		Portfolio	1
	Days	677.00		Days	677.00
	Total	-27109.6524%		Total	-98472.0176%
	Mean	-40.0438%		Mean	-145.4535%
	Std. Error	48.2214%		Std. Error	111.3559%
	t-statistic	-21.60676609		t-statistic	-33.98640485
	p-value	1.99793E-79		p-value	1.0297E-148
Skip a Day	Case	D-D14		Case	D14-D7
	Portfolio	1		Portfolio	1
	Days	338.00		Days	674.00
	Total	-1696.6025%		Total	-32196.6481%
	Mean	-5.0195%		Mean	-47.7695%
	Std. Error	48.2878%		Std. Error	76.5883%
	t-statistic	-1.911103014		t-statistic	-16.19265884
	p-value	0.028419746		p-value	2.39112E-50

Table 6: the worst-performing portfolios for each of the four types of reversal portfolio, for the entire sample period.

If the investor implemented the reversal strategy immediately, the D-D7 combination generally exhibited the worst performance for quantiles of both 100 and 500 shares. If the investor skipped a day before implementation, the worst performance was exhibited by portfolios with one calendar day formation periods and 14 calendar day holding periods (for 100 stocks) as well as 14 calendar day formation periods and 7 calendar day holding periods (for 500 stocks). The worst-performing portfolio for the entire sample period was Extreme 500 D-D7 Run (Portfolio 1) – the investor would have lost on average approximately 1.45 US cents a day or $984.72 over the 677 weeks of implementation.

Table 7 details the worst-performing portfolios, that had the most statistically significant results, for the entire sample period.

The Most Underperforming Portfolios, With the Most Significant Results, For the Entire Sample Period					
	Extreme 100			Extreme 500	
Run Immediately	Case	D-D7		Case	D-D7
	Portfolio	1		Portfolio	1
	Days	677.00		Days	677.00
	Total	-34272.2235%		Total	-98472.0176%
	Mean	-50.6237%		Mean	-145.4535%
	Std. Error	49.2700%		Std. Error	111.3559%
	t-statistic	-26.73410224		t-statistic	-33.98640485
	p-value	2.7385E-108		p-value	1.0297E-148
Skip a Day	Case	D14-D7		Case	D14-D7
	Portfolio	1		Portfolio	1
	Days	674.00		Days	674.00
	Total	-1766.5130%		Total	-32196.6481%
	Mean	-2.6209%		Mean	-47.7695%
	Std. Error	16.0687%		Std. Error	76.5883%
	t-statistic	-4.234549704		t-statistic	-16.19265884
	p-value	1.30435E-05		p-value	2.39112E-50

Table 7: the worst-performing portfolios, that had the most statistically significant results, for the entire sample period.

If the investor implemented the reversal strategy immediately, the D-D7 combination generally yielded the most significant results for quantiles of both 100 and 500 shares. If the investor skipped a day before implementation, the D14-D7 combination generally yielded the most significant results for quantiles of both 100 and 500 shares. The worst-performing portfolio for the entire sample period with the most significant results was Extreme 500 D-D7 Run (Portfolio 1) – the p-value of that portfolio was insignificantly different from zero to 147 decimal places.

Table 8 details the best-performing portfolios for each of the four types of reversal portfolio, before the crash on 29 September 2008.

The Best-Performing Portfolios for Each of the Four Types of Reversal Portfolio, Before the Crash					
	Extreme 100			Extreme 500	
Run Immediately	Case	D7-D7		Case	D7-D21
	Portfolio	6		Portfolio	4
	Days	245.00		Days	81.00
	Total	634.9888%		Total	1343.0825%
	Mean	2.5918%		Mean	16.5813%
	Std. Error	23.9988%		Std. Error	87.0541%
	t-statistic	1.690414826		t-statistic	1.714237134
	p-value	0.046112826		p-value	0.045178609
Skip a Day	Case	D28-D		Case	D-D
	Portfolio	4		Portfolio	3
	Days	920.00		Days	938.00
	Total	578.5636%		Total	2646.8811%
	Mean	0.6289%		Mean	2.8218%
	Std. Error	6.6928%		Std. Error	21.0632%
	t-statistic	2.850030103		t-statistic	4.103066689
	p-value	0.002234627		p-value	2.21597E-05

Table 8: the best-performing portfolios for each of the four types of reversal portfolio, before the crash.

If the investor implemented the reversal strategy immediately, the D7-D7 combination exhibited the best performance for quantiles of 100 shares and the D7-D21 combination exhibited the best performance for 500 shares. If the investor skipped a day before implementation, the best performance was exhibited by portfolios with 28 calendar day formation periods and one calendar day holding periods (for 100 stocks) as well as one calendar day formation and holding periods (for 500 stocks). The best-performing portfolio for the entire sample period was Extreme 500 D-D Run Skip (Portfolio 3) – the investor would have gained on average approximately 2.82 US cents a day or $26.47 over the 938 trading days of implementation.

Table 9 details the best-performing portfolios, that had the most statistically significant results, before the crash on 29 September 2008.

The Best-Performing Portfolios, With the Most Significant Results, Before the Crash					
	Extreme 100			Extreme 500	
Run Immediately	Case	D28-D		Case	D28-D14
	Portfolio	4		Portfolio	6
	Days	921.00		Days	95.00
	Total	628.0247%		Total	1085.0373%
	Mean	0.6819%		Mean	11.4214%
	Std. Error	7.3748%		Std. Error	53.6351%
	t-statistic	2.806041813		t-statistic	2.075554198
	p-value	0.002560634		p-value	0.020333157
Skip a Day	Case	D-D		Case	D-D
	Portfolio	6		Portfolio	3
	Days	938.00		Days	938.00
	Total	627.8192%		Total	2646.8811%
	Mean	0.6693%		Mean	2.8218%
	Std. Error	6.9863%		Std. Error	21.0632%
	t-statistic	2.934185073		t-statistic	4.103066689
	p-value	0.001712907		p-value	2.21597E-05

Table 9: the best-performing portfolios, that had the most statistically significant results, before the crash.

If the investor implemented the reversal strategy immediately, the D28-D combination generally yielded the most significant results for quantiles of 100 shares and the D28-D14 combination generally yielded the most significant results for quantiles of 500 shares. If the investor skipped a day before implementation, the D-D combination generally yielded the most significant results for quantiles of both 100 and 500 shares. The best-performing pre-crash portfolio with the most significant results was Extreme 500 D-D Run Skip (Portfolio 3) – the p-value of that portfolio was insignificantly different from zero to four decimal places.

Table 10 details the best-performing portfolios for each of the four types of reversal portfolio, after the crash on 29 September 2008.

The Best-Performing Portfolios for Each of the Four Types of Reversal Portfolio, After the Crash

	Extreme 100		Extreme 500	
Run Immediately	Case	D21-D	Case	D-D
	Portfolio	1	Portfolio	2
	Days	2331.00	Days	2331.00
	Total	971.4251%	Total	3392.4604%
	Mean	0.4167%	Mean	1.4554%
	Std. Error	14.8530%	Std. Error	26.6218%
	t-statistic	1.354636592	t-statistic	2.639405934
	p-value	0.087832353	p-value	0.004180252
Skip a Day	Case	D-D28	Case	D21-D7
	Portfolio	5	Portfolio	2
	Days	121.00	Days	431.00
	Total	935.5565%	Total	2256.0287%
	Mean	7.7319%	Mean	5.2344%
	Std. Error	29.3641%	Std. Error	41.7063%
	t-statistic	2.896409505	t-statistic	2.605580946
	p-value	0.002243502	p-value	0.004745023

Table 10: the best-performing portfolios for each of the four types of reversal portfolio, after the crash.

If the investor implemented the reversal strategy immediately, the D21-D combination exhibited the best performance for quantiles of 100 shares and the D-D combination exhibited the best performance for 500 shares. If the investor skipped a day before implementation, the best performance was exhibited by portfolios with one calendar day formation periods and 28 calendar day holding periods (for 100 stocks) as well as 21 calendar day formation periods and seven calendar day holding periods (for 500 stocks). The best-performing portfolio for the entire sample period was Extreme 500 D-D Run (Portfolio 2) – the investor would have gained on average approximately 1.45 US cents a day or $33.92 over the 2331 trading days of implementation.

Table 11 details the best-performing portfolios, that had the most statistically significant results, after the crash on 29 September 2008.

The Best-Performing Portfolios, With the Most Significant Results, After the Crash					
	Extreme 100			Extreme 500	
Run Immediately	Case	D28-D28		Case	D21-D7
	Portfolio	6		Portfolio	7
	Days	121.00		Days	431.00
	Total	1025.2689%		Total	1543.7762%
	Mean	8.4733%		Mean	3.5818%
	Std. Error	30.5093%		Std. Error	27.2814%
	t-statistic	3.055013871		t-statistic	2.725701812
	p-value	0.001386732		p-value	0.003339272
Skip a Day	Case	D28-D28		Case	D21-D7
	Portfolio	6		Portfolio	2
	Days	121.00		Days	431.00
	Total	898.7403%		Total	2256.0287%
	Mean	7.4276%		Mean	5.2344%
	Std. Error	31.6810%		Std. Error	41.7063%
	t-statistic	2.578950345		t-statistic	2.605580946
	p-value	0.005558822		p-value	0.004745023

Table 11: the best-performing portfolios, that had the most statistically significant results, after the crash.

If the investor implemented the reversal strategy immediately or skipped a day before implementation, the D28-D28 combination generally yielded the most significant results for quantiles of 100 shares and the D21-D7 combination generally yielded the most significant results for quantiles of 500 shares. The best-performing post-crash portfolio with the most significant results was Extreme 100 D28-D28 Run (Portfolio 6) – the p-value of that portfolio was approximately 0.139%.

Table 12 details the best-performing portfolios for each of the four types of reversal portfolio, for the entire sample period.

The Best-Performing Portfolios for Each of the Four Types of Reversal Portfolio, for the Entire Sample Period					
	Extreme 100			Extreme 500	
Run Immediately	Case	D-D		Case	D-D
	Portfolio	7		Portfolio	2
	Days	3270.00		Days	3270.00
	Total	1107.7830%		Total	4489.7354%
	Mean	0.3388%		Mean	1.3730%
	Std. Error	8.0736%		Std. Error	25.6120%
	t-statistic	2.399456579		t-statistic	3.065508628
	p-value	0.008237535		p-value	0.001095377
Skip a Day	Case	D-D28		Case	D-D
	Portfolio	5		Portfolio	3
	Days	169.00		Days	3269.00
	Total	957.9196%		Total	4137.2170%
	Mean	5.6682%		Mean	1.2656%
	Std. Error	28.9280%		Std. Error	22.6647%
	t-statistic	2.547227107		t-statistic	3.19264731
	p-value	0.005877845		p-value	0.000711566

Table 12: the best-performing portfolios for each of the four types of reversal portfolio, for the entire sample period.

If the investor implemented the reversal strategy immediately, the D-D combination exhibited the best performance for quantiles of 100 and 500 shares. If the investor skipped a day before implementation, the best performance was exhibited by portfolios with one calendar day formation periods and 28 calendar day holding periods (for 100 stocks) as well as one calendar day formation and holding periods (for 500 stocks). The best-performing portfolio for the entire sample period was Extreme 500 D-D Run (Portfolio 2) – the investor would have gained on average approximately 1.37 US cents a day or $44.90 over the 2331 trading days of implementation.

Table 13 details the best-performing portfolios, that had the most statistically significant results, for the entire sample period.

The Best-Performing Portfolios, With the Most Significant Results, for the Entire Sample Period					
	Extreme 100			Extreme 500	
Run Immediately	Case	D28-D		Case	D-D
	Portfolio	4		Portfolio	2
	Days	3252.00		Days	3270.00
	Total	1543.7339%		Total	4489.7354%
	Mean	0.4747%		Mean	1.3730%
	Std. Error	8.6542%		Std. Error	25.6120%
	t-statistic	3.128032824		t-statistic	3.065508628
	p-value	0.000887688		p-value	0.001095377
Skip a Day	Case	D28-D		Case	D-D
	Portfolio	1		Portfolio	3
	Days	3251.00		Days	3269.00
	Total	1546.5446%		Total	4137.2170%
	Mean	0.4757%		Mean	1.2656%
	Std. Error	8.6553%		Std. Error	22.6647%
	t-statistic	3.133797319		t-statistic	3.19264731
	p-value	0.000870489		p-value	0.000711566

Table 13: the best-performing portfolios, that had the most statistically significant results, for the entire sample period.

If the investor implemented the reversal strategy immediately or skipped a day before implementation, the D28-D28 combination generally yielded the most significant results for quantiles of 100 shares and the D-D combination generally yielded the most significant results for quantiles of 500 shares. The best-performing portfolio for the entire sample period with the most significant results was Extreme 500 D-D Run Skip (Portfolio 3) – the p-value of that portfolio was approximately 0.071%.

Table 14 details the best- and worst-performing portfolios for each of the four types of reversal portfolio, before the crash, after the crash and for the entire sample period.

The Best- and Worst-Performing Portfolios Before the Crash, After the Crash and for the Entire Sample Period						
	Pre-Crash		Post-Crash		Entire Sample Period	
Worst Performer	Extreme 500		Extreme 500		Extreme 500	
	Case	D-D7	Case	D-D7	Case	D-D7
	Method	Run Immediately	Method	Run Immediately	Method	Run Immediately
	Portfolio	1	Portfolio	1	Portfolio	1
	Days	246.00	Days	431.00	Days	677.00
	Total	-44453.4144%	Total	-54018.6032%	Total	-98472.0176%
	Mean	-180.7049%	Mean	-125.3332%	Mean	-145.4535%
	Std. Error	154.0127%	Std. Error	69.7328%	Std. Error	111.3559%
	t-statistic	-18.40268329	t-statistic	-37.31366049	t-statistic	-33.98640485
	p-value	2.19375E-48	p-value	3.1917E-137	p-value	1.0297E-148
Best Performer	Extreme 500		Extreme 500		Extreme 500	
	Case	D-D	Case	D-D	Case	D-D
	Method	Skip a Day	Method	Run Immediately	Method	Run Immediately
	Portfolio	3	Portfolio	2	Portfolio	2
	Days	938.00	Days	2331.00	Days	3270.00
	Total	2646.8811%	Total	3392.4604%	Total	4489.7354%
	Mean	2.8218%	Mean	1.4554%	Mean	1.3730%
	Std. Error	21.0632%	Std. Error	26.6218%	Std. Error	25.6120%
	t-statistic	4.103066689	t-statistic	2.639405934	t-statistic	3.065508628
	p-value	2.21597E-05	p-value	0.004180252	p-value	0.001095377

Table 14: the best- and worst-performing reversal portfolios before the crash, after the crash and for the entire sample period.

Note that if the investor had held the best pre-crash portfolio and then held the best post-crash portfolio, he or she would have gained approximately $15.50 more than if he or she had only held the best portfolio for the entire sample period (approximately $60.39 versus $44.89).

Table 15 details the most under- and outperforming portfolios for each of the four types of reversal portfolio, with the most significant results, before the crash, after the crash and for the entire sample period.

The Most Under- and Outperforming Portfolios with the Most Significant Results Before the Crash, After the Crash and for the Entire Sample Period						
	Pre-Crash		Post-Crash		Entire Sample Period	
Worst Performer	Extreme 500		Extreme 500		Extreme 500	
	Case	D-D7	Case	D-D7	Case	D-D7
	Method	Run Immediately	Method	Run Immediately	Method	Run Immediately
	Portfolio	1	Portfolio	1	Portfolio	1
	Days	246	Days	431	Days	677
	Total	-44453.4144%	Total	-54018.6032%	Total	-98472.0176%
	Mean	-180.7049%	Mean	-125.3332%	Mean	-145.4535%
	Std. Error	154.0127%	Std. Error	69.7328%	Std. Error	111.3559%
	t-statistic	-18.40268329	t-statistic	-37.31366049	t-statistic	-33.98640485
	p-value	2.19375E-48	p-value	3.1917E-137	p-value	1.0297E-148
Best Performer	Extreme 500		Extreme 100		Extreme 500	
	Case	D-D	Case	D28-D28	Case	D-D
	Method	Skip a Day	Method	Run Immediately	Method	Skip a Day
	Portfolio	3	Portfolio	6	Portfolio	3
	Days	938	Days	121	Days	3269
	Total	2646.8811%	Total	1025.2689%	Total	4137.2170%
	Mean	2.8218%	Mean	8.4733%	Mean	1.2656%
	Std. Error	21.0632%	Std. Error	30.5093%	Std. Error	22.6647%
	t-statistic	4.103066689	t-statistic	3.055013871	t-statistic	3.19264731
	p-value	2.21597E-05	p-value	0.001386732	p-value	0.000711566

Table 15: the most under- and outperforming portfolios for each of the four types of reversal portfolio, with the most significant results, before the crash, after the crash and for the entire sample period.

Note that if the investor had held the most outperforming pre- and post-crash portfolios with the most significant results, he or she would have gained approximately $4.65 less than if he or she had only held the best portfolio for the entire sample period (approximately $41.37 vs $36.72). Note also that the most outperforming portfolio with the most significant results would yield approximately $19.02 less than would the combination of best-performing pre- and post-crash portfolios (approximately $60.39 vs $41.37).

Figure 1 illustrates the cumulative return to the investor from holding the best-performing reversal portfolio for the entire sample period, the best-performing portfolio with the most statistically significant returns for the entire sample period or the Standard & Poor's 500 Index over the entire sample period.

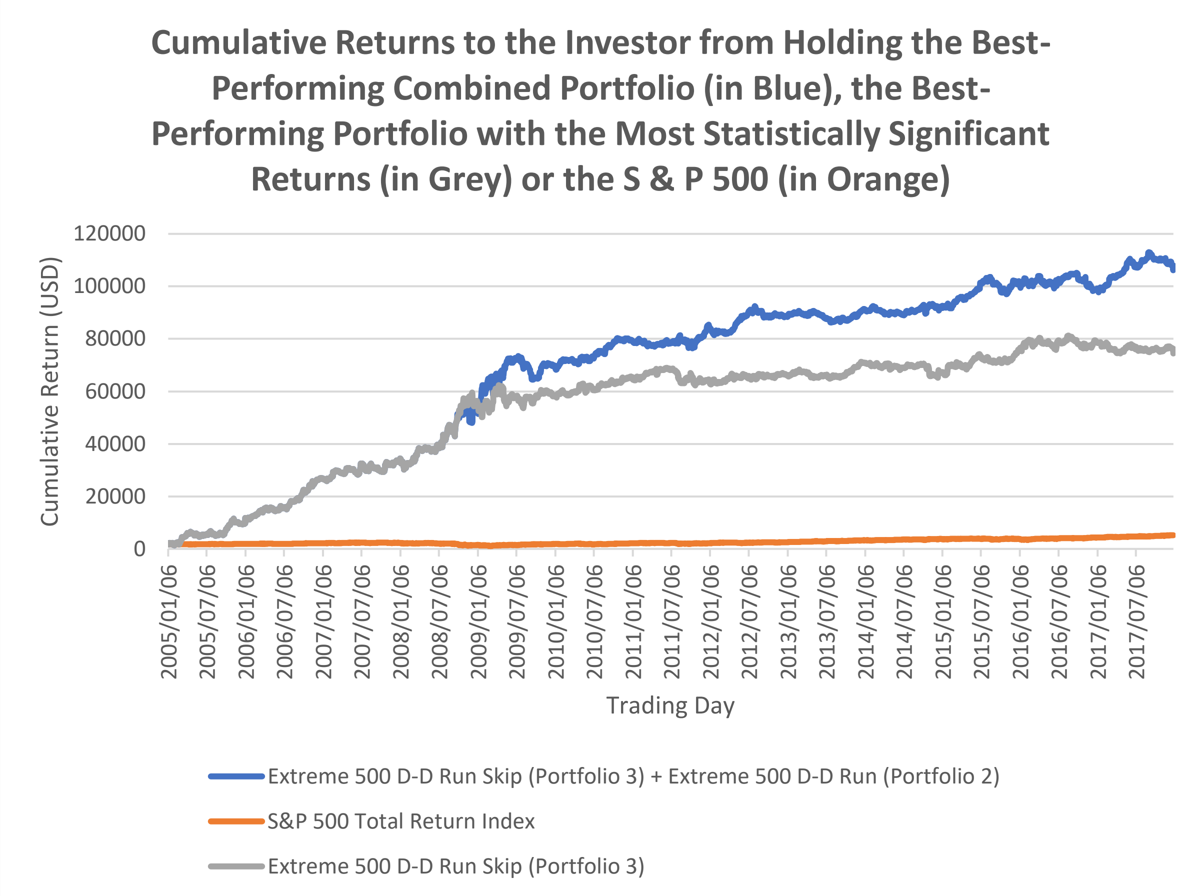

Figure 1: the cumulative returns to the investor from holding the best-performing reversal portfolio for the entire sample period, the best-performing portfolio with statistically significant returns for the entire sample period or the Standard & Poor's 500 Index over the entire sample period.

This comparison is made only because the investor would have had the option – among others – of investing in said index either directly or by means of a sort of index-tracking fund designed and managed in such a way as to yield a return equal to that of the S & P 500 to the investor at the end of the day.

As can be seen, of the three options analysed above, the investor's cumulative return would have been highest if he or she had held the best-performing reversal portfolio over the entire sample period than if he or she had held either the best-performing reversal portfolio with the most significant results or the Standard & Poor's 500 index. The best-performing reversal portfolio yielded a cumulative return of approximately $107933.92 for every $1758.07 invested (the value of the S & P 500 Total Return Index as at the end of 5 January 2005, when the reversal strategy would have been first implemented). The best-performing reversal portfolio with the most significant results yielded a cumulative return of approximately $74493.24 for every $1758.07 invested. The S & P 500 grew that same initial amount to a cumulative return of $5212.76. The growth factors are (to three decimal places) 61.393, 42.372 and 2.965, respectively.

Figures 2 to 4 are pie charts illustrating how many portfolios, of the 1000 portfolios analysed in each time interval, had statistically significant positive average returns, statistically insignificant positive average returns, statistically insignificant negative average returns and statistically significant negative average returns. The pie charts only take into consideration the time interval, not the investor's application method or the number of component shares in the reversal portfolio.

Each of the portfolios falls into one and only one of the following mutually exclusive categories:

1. The portfolio's average return is positive and statistically significant;
2. The portfolio's average return is positive and statistically insignificant;
3. The portfolio's average return is not positive and statistically insignificant;
4. The portfolio's average return is not positive and statistically significant.

Figure 2 illustrates how many portfolios fall into which category, over the entire sample period.

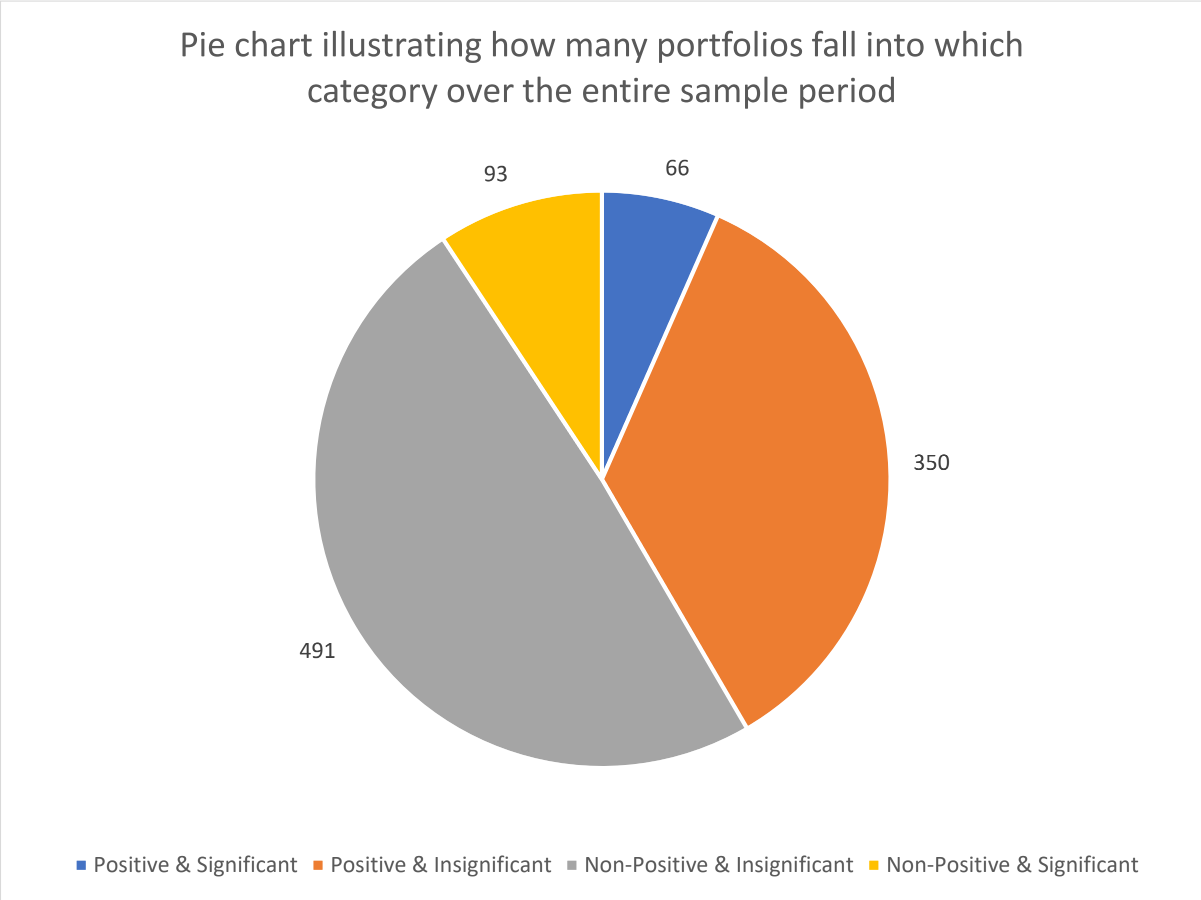

Figure 2: pie chart illustrating how many portfolios fall into which category over the entire sample period.

Figure 3 illustrates how many portfolios fall into which category, over the pre-crash period.

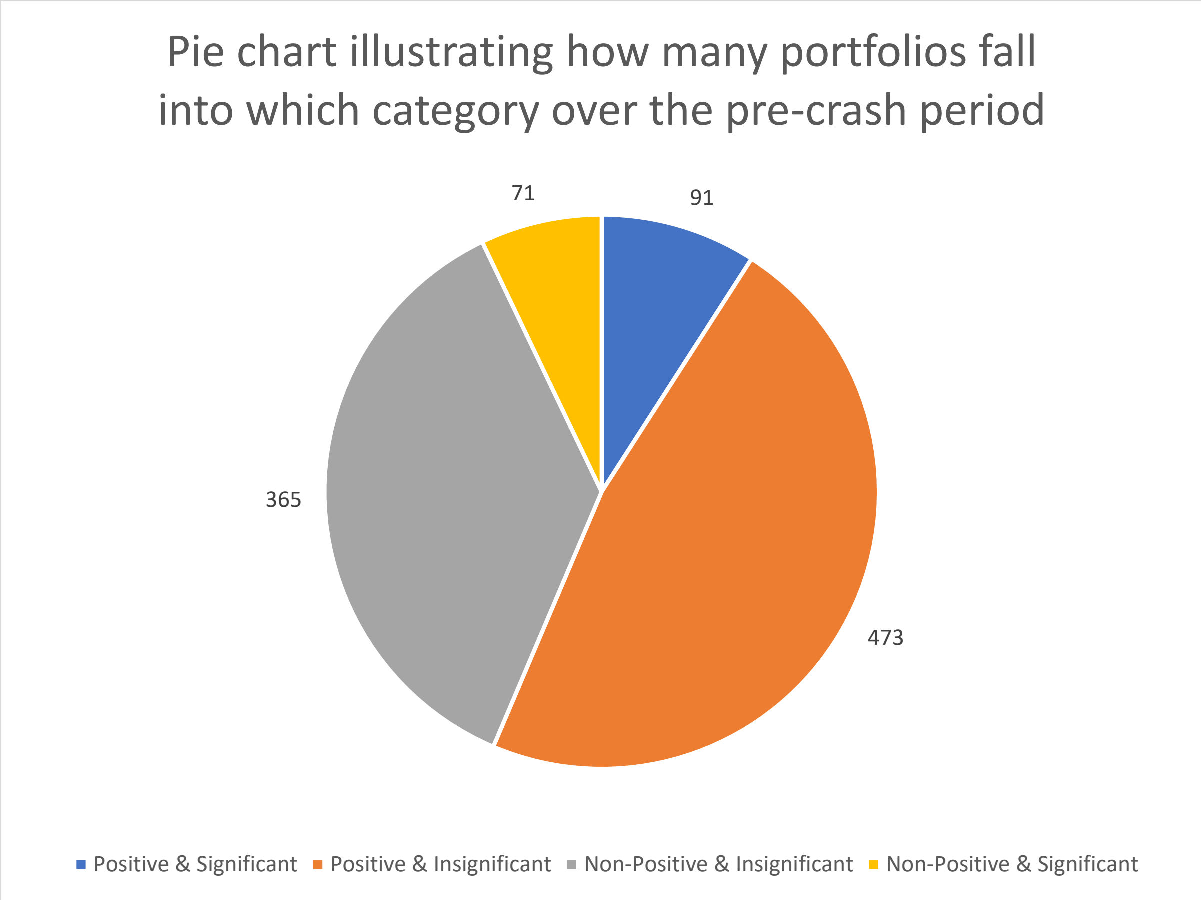

Figure 3: pie chart illustrating how many portfolios fall into which category over the pre-crash period.

Figure 4 illustrates how many portfolios fall into which category, over the pre-crash period.

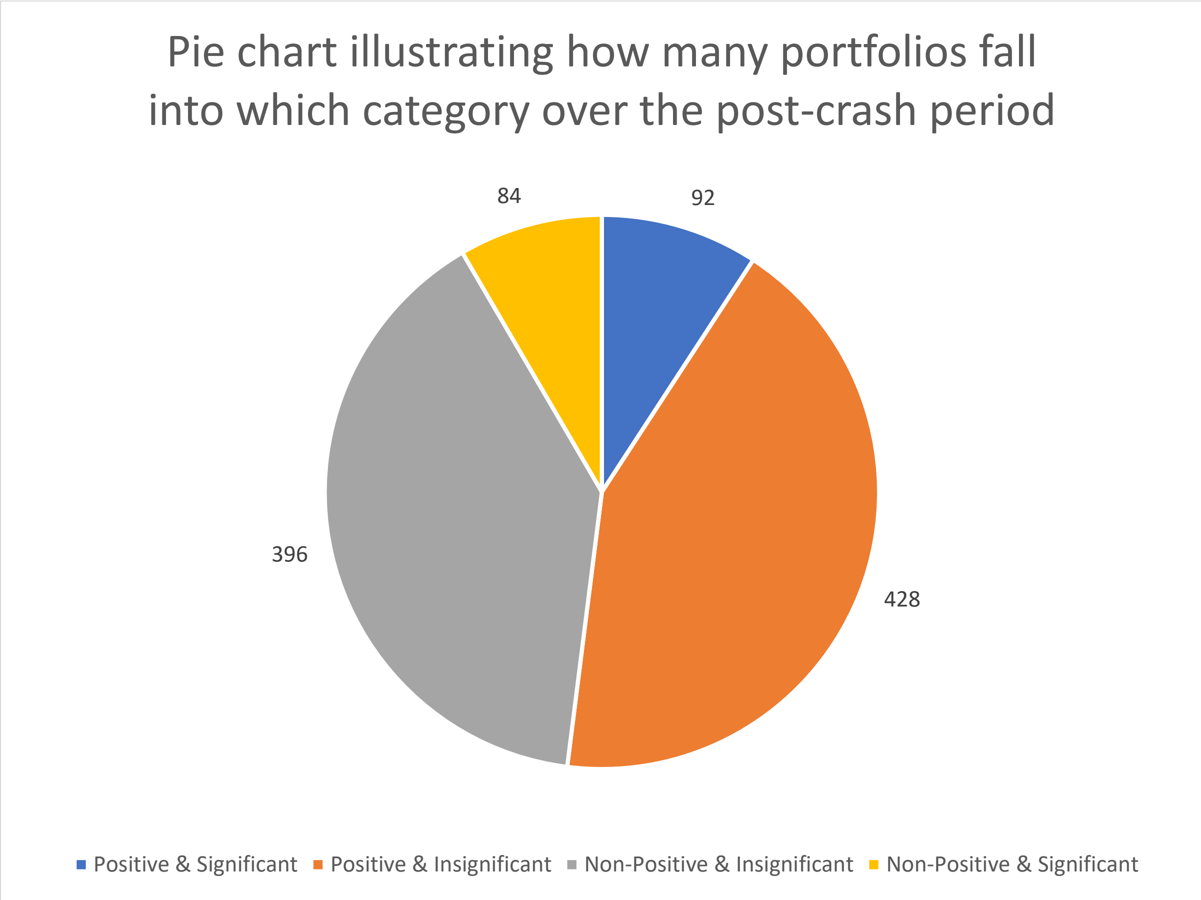

Figure 4: pie chart illustrating how many portfolios fall into which category over the post-crash period.

Chapter 5: Discussion of Results

The objective of this investigation was to test the long-term profitability of the short-term reversal strategy to ascertain whether an investor who had constructed a costless long-short portfolio and implemented a reversal strategy would over the long-run have succeeded in accruing statistically significant positive cash returns from a synthetic zero position in the market.

In pursuit of the above objective, 1000 long-short portfolios with zero net positions were constructed. 25 combinations of formation and holding periods were analysed. Ten reversal portfolios were constructed for each case. Four different methods of assembly were used for each case. The portfolios were constructed in such a way as to have the absolute value of each component of each portfolio be equal in size. The portfolios were analysed over three periods: the period from 1 January 2005 to 29 September 2008, the period from 29 September 2008 to 31 December 2017 and the period from 1 January 2005 to 31 December 2017. T-tests for samples of unequal size with unequal variances were used for all 3000 sub-portfolios. The significance level was set at 5% for all tests – the test result will only be deemed to be statistically significant if the p-value is lower than 5%.

In the pre-crash period, 71 portfolios had significant non-positive average returns, 91 portfolios had significant positive average returns, 365 portfolios had non-significant non-positive average returns and 473 portfolios had non-significant positive average returns.

The worst-performing pre-crash portfolio was Extreme 500 D-D7 Run (Portfolio 1), with a total net return of approximately -$444.53, an average net return of approximately -$1.81 per day and a p-value insignificantly different from zero to 47 decimal places. It was also the worst-performing pre-crash portfolio with the most significant results. The best-performing pre-crash portfolio was Extreme 500 D-D Run Skip (Portfolio 3), with a total net return of approximately $26.46, an average net return of approximately $0.03 per day and a p-value insignificantly different from zero to four decimal places. It was also the best-performing pre-crash portfolio with the most significant results.

In the post-crash period, 84 portfolios had significant non-positive average returns, 92 portfolios had significant positive average returns, 396 portfolios had non-significant non-positive average returns and 428 portfolios had non-significant positive average returns.

The worst-performing post-crash portfolio was Extreme 500 D-D7 Run (Portfolio 1), with a total net return of approximately -$540.19, a net average return of approximately -$1.25 per day and a p-value insignificantly different from zero to 136 decimal places. It was also the worst-performing post-crash portfolio with the most significant results. The best-performing post-crash portfolio was Extreme 500 D-D Run (Portfolio 2), with a total net return of approximately $33.92, an average net return of approximately $0.01 per day and a p-value of approximately 0.418%. The best-performing portfolio with the most significant results was Extreme 100 D28-D28 Run (Portfolio 6), with a total net return of approximately $10.25, an average net return of approximately $0.08 per day and a p-value of approximately 0.139%.

In the entire sample period, 93 portfolios had significant non-positive average returns, 66 portfolios had significant positive average returns, 491 portfolios had non-significant non-positive average returns and 350 portfolios had non-significant positive average returns.

The worst-performing portfolio for the entire sample period was Extreme 500 D-D7 Run (Portfolio 1), with a total net return of approximately -$984.72, a net average return of approximately -$1.45 per day and a p-value insignificantly different from zero to 147 decimal places. It was also the worst-performing portfolio for the entire sample period with the most significant results. The best-performing portfolio for the entire sample period was Extreme 500 D-D Run (Portfolio 2), with a total net return of approximately $44.90, an average net return of approximately $0.01 per day and a p-value of approximately 0.110%. The best-performing portfolio for the entire sample period with the most significant results was Extreme 500 D-D Run Skip (Portfolio 3), with a total net return of $41.37, an average net return of $0.01 per day and a p-value of approximately 0.071%.

If the investor had held the best-performing pre- and post-crash portfolios with the most significant results, he or she would have gained approximately $36.72. If he or she had held the best-performing portfolio for the entire sample period with the most significant results, then he or she would have gained approximately $41.37. If the investor had held the best-performing portfolio for the entire sample period (not necessarily with the most significant results), then he or she would have gained approximately $44.89. But if he or she had instead held the best-performing pre- and post-crash portfolios (not necessarily the ones with the most significant results), then he or she would have gained approximately $60.39.

These results are of interest to investors because an investor that has committed to invest his or her surplus funds seeks to maximise the benefit that he or she derives therefrom, given the inherent riskiness of that investment. Accordingly, such an investor will invest in the available opportunity that offers the highest expected return and which best suits his or her risk profile (Tobin, 1958). If said investment performs according to expectations or surpasses said expectations, that investor will be satisfied and, in said state of satisfaction, will likely attribute the positive outcome to his or her own investment savvy. If said investment performs below expectations, then that investor will likely attribute the negative outcome to causes beyond his or her own choices and only then will said investor possibly be interested in the p-value of the investment's performance (an example of the self-serving bias, a human tendency to attribute positive outcomes to one's own character and decisions and to attribute negative outcomes to external factors [Boyes, 2013]). What the results above indicate is that the hypothetical investor who invested in Extreme 500 D-D Run Skip (Portfolio 3) between 1 January 2005 and 28 September 2008 and in Extreme 500 D-D Run (Portfolio 2) from 29 September 2008 to 31 December 2017 not only derived the most benefit from his or her investment (approximately $60.39) but also gained a gross return approximately 20.7057 times larger than that of the S & P 500 ($1 invested in the S & P 500 grew to approximately $2.97; $1 invested in the combination of best-performing pre- and post-crash portfolios grew to approximately $61.39).

While the worst-performing portfolios for the pre-crash period, the post-crash period and the entire sample period were one and the same portfolio, adjusted for running time, the best-performing portfolios for those time intervals differed. The difference in best-performing portfolios for the pre-crash, post-crash and entire sample periods likely indicates a change in market behaviour between the pre- and post-crash periods.

During the pre-crash period, there was a general sense of global prosperity. Housing valuations were climbing, borrowing costs were low and opportunities for profitable commercial ventures were plentiful. Many a market participant would have felt little need to rush into a specific trade, believing themselves safe in the expectation that, just as in preceding days, the overall market would always be rising in value. As a result, it would have been rational for an investor invested in a reversal portfolio to skip a day before re-balancing his or her portfolio, rather than re-balancing directly after a holding period ended. Given the benefits that were to be gained from the bullish global markets, it was more prudent to have shorter formation and holding periods, as the resultant flexibility would allow for maximal benefit from market participation.

The post-crash period, however, was a different time. The global financial system had just suffered a major setback. The effects of leverage as an unbiased amplifier of both good and bad performance were manifested globally as individuals and entities that had made unwise financial decisions found themselves suffering significant losses – even ruinous losses, in some notable cases (e.g. the collapse of Lehman Brothers, resulting in a declaration of bankruptcy on 15 September 2008 [Peacock and Martin, 2018]; the $182.3 million bailout the United States government handed to the American International Group Inc. (AIG) after AIG incurred losses on collateralised debt obligations that it had insured [Amadeo, 2019]; and the $7.9 billion write-off of collateralised debt obligations by Merrill Lynch that facilitated its acquisition by Bank of America [Stalter, 2017]). As a result, the global markets became more bearish than before. While shorter formation and holding periods were still preferable (to maximise the gains offered by flexibility), it had become more prudent to execute trades earlier and faster than before, to minimise one's losses and to reduce the probability of failing to successfully liquefy a position. It would have been rational for an investor invested in a reversal portfolio to re-balance directly after a holding period ended, rather than skipping a day prior to implementation.

The conclusion that can be drawn from the above results obtained in this investigation is that it was indeed possible for an investor who had constructed a costless long-short portfolio and implemented a reversal strategy to succeed over the long-run in accruing statistically significant positive cash returns from a synthetic zero position in the market. Depending on the time interval being considered, between 66 and 92 reversal portfolios yielded statistically significant positive returns for their holders. A reversal portfolio investor who had held first the best-performing pre-crash and then the best-performing post-crash portfolios would have gained a net return of approximately \$60.39 for every \$1 invested. During the sample period, it was possible to derive significant benefits from market activities despite effectively having no net position in the market at all. The possibility may yet exist today for a suitably resourced investor with a suitable level of risk tolerance, but in the absence of out-of-sample testing, nothing more conclusive can be said.

Chapter 6: Conclusion

6.1: Principal and Secondary Findings

The principal, empirical finding of the investigation is that, while the reversal portfolio is more likely than not to yield average returns that are insignificantly different from zero, it is still possible in isolated cases to earn positive average returns from the market's activities, despite effectively having no net position whatsoever in the market.

The results of the investigation found that between 66 and 92 of the 1000 portfolios tested in each time interval yielded average returns that were positive and statistically significant at the 5% level. The results of the investigation also yielded the insight that the best-performing reversal portfolio outperformed not only the zero portfolio but also the S & P 500 over the same period.

If the investor rebalanced his or her reversal portfolio immediately after the preceding holding period ended, then the D-D7 combination (the shares to comprise the long and short positions are chosen based on the preceding one calendar day's returns, then the resultant zero-cost long-short portfolio are held for the following seven calendar days) was the worst-performing combination tested before the crash, after the crash or over the entire sample period, for portfolios drawn from 100 or 500 shares. Over the entire sample period, an investor would have lost approximately $984.72. With a p-value insignificantly different from zero to 147 decimal places, the D-D7 portfolio's results were also the most statistically significant.

If the investor rebalanced his or her reversal portfolio immediately after the preceding holding period ended, then the D28-D combination was the combination with the most significant results for portfolios drawn from 100 shares, with a positive net return. It was also the best-performing portfolio for portfolios drawn from 100 shares: an investor would have gained approximately $15.44 and its p-value was approximately 0.089%. The D-D combination was both the best-performing combination for portfolios drawn from 500 shares and the combination with the most significant results. Its p-value was approximately 0.110% and an investor would have gained approximately $44.90.

If the investor rebalanced his or her reversal portfolio a day after the preceding holding period ended, then the D14-D7 combination (the shares to comprise the long and short positions are chosen based on the preceding fourteen calendar days' returns, then the resultant zero-cost long-short portfolio are held for the following seven calendar days) was the combination with the most significant results over the entire sample period, for portfolios drawn from 100 or 500 shares, with a negative net return. The p-value of the portfolio was insignificantly different from zero to four decimal places (for portfolios drawn from 100 shares) and insignificantly different from zero to 49 decimal places (for portfolios drawn from 500 shares). The worst-performing combination over the entire sample period for portfolios drawn from 500 shares was also the D14-D7 combination (an investor would have lost approximately $321.97); for portfolios drawn from 100 shares, the worst-performing combination over the entire sample period was the D-D14 combination (an investor would have lost approximately $20.03).

If the investor rebalanced his or her reversal portfolio a day after the preceding holding period ended, then the D28-D combination was the combination with the most significant results for portfolios drawn from 100 shares, with a positive net return. It was also the best-performing portfolio for portfolios drawn from 100 shares: an investor would have gained approximately $15.47 and its p-value was approximately 0.087%. The D-D combination was both the best-performing combination for portfolios drawn from 500 shares and the combination with the most significant results for portfolios with positive net returns. Its p-value was approximately 0.071% and an investor would have gained approximately $41.37.

The worst-performing portfolio for the entire sample period was Extreme 500 D-D7 Run (Portfolio 1), with a total net return of approximately -$984.72, a net average return of approximately -$1.45 per day and a p-value insignificantly different from zero to 147 decimal places. It was also the worst-performing portfolio for the entire sample period with the most significant results. The best-performing portfolio for the entire sample period was Extreme 500 D-D Run (Portfolio 2), with a total net return of approximately $44.90, an average net return of approximately $0.01 per day and a p-value of approximately 0.110%. The best-performing portfolio for the entire sample period with the most significant results was Extreme 500 D-D Run Skip (Portfolio 3), with a total net return of approximately $41.37, an average net return of $0.01 per day and a p-value of approximately 0.071%.

If the investor had held the best-performing pre- and post-crash portfolios with the most significant results, he or she would have gained approximately $36.72. If he or she had held the best-performing portfolio for the entire sample period with the most significant results, then he or she would have gained approximately $41.37. If the investor had held the best-performing portfolio for the entire sample period (not necessarily with the most significant results), then he or she would have gained approximately $44.89. But if he or she had instead held the best-performing pre- and post-crash portfolios (not necessarily the ones with the most significant results), then he or she would have gained approximately $60.39.

The secondary finding of the investigation is that, as was discovered by earlier authors, there appears to be sufficient evidence to disprove Fama's (1970) Efficient Market Hypothesis.

While few of the costless portfolios tested yielded statistically significant positive average returns, the fact that some of the costless portfolios *did* yield statistically significant positive average returns implies that the possibility of gaining reward from effectively having a zero position in the market *does* exist. The success of some of the costless portfolios also implies that it is possible to use public information to construct a portfolio that outperforms the market, thus disproving the argument to the contrary that Fama (1970) posited.

6.2: Limitations of the Investigation

This investigation does have its limitations.

Limitation One:

The findings of this investigation say nothing about whether the observed profitability of the reversal strategy endures once transaction costs are taken into consideration. While one may infer from the results of the analyses the level at which transaction costs would have to be set to eliminate profits entirely, the absence of explicit testing for transaction costs renders the findings limited in their scope.

Limitation Two:

It is assumed that the long and short positions are collectively of equal absolute value (i.e. their distances from zero on the real number line are equal [Varsity Tutors, 2007]) and that the absolute values of the long and short positions are all equal. But said assumptions may not always hold.

In the composition of each reversal portfolio, the number of units of each share to be bought or sold must be an integer (shares are only traded in integer quantities). Accordingly, said quantities are the solutions of the following linear polynomial equation: $L_1P_1 + L_2P_2 + \cdots + L_{X-1}P_{X-1} + L_XP_X - (S_1Q_1 + S_2Q_2 + \cdots + S_{X-1}Q_{X-1} + S_XQ_X) = 0$, where the indexed L's are the quantities of shares to be purchased for the long positions, the indexed S's are the quantities of shares to be sold for the short positions, the indexed P's are the prices of the shares in the long positions, the indexed Q's are the prices of the short positions and X equals either five (for reversal portfolios from 100 shares) or 25 (for reversal portfolios from 500 shares).

The indexed L's and S's must be whole numbers because shares are not traded in fractional quantities. Accordingly, the above linear polynomial equation admits only integer solutions and is therefore Diophantine (Weisstein, 2019). If the above Diophantine equation is unsolvable using Diophantine methods (i.e. if there exists no set of integers such that the equation is entirely satisfied), then it will be impossible for the investor to construct the necessary zero-investment portfolio for the reversal strategy. Even if the above Diophantine equation is solvable, the prices will almost certainly differ and it is almost certain that the absolute values of the weighted components will differ, which will mean that the absolute values of the individual positions will differ.

Limitation Three:

In practice, there will be statutory restrictions on the degree to which one can execute short sales in the market, which will curtail the investor's flexibility and, hence, restrict the effectiveness of the reversal strategy or render it impossible to execute in that market.

Limitation Four:

There will also be a borrowing cost involved, which is not considered in this investigation. Short selling is by definition the sale of securities that one does not own. Therefore, said securities must be borrowed from their actual owners, who will charge a borrowing fee equal to some proportion of the value of the securities in addition to requiring the setup of a margin account (to hold some of the proceeds and mark the position to market) and requiring that the short seller make good on any cash incomes that would ordinarily have come to the owner of the shares had said owner been holding the shares as per normal. The findings of this investigation are therefore limited in that regard.

Limitation Five:

The buying and selling of shares are subject to diminishing marginal returns. As one purchases more and more shares, the purchase price increases because there are only so many shares available on the market at a given price for purchase, after which one moves to satisfy more expensive offers. As one sells more and more shares, the selling price decreases for much the same reason. The diminishing marginal returns in both cases will eat into the cash returns from the reversal portfolio and may serve to eliminate them entirely.

Limitation Six:

Shares on the market are bought and sold in blocks of sizes chosen by the relevant market participants as per their individual needs. It may not always be possible to purchase or sell precisely the number of shares required to assemble the long or short positions properly. In such cases, the net position will not be zero.

6.3: Suggestions for Further Research

It is suggested that future research include some means of including average trading and borrowing costs in the analysis. It is also suggested that future research consider statutory restrictions on short selling that may apply in a given financial market. Finally, it is suggested that future research have an expanded scope to include out-of-sample testing of the profitability of the return reversal strategy as implemented using a costless portfolio.

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Appendices

Appendix 1: The sources of the sample data for this investigation

The following 780 companies' ordinary shares were included in the S & P 500 index between 3 January 2005 and 29 December 2017.

1. 21st Century Fox Inc
2. 3M Co
3. A.O. Smith Corp
4. Abbott Laboratories
5. AbbVie Ltd
6. Abercrombie & Fitch
7. Accenture PLC
8. Activision Blizzard Inc
9. Acuity Brands Inc
10. ADC Telecommunications
11. Adobe Systems Inc
12. ADT
13. Adtalem Global Education Inc
14. Advance Auto Parts Inc
15. Advanced Micro Devices Inc
16. AES Corp
17. Aetna Inc
18. Affiliated Computer Services
19. Affiliated Managers Group Inc
20. Aflac Inc
21. Agilent Technologies Inc
22. AIG Inc
23. Air Products and Chemicals Inc
24. Airgas Inc
25. AK Steel Holding Corp
26. Alaska Air Group Inc
27. Albemarle Corp
28. Alberto Culver Co
29. Alcoa Corp
30. Alexandria Real Estate Equities Inc
31. Alexion Pharmaceuticals Inc
32. Align Technology Inc
33. Allegheny Technologies Inc
34. Allegion PLC
35. Allergan plc
36. Alliance Data Systems Corp
37. Alliant Energy Corp
38. Allied Waste Industries LLC
39. Allstate Corp
40. Alpha Natural Resources
41. Alphabet Inc
42. Altaba Inc
43. Altria Group Inc
44. Amazon.com Inc
45. Ambac Financial Group Inc
46. Ameren Corp
47. American Airlines Group Inc
48. American Capital
49. American Electric Power Company Inc
50. American Express Co
51. American Power
52. American Tower Corp
53. Ameriprise Financial Inc
54. AmerisourceBergen Corp
55. Ametek Inc
56. Amgen Inc
57. Amphenol Corp
58. AmSouth Bancorp
59. Anadarko Petroleum Corp
60. Analog Devices Inc
61. Andeavor Logistics LP
62. Andrew Corp
63. Anheuser-Busch Companies
64. ANSYS Inc
65. Anthem Inc
66. Anthem Inc
67. AON PLC
68. Apache Corp
69. Apartment Investment & Management Co
70. Apollo Education Group
71. Apple Inc
72. Applied Materials Inc
73. Applied Micro Circuits
74. Aptiv PLC
75. Archer Daniels Midland Co
76. Archstone-Smith Trust
77. Arconic Inc
78. Arthur J Gallagher & Co
79. Ashland Global Holdings Inc
80. Assurant Inc
81. AT&T Inc
82. Autodesk Inc
83. Automatic Data Processing Inc
84. AutoNation Inc
85. Autozone Inc
86. AvalonBay Communities Inc
87. Avaya
88. Avery Dennison Corp
89. Avis Budget Corp
90. Avon Products Inc
91. Baker Hughes GE
92. Ball Corp
93. Bank of America Corp
94. Bank of New York Mellon Corp
95. Barr Pharmaceuticals
96. Bausch & Lomb

97. Baxalta
98. Baxter International
99. BB&T Corp
100. Beam
101. Bear Stearns
102. Becton Dickinson & Co
103. Bed Bath & Beyond Inc
104. Bemis Company Inc
105. Berkshire Hathaway Inc
106. Best Buy Co Inc
107. Big Lots Inc
108. Biogen Inc
109. BJ Services
110. BlackRock Inc
111. BMC Software
112. Boeing Co
113. Booking Holdings Inc
114. BorgWarner Inc
115. Boston Properties Inc
116. Boston Scientific Corp
117. Brighthouse Financial Inc
118. Bristol-Myers Squibb Co
119. Broadcom Corp
120. Broadcom Inc
121. Brown-Forman Corp
122. Brunswick Corp
123. Burlington Rescue
124. C R Bard
125. C.H. Robinson Worldwide
126. CA Inc
127. Cablevision Systems Corp
128. Cabot Oil and Gas Corp
129. Cadence Design Systems Corp
130. Caesars Entertainment Corp
131. Calpine
132. Cameron International
133. Campbell Soup Co
134. Capital One Financial Corp
135. Cardinal Health Inc
136. CareFusion
137. Caremark Rx Inc
138. CarMax
139. Carnival Corp
140. Caterpillar Inc
141. CBOE Global Markets Inc
142. CBRE Group
143. CBS Corp
144. Celgene Corp
145. Centene Corp
146. CenterPoint Energy Inc
147. Centex Corp
148. CenturyLink
149. Cephalon
150. Cerner Corp
151. CF Industries Holdings
152. Charles Schwab Corp
153. Charter Communications Inc
154. Chesapeake Energy Corp
155. Chevron Corp
156. Chipotle Mexican Grill
157. Chiron Corp
158. Chubb Corp
159. Chubb Ltd
160. Church & Dwight Co Inc
161. Cimarex Energy Co
162. Cincinnati Financial Corp
163. Cinergy
164. Cintas Corp
165. Circuit City Stores
166. Cisco Systems Inc
167. CIT Group Inc
168. Citigroup Inc
169. Citizens Financial Group Inc
170. Citrix Systems Inc
171. Clear Channel Communications
172. Cleveland-Cliffs Inc
173. Clorox Co
174. CME Group Inc
175. CMS Energy Corp
176. CNO Financial Group Inc
177. CNX Resources Corp
178. Coca-Cola Co
179. Coca-Cola European Partners PLC
180. Cognizant Technology Solutions Corp
181. Colgate-Palmolive Co
182. Columbia Pipeline Group
183. Comcast Corp
184. Comerica Inc
185. Compass Bancshare
186. Compuware
187. Comverse Technology
188. Conagra Brands Inc
189. Concho Resources Inc
190. Conexant Systems
191. ConocoPhillips
192. Consolidated Edison Inc
193. Constellation Brands Inc
194. Convergys
195. Cooper Companies Inc
196. Cooper Industries
197. Cooper Tire and Rubber Co
198. Corning Inc
199. Costco Wholesale Corp
200. Coty Inc
201. Crane Co
202. Crown Castle International Corp
203. CSRA
204. CSX Corp
205. Cummins Inc
206. CVS Health Corp

207. D. R. Horton Inc
208. Dana Inc
209. Danaher Corp
210. Darden Restaurants Inc
211. DaVita Inc
212. DDR Corp
213. Dean Foods Co
214. Deere and Co
215. Dell
216. Delphi Corp
217. Delta Air Lines Inc
218. Deluxe Corp
219. Denbury Resources Inc
220. Dentsply Sirona Inc
221. Devon Energy Corp
222. Diamond Offshore Drilling Inc
223. Digital Realty Trust Inc
224. Dillard's Inc
225. Discover Financial Services
226. Discovery Inc
227. DISH Network Corp
228. Dollar General Corp
229. Dollar Tree Inc
230. Dominion Energy Inc
231. Dover Corp
232. Dow Chemical
233. Dow Jones
234. DowDuPont Inc
235. DTE Energy Co
236. Duke Energy Corp
237. Duke Realty Corp
238. Dun & Bradstreet Corp
239. DXC Technology Co
240. Dynegy
241. E I du Pont de Nemours & Co
242. E*TRADE Financial Corp
243. E. W. Scripps Co
244. Eastman Chemical Co
245. Eastman Kodak Co
246. Eaton Corporation PLC
247. eBay Inc
248. Ecolab Inc
249. Edison International
250. Edwards Lifesciences Corp
251. El Paso Electric Co
252. Electronic Arts Inc
253. Electronic Data Systems
254. Eli Lilly and Co
255. Embarq Corporation
256. EMC
257. Emerson Electric Co
258. Encompass Health Corp
259. Endo International PLC
260. Ensco PLC
261. Entergy Corp
262. Enterprise Products Partners LP
263. Envision Healthcare Corp
264. EOG Resources Inc
265. EQT Corp
266. Equinix Inc
267. Equity Office
268. Equity Residential
269. Essex Property Trust Inc
270. Estee Lauder Companies Inc
271. Everest Re Group Inc
272. Eversource Energy
273. Exelon Corp
274. Expeditors International of Washington Inc
275. Express Scripts Holding Co
276. Extra Space Storage Inc
277. Exxon Mobil Corp
278. F5 Networks Inc
279. Facebook Inc
280. Family Dollar Stores
281. Fastenal Co
282. Federal Home Loan Mortgage Corp
283. Federal National Mortgage Association
284. Federal Realty Investment Trust
285. Federated Investors Inc
286. FedEx Corp
287. Fidelity National Information Services Inc
288. Fifth Third Bancorp
289. First Data Corp
290. First Horizon National Corp
291. First Solar Inc
292. FirstEnergy Corp
293. Fiserv Inc
294. FLIR Systems Inc
295. Flowserve Corp
296. Fluor Corp
297. FMC Corp
298. Foot Locker Inc
299. Ford Motor Co
300. Forest Laboratories
301. Fortive Corp
302. Fortune Brands Home & Security Inc
303. Fossil Group Inc
304. Franklin Resources Inc
305. Freeport-McMoRan Inc
306. Freescale Semiconductors
307. Frontier Communications Corp
308. GameStop Corp
309. Gap Inc
310. Garmin Ltd
311. Gartner Inc
312. Gateway
313. General Dynamics Corp
314. General Electric Co
315. General Mills Inc
316. General Motors Co

317. Genuine Parts Co
318. Genworth Financial Inc
319. Genzyme
320. Georgia-Pacific
321. Gilead Sciences Inc
322. Gillette
323. Global Payments Inc
324. Golden West Finance
325. Goldman Sachs Group Inc
326. Goodrich Petroleum Corp
327. Goodyear Tire and Rubber Co
328. Graham Holdings Co
329. Great Lakes Chemicals
330. Guidant
331. H & R Block Inc
332. Halliburton Co
333. HanesBrands Inc
334. Harley-Davidson Inc
335. Harman International
336. Harris Corp
337. Hartford Financial Services Group Inc
338. Hasbro Inc
339. HCA Healthcare Inc
340. HCP Inc
341. Health Management Associates
342. Helmerich and Payne Inc
343. Henry Schein Inc
344. Hercules
345. Hershey Co
346. Hess Corp
347. Hewlett Packard Enterprise Co
348. Hillshire Brands
349. Hilton Worldwide Holdings Inc
350. HJ Heinz
351. Hologic Inc
352. Home Depot Inc
353. Honeywell International Inc
354. Hormel Foods Corp
355. Hospira
356. Host Hotels & Resorts Inc
357. HP Inc
358. Hudson City Bancorp
359. Humana Inc
360. Huntington Bancshares Inc
361. IBM Corp
362. IDEXX Laboratories Inc
363. IHS Markit Ltd
364. Illinois Tool Works Inc
365. Illumina Inc
366. Incyte Corp
367. Ingersoll-Rand PLC
368. Integrys Energy Group
369. Intel Corp
370. InterActiveCorp
371. Intercontinental Exchange Inc
372. International Flavors & Fragrances Inc
373. International Game Technology PLC
374. International Paper Co
375. Interpublic Group of Companies Inc
376. Intuit Inc
377. Intuitive Surgical Inc
378. Invesco Ltd
379. IQVIA Holdings Inc
380. Iron Mountain Inc
381. ITT Inc
382. J B Hunt Transport Services Inc
383. J C Penney Company Inc
384. J M Smucker Co
385. Jabil Inc
386. Jacobs Engineering Group Inc
387. Janus Capital Group
388. Jefferies Financial Group Inc
389. Jefferson Pilot
390. Johnson & Johnson
391. Johnson Controls International PLC
392. Jones Group
393. Joy Global
394. JP Morgan Chase & CO
395. Juniper Networks Inc
396. Kansas City Southern
397. Kate Spade and Co
398. KB Home
399. Kellogg Co
400. Kerr-McGee
401. Keurig Dr Pepper Inc
402. Keurig Green Mountain
403. KeyCorp
404. Keyspan Corp
405. Kimberly-Clark Corp
406. Kimco Realty Corp
407. Kinder Morgan Inc
408. KLA-Tencor Corp
409. Knight Ridder
410. Kohls Corp
411. Kroger Co
412. L Brands Inc
413. L3 Technologies Inc
414. Laboratory Corporation of America Holdings
415. Lam Research Corp
416. Las Vegas Sands Corp
417. Legg Mason Inc
418. Leggett & Platt Inc
419. Lehman Brothers Holdings
420. Leidos Holdings Inc
421. Lennar Corp
422. Level 3 Communications
423. Lexmark International
424. Life Technologies
425. Lincoln National Corp

426. Linear Technology
427. LKQ Corp
428. Lockheed Martin Corp
429. Loews Corp
430. Lorillard Inc
431. Louisiana-Pacific Corp
432. Lowe's Companies Inc
433. LSI
434. Lucent Technology
435. LyondellBasell Industries NV
436. M&T Bank Corp
437. Macerich Co
438. Macy's Inc
439. Mallinckrodt PLC
440. Manitowoc Company Inc
441. Manor Care
442. Marathon Oil Corp
443. Marathon Petroleum Corp
444. Marriott International Inc
445. Marsh & McLennan Companies Inc
446. Martin Marietta Materials Inc
447. Masco Corp
448. Massey Energy
449. Mastercard Inc
450. Mattel Inc
451. Maxim Integrated Products Inc
452. MBIA Inc
453. MBNA Corp
454. McCormick and Company Inc
455. McDermott International Inc
456. McDonald's Corp
457. McKesson Corp
458. Mead Johnson Nutrition
459. Meadwestvaco
460. Medco Health Solutions
461. Medimmune
462. Medtronic PLC
463. Mellon Financial
464. Merck & Co Inc
465. Mercury Interactive
466. Meredith Corp
467. MetLife Inc
468. Mettler-Toledo International Inc
469. MGIC Investment Corp
470. MGM Resorts International
471. Michael Kors Holdings Ltd
472. Microchip Technology Inc
473. Micron Technology Inc
474. Microsoft Corp
475. Mid-America Apartment Communities Inc
476. Millipore Corp
477. Mohawk Industries Inc
478. Molex
479. Molson Coors Brewing Co
480. Mondelez International Inc
481. Monsanto
482. Monster Beverage Corp
483. Monster Worldwide
484. Moody's Corp
485. Morgan Stanley
486. Mosaic Co
487. Motorola Mobility Holdings
488. Motorola Solutions Inc
489. Motors Liquidation Co
490. Murphy Oil Corp
491. Mylan NV
492. Nabors Industries Ltd
493. Nasdaq Inc
494. National City
495. National Oilwell Varco Inc
496. National Semiconductor
497. Navient Corp
498. Navistar International Corp
499. NCR Corp
500. NetApp Inc
501. Netflix Inc
502. New York Times Co
503. Newell Brands Inc
504. Newfield Exploration Co
505. Newmont Mining Corp
506. News Corp
507. Nextel Comms
508. Nextera Energy Inc
509. Nielsen Holdings PLC
510. Nike Inc
511. NiSource Inc
512. Noble Corporation PLC
513. Noble Energy Inc
514. Nordstrom Inc
515. Norfolk Southern Corp
516. Nortel Networks
517. North Fork Bancorp
518. Northern Trust Corp
519. Northrop Grumman Corp
520. Norwegian Cruise Line Holdings Ltd
521. Novell
522. Novellus System
523. NRG Energy Inc
524. Nucor Corp
525. NVIDIA Corp
526. NYSE Euronext
527. Occidental Petroleum Corp
528. Office Depot Inc
529. OfficeMax
530. Omnicom Group Inc
531. ONEOK Inc
532. Oracle Corp
533. O'Reilly Automotive Inc
534. Owens-Illinois Inc
535. Paccar Inc

536. Packaging Corp of America
537. Pactiv
538. Pall Inc
539. Palm Inc
540. Park Hotels & Resorts Inc
541. Parker-Hannifin Corp
542. Patterson Companies Inc
543. Paychex Inc
544. PayPal Holdings Inc
545. Peabody Energy Corp
546. Pentair PLC
547. Peoples Energy
548. People's United Financial Inc
549. Pepsi Bottling Corporation
550. PepsiCo Inc
551. PerkinElmer Inc
552. Perrigo Company PLC
553. PetSmart
554. Pfizer Inc
555. PG&E Corp
556. Philip Morris International Inc
557. Phillips 66
558. Pinnacle West Capital Corp
559. Pioneer Natural Resources Co
560. Pitney Bowes Inc
561. Plum Creek Timber Company
562. PMC Sierra
563. PNC Financial Services Group Inc
564. Power One
565. PPG Industries Inc
566. PPL Corp
567. Praxair Inc
568. Precision Castparts
569. Principal Financial Group Inc
570. Procter & Gamble Co
571. Progress Energy
572. Progressive Corp
573. Prologis Inc
574. Providian Financial
575. Prudential Financial
576. PTC Inc
577. Public Service Enterprise Group Inc
578. Public Storage
579. PulteGroup Inc
580. PVH Corp
581. QEP Resources Inc
582. QLogic
583. Qorvo Inc
584. Qualcomm Inc
585. Quanta Services Inc
586. Quest Diagnostics Inc
587. Questar
588. Qwest Communications International
589. Ralph Lauren Corp
590. Range Resources Corp
591. Raymond James Financial Inc
592. Raytheon Co
593. Realogy Holdings Corp
594. Realty Income Corp
595. Red Hat Inc
596. Reebok International
597. Regency Centers Corp
598. Regeneron Pharmaceuticals Inc
599. Regions Financial Corp
600. Republic Services Inc
601. Resmed Inc
602. Reynolds American
603. Robert Half International Inc
604. Rockwell Automation Inc
605. Rockwell Collins Inc
606. Rohm & Haas
607. Roper Technologies Inc
608. Ross Stores Inc
609. Rowan Companies PLC
610. Royal Caribbean Cruises Ltd
611. RR Donnelley & Sons Co
612. RS Legacy
613. Ryder System Inc
614. S&P Global Inc
615. Sabre Corp
616. Sabre Holdings
617. Safeco
618. Safeway
619. Salesforce.com Inc
620. SanDisk
621. Sanmina Corp
622. Santander Consumer USA Holdings Inc
623. Sapient
624. SBA Communications Corp
625. SCANA Corp
626. Schlumberger NV
627. Scientific Atlanta
628. Scripps Network Interactive
629. Seagate Technology PLC
630. Sealed Air Corp
631. Sears Holdings Corp
632. Sempra Energy
633. Sherwin-Williams Co
634. Siebel Systems
635. Sigma Aldrich
636. Signet Jewellers Ltd
637. Simon Property Group Inc
638. Skyworks Solutions Inc
639. SL Green Realty Corp
640. SLM Corp
641. Smith International
642. Snap-On Inc
643. Solectron Corp
644. Southern Co
645. Southwest Airlines Co

646. Southwestern Energy Co
647. Spectra Energy
648. Spectra Energy Partners LP
649. Sprint Corp
650. Sprint Nextel
651. St Jude Medical
652. Stanley Black & Decker Inc
653. Staples
654. Starbucks Corp
655. Starwood Hotels & Resorts Worldwide
656. State Street Corp
657. Stericycle Inc
658. Stryker Corp
659. Sun Microsystems
660. SunEdison
661. SunGard Data
662. Sunoco
663. SunTrust Banks Inc
664. Supervalu Inc
665. Symantec Corp
666. Symbol Technologies
667. Synchrony Financial
668. Synovus Financial Corp
669. Sysco Corp
670. T. Rowe Price Group Inc
671. Tapestry Inc
672. Target Corp
673. TE Connectivity Ltd
674. TechnipFMC PLC
675. Teco Energy
676. Tegna Inc
677. Tektronix
678. Tellabs
679. Temple Inland
680. Tenet Healthcare Corp
681. Teradata Corp
682. Teradyne Inc
683. Terex Corp
684. Tesla Inc
685. Texas Instruments Inc
686. Textron Inc
687. Thermo Fisher Scientific Inc
688. Thomas and Betts
689. Tiffany and Co
690. Time Warner
691. Time Warner Cable
692. Titanium Metals
693. TJX Companies Inc
694. T-Mobile US Inc
695. Torchmark Corp
696. Total System Services Inc
697. Tractor Supply Co
698. Trane
699. TransDigm Group Inc
700. Transocean Ltd
701. Travelers Companies Inc
702. Tribune Media Co
703. TripAdvisor Inc
704. Tupperware Brands Corp
705. TXU
706. Tyson Foods Inc
707. U.S. Bancorp
708. UDR Inc
709. Ulta Beauty Inc
710. Under Armour Inc
711. Union Pacific Corp
712. Unisys Corp
713. United Continental Holdings Inc
714. United Rentals Inc
715. United States Steel Corp
716. United Technologies Corp
717. UnitedHealth Group Inc
718. Universal Health Services Inc
719. Univision
720. Unocal Corp
721. Unum Group
722. UPS Inc
723. Urban Outfitters Inc
724. US Airways Group
725. UST
726. Varian Medical Systems Inc
727. Ventas Inc
728. Verisign Inc
729. Verisk Analytics Inc
730. Veritas Software
731. Verizon Communications Inc
732. Vertex Pharmaceuticals Inc
733. VF Corp
734. Viacom Inc
735. Viavi Solutions Inc
736. Visa Inc
737. Visteon Corp
738. Vitesse Semiconductor
739. Vornado Realty Trust
740. Vulcan Materials Co
741. W W Grainger Inc
742. Wachovia Corp
743. Walgreens Boots Alliance Inc
744. Walmart Inc
745. Walt Disney Co
746. Washington Mutual
747. Waste Management Inc
748. Waters Corp
749. Weatherford International PLC
750. WEC Energy Group Inc
751. Wells Fargo and Co
752. Welltower Inc
753. Wendy's CO
754. Wendy's International
755. Western Digital Corp

756. Western Union Co
757. WestRock Co
758. Weyerhaeuser Co
759. Whirlpool Co
760. Whole Foods Market Co
761. Williams Companies Inc
762. Willis Towers Watson PLC
763. Windstream Holdings Inc
764. Winn Dixie Stores
765. WM Wrigley Jr
766. Worthington Industries Inc
767. WPX Energy Inc
768. Wyeth
769. Wyndham Destinations Inc
770. Wynn Resorts Ltd
771. Xcel Energy Inc
772. Xerox Corp
773. Xilinx Inc
774. XL Group
775. XTO Energy
776. Xylem Inc
777. Yum! Brands Inc
778. Zimmer Biomet Holdings Inc
779. Zions Bancorp
780. Zoetis Inc

Appendix 2: The Key for the Tables in Chapter 4 and the Figures in Appendix 3

The key for the tables and the figures is as follows.

"Extreme" indicates that the portfolio in question was constructed using the extreme quantiles method.

"100" or "500" indicates that the portfolio was constructed as a quantile of 100 or 500 shares, respectively.

"Run Immediately" or "Run" indicates that the investor implemented the reversal strategy immediately after the designated formation period closed.

"Skip a Day" or "Run Skip" indicates that the investor waited a day after the designated formation period closed before implementing the reversal strategy.

"Portfolio *k*" indicates that the portfolio was constructed using Quantile *k*, which consisted of equally weighted long positions in the twentieth of the shares in the sub-sample at position 21-*k* and equally weighted short positions in the twentieth of the shares at position *k*.

The shorthand notation for naming the 25 cases analysed gives the formation period first, followed by the holding period, joined by a hyphen.

"D" indicates a period of one calendar day.

"D7" indicates a period of seven calendar days.

"D14" indicates a period of fourteen calendar days.

"D21" indicates a period of twenty-one calendar days.

"D28" indicates a period of twenty-eight calendar days.

For example, "D14-D21" indicates that the formation period for the portfolio was fourteen calendar days and that the holding period was twenty-one days.

Appendix 3: Charts Illustrating the Results of this Investigation

Figures 5 to 11 are charts illustrating the cumulative returns that the investor would have realised for each $1 invested under any of the circumstances outlined. Figures 5 to 7 illustrate the cumulative returns to the investor from holding the worst-performing portfolios. Figures 8 to 10 illustrate the cumulative returns to the investor from holding the best-performing portfolios. Figure 11 illustrates the difference in cumulative returns depending on whether the investor held the best-performing portfolio for the entire sample period without interruptions or the investor held first the best-performing pre-crash portfolio, followed by a switch to the best-performing post-crash portfolio.

The key for the charts below is as given in Appendix 2.

Figure 5 illustrates the cumulative return to the investor from holding the worst-performing pre-crash portfolio. "Extreme 500 D-D7 Run (Portfolio 1)" means the following. The extreme twentieths method was used to construct the portfolio, using a sub-sample of 500 shares. The formation period was one calendar day, the holding period was seven calendar days. The investor implemented the reversal strategy immediately after the formation period closed and the portfolio in question consisted of long positions in shares 476-500 balanced against short positions in shares 1-25, as ranked based upon performance in the formation period.

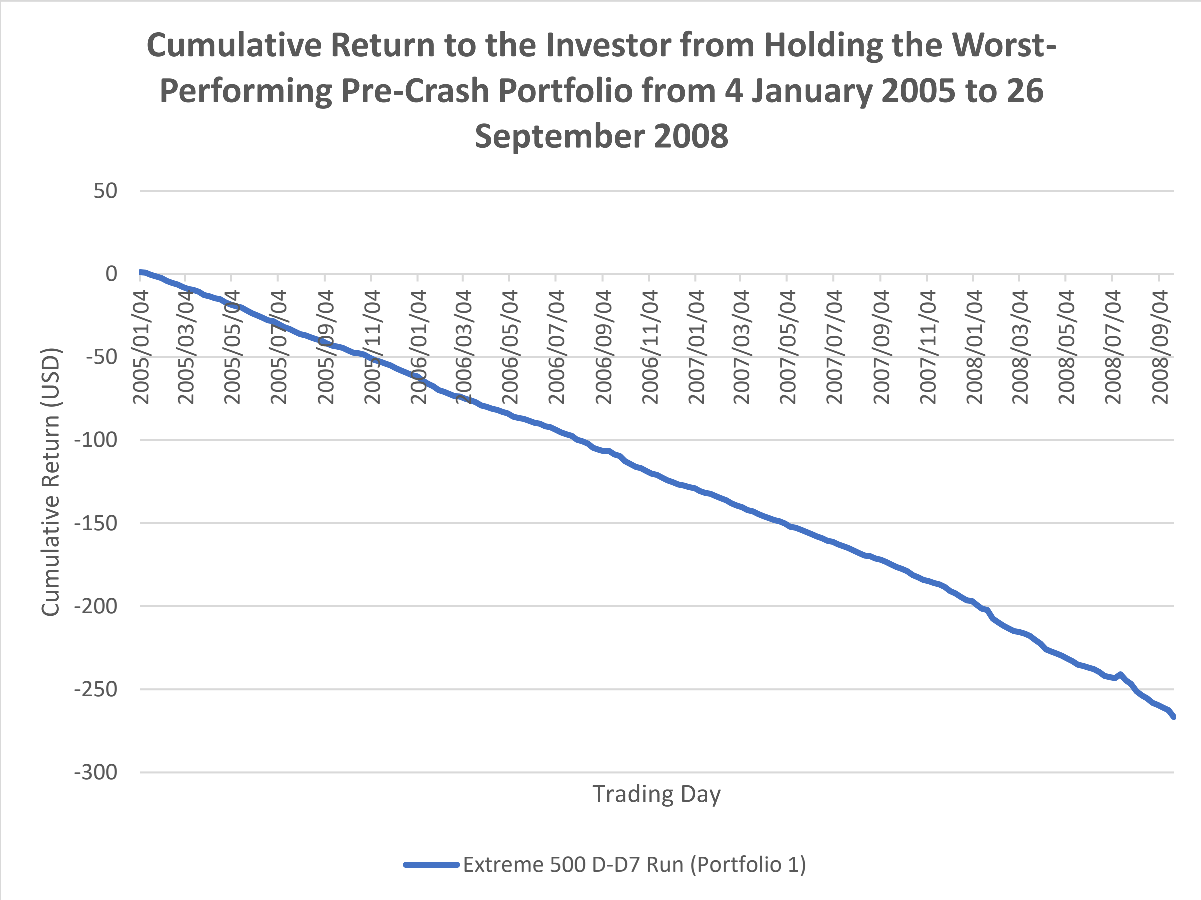

Figure 5: the cumulative return to the investor from holding the worst-performing pre-crash portfolio from 4 January 2005 to 26 September 2008.

As can be seen, the investor would have lost money almost immediately after implementing the reversal strategy and would have continued to lose money over time, until finally realising a negative cumulative return of approximately $266.62 for every $1 invested.

Figure 6 illustrates the cumulative return to the investor from the worst-performing post-crash portfolio.

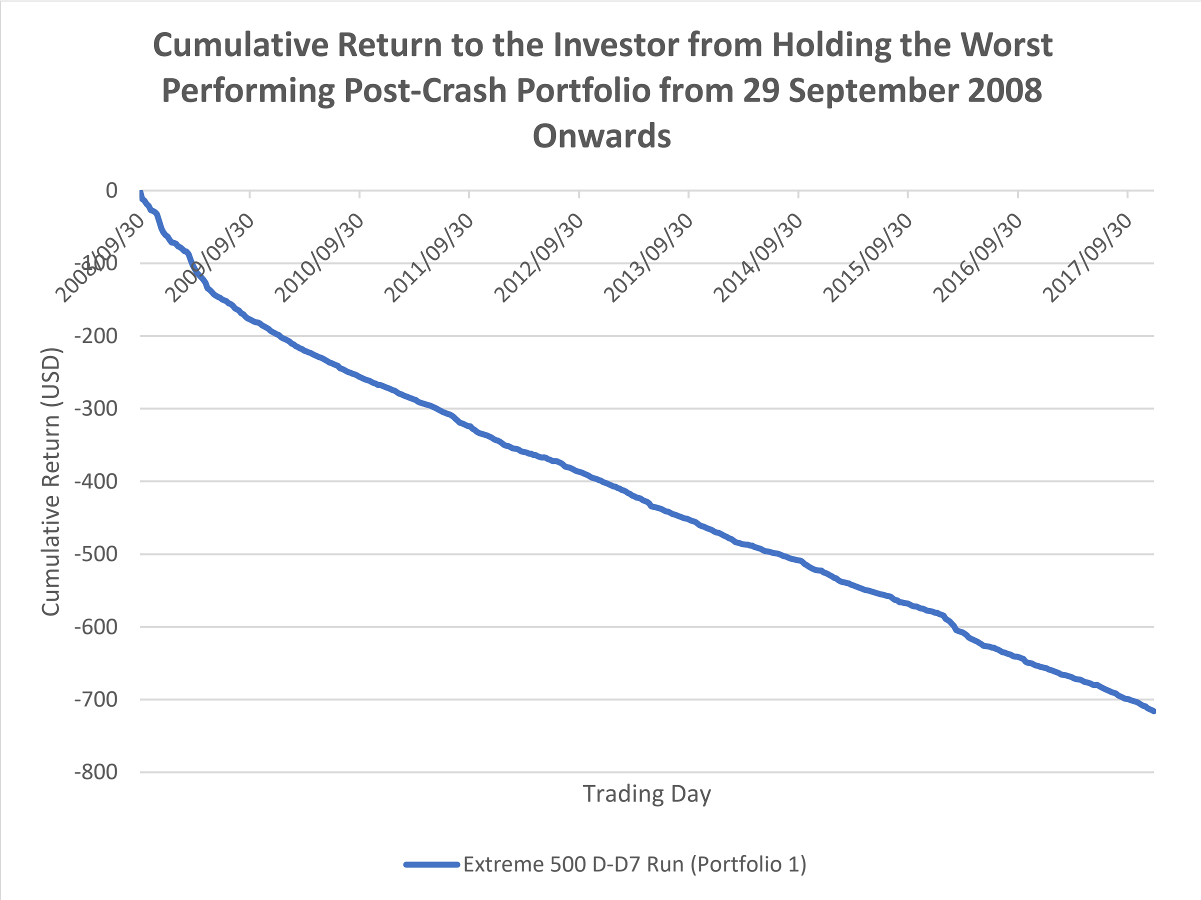

Figure 6: the cumulative return to the investor from holding the worst-performing post-crash portfolio from 29 September 2008 to 29 December 2017.

As can be seen, the investor would have incurred cash losses almost immediately after implementing the reversal strategy and said losses would have increased over time, culminating in a negative cumulative return of approximately $716.10 for every $1 invested.

Figure 7 illustrates the cumulative return to the investor from holding the worst-performing portfolio for the entire sample period.

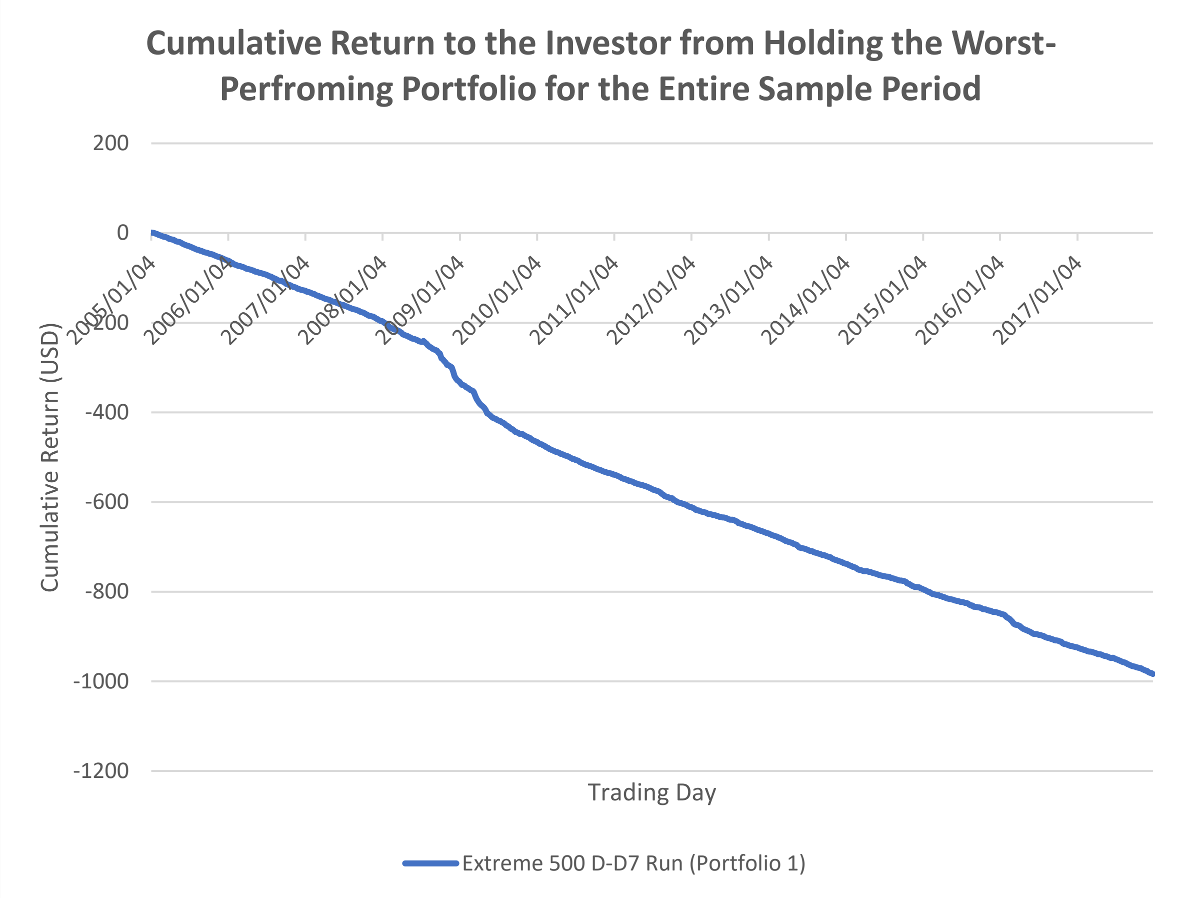

Figure 7: the cumulative return to the investor from holding the worst-performing portfolio from 4 January 2005 to 29 December 2017.

As can be seen, the investor would have incurred cash losses almost immediately after first implementing the strategy and said losses would only have increased with time, rising to a negative cumulative return of approximately $983.72 for every $1 invested in the reversal portfolio.

Figure 8 illustrates the cumulative return to the investor from holding the best-performing pre-crash portfolio. "Extreme 500 D-D Run Skip (Portfolio 3)" means the following. The extreme twentieths method was used to construct the portfolio, using a sub-sample of 500 shares. The formation and holding periods were both one calendar day. The investor implemented the reversal strategy a day after the formation period closed and the portfolio in question consisted of long positions in shares 426-450 balanced against short positions in shares 51-75, as ranked based upon performance in the formation period.

Figure 8: the cumulative return to the investor from holding the best-performing pre-crash portfolio from 5 January 2005 to 26 September 2008.

As can be seen, the investor would have made cash gains almost immediately after implementing the reversal strategy and would generally have continued to do so in each period thereafter, culminating in a positive cumulative return of approximately $27.47 for every $1 invested.

Figure 9 illustrates the cumulative return to the investor from holding the best-performing post-crash portfolio. “Extreme 500 D-D Run (Portfolio 2)” means the following. The extreme quantiles method was used to construct the portfolio, using a sub-sample of 500 shares. The formation and holding periods were both one calendar day. The investor implemented the reversal strategy immediately after the formation period closed and the portfolio in question consisted of long positions in shares 451-475 balanced against short positions in shares 26-50, as ranked based upon performance in the formation period.

Figure 9: the cumulative return to the investor from holding the best-performing post-crash portfolio, from 29 September 2008 to 29 December 2017.

As can be seen, the investor would have made cash gains almost immediately after implementing the reversal strategy and would generally have continued to do so in each period thereafter, culminating in a positive cumulative return of approximately $34.92 for every $1 invested.

Figure 10 illustrates the cumulative return to the investor from holding the best-performing portfolio for the entire sample period.

Figure 10: the cumulative return to the investor from holding the best-performing portfolio from 4 January 2005 to 29 December 2017.

The performance of the portfolio was slow but positive in the first two years, but a patient investor would have seen a subsequent rally followed by a more gradual and relatively constant growth, culminating in a positive cumulative return of approximately $45.90 for every $1 invested.

Figure 11 illustrates the cumulative return to the investor from holding the best-performing portfolio for the entire sample period as opposed to holding the best-performing pre- and post-crash portfolios.

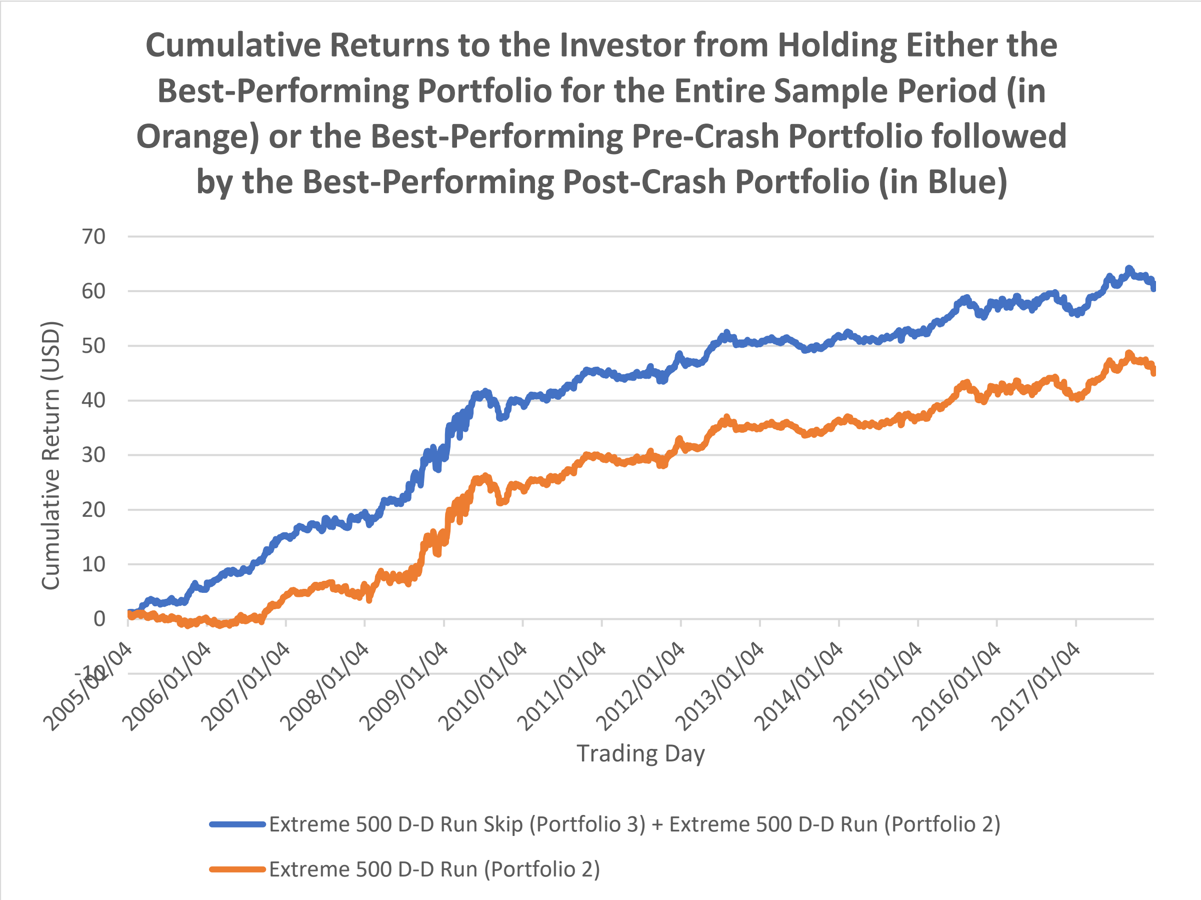

Figure 11: a side-by-side comparison of the cumulative returns to the investor from holding either the best-performing portfolio for the entire sample period or the best-performing pre- and post-crash portfolios.

As can be seen, the investor's cumulative return would have been higher if he or she had held the best-performing pre- and post-crash portfolios, than if he or she had only held the best-performing portfolio for the entire sample period. The orange option yields a total cumulative return of approximately $45.90 for every $1 invested; the blue option yields a total cumulative return of $61.39 for every $1 invested.

Appendix 4: Tables of portfolios with positive average returns and significant average returns, over the three time periods considered

The following tables indicate which reversal portfolios had positive average returns and which reversal portfolios had significant average returns, for every case considered in each of the time periods of interest.

The key for reading the tables, which is also in Appendix 2, is as follows.

A specific case is to be identified first by its formation period, then by its holding period. To that end, one must first scroll horizontally to find the appropriate formation period, then vertically to find the appropriate holding period for that case.

The numbers in the cells indicate the reversal portfolios in that case, for that grouping, that met the criterion of the table in question over the time period of interest. An empty cell indicates that no portfolio satisfied the criterion of the table in that case, for that grouping.

The shorthand notation for naming the 25 cases analysed gives the formation period first, followed by the holding period, joined by a hyphen.

"D" indicates a period of one calendar day.

"D7" indicates a period of seven calendar days.

"D14" indicates a period of fourteen calendar days.

"D21" indicates a period of twenty-one calendar days.

"D28" indicates a period of twenty-eight calendar days.

For example, "D-D7" indicates that the formation period for the portfolio was one calendar day and that the holding period was seven calendar days.

The following six tables relate to portfolios constructed as quantiles of 100 shares, where the investor implemented the reversal strategy immediately.

Table 16 details the portfolios in each case that had positive average returns, over the entire sample period. Table 17 details the portfolios in each case that had significant average returns, over the entire sample period.

Portfolios with positive average returns, in each case, over the entire sample period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	2,3,4,5,6,7,8,9	1,2,3,4,5,6,7,8,10	1,2,3,4,5,7,8,9,10	1,2,3,4,5,6,7,8,9,10	2,3,5
	D7		6	3,5,10	5,6,9,10	4,6,8,9
	D14			8,10	4,6,8,9	4,6,8,9
	D21	4,8	1,2,3,4,5,6,9,10	2,5,7,8,9,10	4,5,7,8,9	3,4,8,9,10
	D28	5,9	2,3,5,7,9,10	7,8,9	1,4,6,7,8,9,10	1,4,6,7,8,9

Table 16: portfolios with positive average returns, in each case, over the entire sample period.

Portfolios with significant average returns, in each case, over the entire sample period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	1,7,10	4	4	4	4
	D7	1,2,3,4,5,6,7,8,9,10	4	1,6,9	1,6	1,2
	D14		1,2,3,4,5,7,10	1,3	1,2,5	2
	D21	3			2	4
	D28	3,4	5			6

Table 17: portfolios with significant average returns, in each case, over the entire sample period.

Table 18 details the portfolios in each case that had positive average returns, over the pre-crash period. Table 19 details the portfolios in each case that had significant average returns, over the pre-crash period.

Portfolios with positive average returns, in each case, over the pre-crash period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	2,3,4,6,7,9,10	1,3,4,5,6,10	1,3,4,5,7,8,9,10	3,4,5,6,7,9	3,4,5,6,7,8,10
	D7		2,4,5	3,5,8,10	5,6,9,10	4,6,8,9
	D14			8	9	6,8,9
	D21	1,2,3,7	4,6	5,9	4,8,9	4,7
	D28	2	2,4,5,6,7,8,9	4,5	9,10	1,7,8

Table 18: portfolios with positive average returns, in each case, over the pre-crash period.

Portfolios with significant average returns, in each case, over the pre-crash period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	1,6,7	5		4	4,7
	D7	1,2,3,4,5,6,7,8,9,10	9	1	1,6,8	1
	D14	1,2,3,4,6,8,9	4,7,9,10	1,2,3	1	1
	D21	3,6		3,4	3,10	
	D28	1,6		1	3	3,10

Table 19: portfolios with significant average returns, in each case, over the pre-crash period.

Table 20 details the portfolios in each case that had positive average returns, over the post-crash period. Table 21 details the portfolios in each case that had significant average returns, over the post-crash period.

Portfolios with positive average returns, in each case, over the post-crash period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	2,3,4,5,6,7,8,9,10	1,2,3,4,6,7,8,10	1,2,3,4,5,7,8,9,10	1,2,4,5,6,7,8,10	1,4,6,7,8,9,10
	D7			2,3,4,5	4,5,6,8,9,10	3,4,5,6,7,8,9,10
	D14			8,9,10	4,6,8,9	4,8,10
	D21	1,4,7	1,2,3,4,5,6,9,10	1,2,3,4,5,6,7,8,9,10	1,5,6,7,8,9,10	1,2,3,4,8,9,10
	D28	5,6,7,8,9	2,3,7,9,10	1,6,7,8,9	1,3,4,6,7,8,10	1,3,4,6,7,8,9,10

Table 20: portfolios with positive average returns, in each case, over the post-crash period.

Portfolios with significant average returns, in each case, over the post-crash period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	7,8,9,10	4	5,7	4	4
	D7	1,2,3,4,5,6,7,8,9,10	3,4	1,6,9		2
	D14	1,2,3,4,5,6,7,8,9,10	1,7,10	1	5	2
	D21	10	9	2,7,8		3
	D28	3	7			6

Table 21: portfolios with significant average returns, in each case, over the post-crash period.

The following six tables relate to portfolios constructed as quantiles of 500 shares, where the investor implemented the reversal strategy immediately.

Table 22 details the portfolios in each case that had positive average returns, over the entire sample period. Table 23 details the portfolios in each case that had significant average returns, over the entire sample period.

Portfolios with positive average returns, in each case, over the entire sample period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	1,2,3,4,5,6,7,8,9, 10	3,6,8	1,2,3,6,8, 10	1,2,3,4,5,6,7,8	1,2,3,4,5,6, 7,8,9
	D7		7,9	10	2,3,5,7,8	2,6,8,9,10
	D14	10		4,10	2,5,7,8,9,10	5,6,8,9
	D21	2,5,6,7,10	1,2,4,6,8,9	2,3,7,8	2,4,5,7,9,10	2,5,9
	D28	6,10	2,4,5,6,7,8,9,10	1,2,3,4,5, 8,10	2,4,5,6,9,10	2,3,4,5,6

Table 22: portfolios with positive average returns, in each case, over the entire sample period.

Portfolios with significant average returns, in each case, over the entire sample period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	2,7,8	7	1,3,4	10	2,7
	D7	1,2,3,4,5,6,7,8,9	1	1,2,3,4,5,6,7,8,9		
	D14	1,2,3,4,5,6,7,8	1,2,3	1,3,6,8,9	1	1
	D21		9			
	D28	3,8,10			4,5,10	4

Table 23: portfolios with significant average returns, in each case, over the entire sample period.

Table 24 details the portfolios in each case that had positive average returns, over the pre-crash period. Table 25 details the portfolios in each case that had significant average returns, over the pre-crash period.

Portfolios with positive average returns, in each case, over the pre-crash period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	2,5,6,7,8,9	1,2,3,6,8,10	1,3,4,6,10	1,2,3,4,5,6,8,9	1,2,3,5,7,8,9,10
	D7		4,6,7,9	10	2,5,6,8,10	2,7,8,9,10
	D14		7,10	10	5,10	2,6,8,9
	D21	2,4,5,6,7,9,10	4,6,8,9	3,5,6,7,10	3,5,6,7,9,10	3,4,5,9
	D28	10	2,3,4,6,7,8	3,4,6,8,10	4,5,7,10	4,8

Table 24: portfolios with positive average returns, in each case, over the pre-crash period.

Portfolios with significant average returns, in each case, over the pre-crash period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	6,8	4,7		9	9
	D7	1,2,3,4,5,6,7,8,9		1,2,3,4,5,6,7,8,9	7	
	D14	1,2,3,4,5,6,8	1,2,9	1	1,3	1,5,6,7
	D21	5	4			
	D28	1,2,8	9		3	

Table 25: Portfolios with significant average returns, in each case, over the pre-crash period.

Table 26 details the portfolios in each case that had positive average returns, over the post-crash period. Table 27 details the portfolios in each case that had significant average returns, over the post-crash period.

Portfolios with positive average returns, in each case, over the post-crash period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	1,2,3,4,5,6,7,8 ,9, 10	3,4,6,8	1,2,3,4,5,6,7,8,9, 10	1,2,3,4,5,6, 7,8	1,2,3,4,5,6,7,8,9
	D7		9		2,3,4,5,7,8	2,5,6,8
	D14	10	9	2,4,10	2,3,4,6,7,8, 9,10	5,7,8,9,10
	D21	5,6,10	1,2,6,7,9	1,2,7,8,9	2,4,5,7,9,10	1,2,5,7
	D28	2,6,10	2,4,5,6,9, 10	2,4,7,8,10	1,2,3,4,5,6, 9,10	2,3,4,5,6,7,9,10

Table 26: portfolios with positive average returns, in each case, over the post-crash period.

Portfolios with significant average returns, in each case, over the post-crash period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	2,7		3,7	7,9,10	7
	D7	1,2,3,4,5,6,7,8,9	1	1,2,3,4,5,6,7,8,9	7,10	
	D14	1,2,3,4,5,7,8	1,2,7,8,10	9		
	D21		9	2		
	D28	10			4,10	2,4,5

Table 27: portfolios with significant average returns, in each case, over the post-crash period.

The following six tables relate to portfolios constructed as quantiles of 100 shares, where the investor skipped a day before implementing the reversal strategy.

Table 28 details the portfolios in each case that had positive average returns, over the entire sample period. Table 29 details the portfolios in each case that had significant average returns, over the entire sample period.

Portfolios with positive average returns, in each case, over the entire sample period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	1,4,5,6,7,8,9,10	1,2,3,4,5,6,7,8,9,10	1,2,5,6,7,9,10	1,2,3,5,6,7,9	4,6,7,8,9,10
	D7	1,2,3,4,5,6,7,8,9	1,2,3,6,7,8,9	3,5,10	1,3,4,5,6,7,9,10	3,4,5,6,7,8,9
	D14	5,6,7	2,3,6,8	2,4,5,8,9,10	3,4,6,7,8,9,10	1,3,4,6,8,9,10
	D21	1,2,4,5,6,8	1,3,9,10	2,5,7,8,9,10	7,8,9	3,4,6,8,9,10
	D28	5,6,9	2,3,5,7,8,9,10	6,7,8,9	1,4,7,8,9,10	1,6,7,8,9

Table 28: portfolios with positive average returns, in each case, over the entire sample period.

Portfolios with significant average returns, in each case, over the entire sample period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	6,7	2,3,4,6,9	9		4
	D7			1,6,7,9	6,9	6
	D14	1,3		10	6	2
	D21	3			2,3	
	D28	3	7,9		2	6

Table 29: portfolios with significant average returns, in each case, over the entire sample period.

Table 30 details the portfolios in each case that had positive average returns, over the pre-crash period. Table 31 details the portfolios in each case that had significant average returns, over the pre-crash period.

Portfolios with positive average returns, in each case, over the pre-crash period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	1,2,3,4,5,6,7,8,9,10	1,2,3,4,6,7,8,9,10	1,3,5,6,9	2,3,4,8,9,10	3,4,5,6,7,8,10
	D7	3,5,6,9	1,6,7,8	3,5,8,10	3,6,9,10	3,6,9
	D14	5,6,7,10	2,5,6	4,5,6,8	2,3,4,5,6,8,9,10	6,8,9,10
	D21	1,4,6,8,10		5	4,8,9	4,6
	D28	2,9	2,3,4,5,6,7,8,9,10	5,8	9,10	1,7,8

Table 30: portfolios with positive average returns, in each case, over the pre-crash period.

Portfolios with significant average returns, in each case, over the pre-crash period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	5,6,10	1,3,5			4,7
	D7			1	6,8	1,6
	D14	1				
	D21	3,8		1,3,4	3,10	1
	D28		8		2	3,10

Table 31: portfolios with significant average returns, in each case, over the pre-crash period.

Table 32 details the portfolios in each case that had positive average returns, over the post-crash period. Table 33 details the portfolios in each case that had significant average returns, over the post-crash period.

Portfolios with positive average returns, in each case, over the post-crash period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	1,4,6,7,8, 9,10	1,2,3,4,5,6,7 ,8,9,10	2,5,6,7,9,10	1,2,3,5,6,7	4,6,7,8,9,10
	D7	1,2,3,4,5, 6,7,8, 9	1,2,3,6,7,9	2,3,4,5	1,3,4,5,6,7,8,9,10	1,3,4,5,6,7,8,9 ,10
	D14	2,5,7,8	2,3,4,6,8,9	2,5,7,8,9,10	1,3,4,6,7,8,9,10	1,3,4,7,8,9,10
	D21	1,2,5,7	1,2,3,4,5,6,9 ,10	1,2,3,4,5,6, 7,8,9,10	2,3,4,6	1,3,4,8,9,10
	D28	1,5,6,7,8, 9	2,3,7,9,10	1,6,7,8,9	1,3,4,6,7,8,10	1,3,6,7,8,9,10

Table 32: portfolios with positive average returns, in each case, over the post-crash period.

Portfolios with significant average returns, in each case, over the post-crash period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	2	2,5,6	9		4
	D7			1,6,9	5,9	4,7,9
	D14	3,10		10	6	
	D21	3,10			2	9,10
	D28	5				7

Table 33: portfolios with significant average returns, in each case, over the post-crash period.

The following six tables relate to portfolios constructed as quantiles of 500 shares, where the investor skipped a day before implementing the reversal strategy.

Table 34 details the portfolios in each case that had positive average returns, over the entire sample period. Table 35 details the portfolios in each case that had significant average returns, over the entire sample period.

Portfolios with positive average returns, in each case, over the entire sample period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	1,2,3,4,5,6	2,6,7,8	1,2,3,4,5,6,7,9,10	1,2,3,4,5,6, 7,8	2,4,5,6,7,8,9,10
	D7	1,2,3,4,5,6 ,8,9,10	1,2,4,5,6,7,9, 10	10	1,2,3,4,5,6, 7,8	2,4,5,6,8,10
	D14	6,9,10	4,5,6,7,9	2,3,4,7,10	2,3,4,5,6,7, 8,9,10	2,4,5,6,8,9,10
	D21	4,5,7,10	4,6,9	2,6,7,8	5,7,9,10	2,5,6,9
	D28	6,10	1,2,3,4,5,6,7, 8,9,10	2,3,4,8,10	2,4,5,6,9,10	2,4,5

Table 34: portfolios with positive average returns, in each case, over the entire sample period.

Portfolios with significant average returns, in each case, over the entire sample period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	2,3	1,8	7	5	
	D7	3,5,10	9	1,2,3,4,5,6,7,8,9	2	
	D14	4,8		8,9	2	
	D21	5	5,9		1	
	D28	8,10	4,6		4	

Table 35: portfolios with significant average returns, in each case, over the entire sample period.

Table 36 details the portfolios in each case that had positive average returns, over the pre-crash period. Table 37 details the portfolios in each case that had significant average returns, over the pre-crash period.

Portfolios with positive average returns, in each case, over the pre-crash period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	1,2,3,4,5,6,7,8	1,2,6	1,3,4,5,7,9, 10	1,2,3,5,6,8,10	2,4,5,6,8,9, 10
	D7	2,3,4,5,6,7,8,9,10	2,3,4,6,7,9	10	2,5,6,8,10	6,8,10
	D14	2,3,5,7,9	4,6,7,8,10	2,3,4,6,8,9, 10	1,2,5,6,10	1,3,5,7,10
	D21	2,4,5,7,9,10	4,6,8,9	3,5,6,7,8	5,7,9,10	6,8,9
	D28	4,7,10	1,2,3,4,5,6,7, 8	3,4,6,8,10	4,5,7	4

Table 36: portfolios with positive average returns, in each case, over the pre-crash period.

Portfolios with significant average returns, in each case, over the pre-crash period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	2,3,6		9	5,9	
	D7	5	9	1,2,3,4,5,6,7,8,9		
	D14	1			5,10	5,6,7,8
	D21		4	1,7		7
	D28	8	2		1,3	5

Table 37: portfolios with significant average returns, in each case, over the pre-crash period.

Table 38 details the portfolios in each case that had positive average returns, over the post-crash period. Table 39 details the portfolios in each case that had significant average returns, over the post-crash period.

Portfolios with positive average returns, in each case, over the post-crash period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D	2,3,5,6	2,3,6,7,8	2,3,5,6,7	1,2,3,4,5,7,8,9	2,5,6,7,8,9,10
	D7	1,2,3,4,5,6,8,9,10	1,2,4,5,6,7,9		1,2,3,4,5,7,8,9	1,2,3,4,5,6,8
	D14	6,10	1,2,4,5,6,9	2,4,5,7,10	2,3,4,5,6,7,8,9,10	1,2,5,7,8,9,10
	D21	1,3,5,6,10	1,2,6,7,9	1,2,7,8,9	2,4,5,7,9,10	1,2,5
	D28	2,6,10	2,4,5,6,9,10	2,4,8,10	2,3,4,5,6,9,10	2,3,4,5,7,9,10

Table 38: portfolios with positive average returns, in each case, over the post-crash period.

Portfolios with significant average returns, in each case, over the post-crash period						
		Formation Period				
		D	D7	D14	D21	D28
Holding Period	D		1,8	6	10	
	D7	8,10		1,2,3,4,5,6,7,8,9	2,3,7	1,2
	D14	4,8,10		9	4,7	5
	D21		9	2		2
	D28	10	6		4	2,4,5

Table 39: portfolios with significant average returns, in each case, over the post-crash period.