Firm characteristics that drive the momentum pattern in the UK stock market

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Abstract

Previous studies have estimated the company characteristics of previous winners and losers to explore the momentum effect. Using UK data, this study focuses on the characteristics of companies that actually generate the momentum pattern. These are previous winners who keep performing well (WW) and past losers who consistently perform poorly (LL). This study illustrates that WW and LL firms may experience similar market-based characteristics such as young, low-priced, small capitalization, but that there are significant differences. Accounting and fundamental signals (e.g., profitability, value/growth) tend to distinguish winners from losers. Based on firm characteristics, we further develop investment strategies that can outperform significantly the profitability of the momentum strategy.

Keywords: Stock market efficiency, momentum effect, logit analysis, missing data.

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1. Introduction

One of the most widely discussed stock market anomalies in the literature is the momentum effect. Using US data, Jegadeesh and Titman (1993) report that the best performing shares (worst) over the previous three to twelve months tend to perform well (poorly) over the following three to twelve months. An investment method which buys the best performing firms (winners) over the previous three to twelve months and sells short firms which performed the worst (losers) over the past three to twelve months can generate abnormal profitability of approximately 1 percent per month. A number of studies have shown that momentum returns exist for a global range of stock markets (e.g., Griffin et al., 2003; Meade and Beasley, 2010). Moreover returns cannot be explained by commonly used proxies of risk such as the Capital Asset Pricing Model and the Three-Factor Model (Liu et al., 1999).

A number of studies have analyzed the characteristics of companies to explain the momentum returns by exploring the previous winner and loser portfolios. Hong et al. (2000) report the significance of market capitalization on the magnitude of momentum returns. They conclude that beyond the first few small capitalization companies, there is a continuous decline of momentum

profits as the investor moves to portfolios of shares with higher market values. Liu et al. (1999) find that winners and losers tend to be low-priced companies, but winners tend to be glamour companies and losers seem to be value firms. Lee and Swaminathan (2000) report that firms with high (low) trading volume experience glamour (value) characteristics and realize low (high) returns over the following period. A number of studies (e.g., Liu et al., 1999) have found that winners and losers tend to have higher betas in relation to the remaining sample, but winners' betas are lower than those of losers. Nevertheless none of these alternative explanations appear able to subsume the effect (e.g., Fama and French, 1996).

The present study offers an insight into the sort of companies that drive the momentum pattern. Prior studies (e.g, Jegadeesh and Titman, 1993) have incorporated all firms into the winner and loser portfolios to explore the momentum effect. This paper argues that the momentum effect is driven by the prior winners (losers) that keep performing well (poorly) rather than the whole prior winner/loser portfolio. For example, some of the previous winners (losers) may perform poorly (well) over the next period. This study focuses on the characteristics of the previous winners (losers) that keep performing well, WW (poorly, LL).

This study uses UK data and employs the following fourteen firm characteristics to explore the momentum pattern; market capitalization, price, trading volume, book/market, sales/market, standard deviation, beta, age,

profit margin, current ratio, return on common equity, return on capital employed, profits/losses and growth in sales. The selected variables are based on previous factors which have been shown to be associated with momentum and on key fundamental factors of companies with a theoretical motivation. These firm characteristics are not an exhaustive list of potential factors. They can however offer a good basis on which to develop an insight into the sort of companies that generate the momentum pattern.

This study's findings indicate that WW and LL companies share some common characteristics: they are small, low-priced and young. They differ significantly, however, with respect to other variables. LL firms are glamour, non-profitable and high-risk companies. WW securities are instead value companies with high book-to-market, net sales to market ratio and high trading volume. These results show that extreme winner and loser performers may experience similar market-based signals, but accounting and fundamental signals tend to distinguish winners from losers. We further explore the extent our models can be employed for investment purposes. We find that hybrid strategies that combine momentum and models developed in this study can enjoy returns significantly higher than those found in the momentum strategy.

The remainder of this paper is set out as follows: - Section 2 explains the data and how it has been utilized; Section 3 shows empirical results; and Section 4 concludes the study.

2. Calculation of momentum returns and data collection

2.1. Estimation of momentum profits

This study calculates momentum profits by ranking companies on the basis of their stock market performances over the previous twelve months (rank period). Companies should have traded for the full twelve months to be included in the sample. The quintile portfolio with the best (worst) performance is the winner, W (loser, L) portfolio. This study uses quintiles to define winners and losers rather than deciles because this paper uses a larger number of portfolios than a conventional momentum study, and therefore by using quintiles, each portfolio includes a reasonable number of companies.

The momentum effect is calculated on the compound returns of each of the equally-weighted portfolios over the following twelve-month period after the rank period (test period). If a company becomes delisted during the test period, the respective return is assigned a value equal to zero from the date of delisting. The study period of twelve months was selected to follow the momentum strategy, since only long-term momentum strategies can be exploitable within a practical setting (Agyei-Ampomah, 2007). This procedure is repeated for each non-overlapping twelve-month period. The difference between winner and loser portfolio returns (W-L) shows the profitability of the momentum strategy.

2.2. Data

This study utilizes monthly return information ($\ln ri_t - \ln ri_{t-1}$) for all listed ($fbrit$) and delisted ($deaduk$) non-financial ($icbic = 8{,}000$) UK companies reported by Datastream. The inclusion of dead companies ensures that the sample is free of survivorship bias. The period extends from August 1988 to July 2006. The sample period focuses on the post-1988 period, since Datastream only offers share returns, including dividend information, post-1988. Foreign firms are identified using the $geog$ datatype, non-equities using the $type$ datatype and preference shares with a 'pf' or 'pref' in their name. All of these firms are excluded. The total number of firms analyzed is 2,689, with on average 820 companies per period.

The following company characteristics are collected from Datastream:

SIZE (mv) shows the market capitalization (in £ millions). The time selected is a month before each rank period. A number of studies (e.g., Hong et al., 2000) have shown that small capitalization companies tend to drive the momentum pattern. [1]

PRICE (up) shows the share price of companies (£ in pence). This is an unadjusted price for bonus and rights issues and shows the actual price as it

[1] In unreported results, this study also investigates whether empirical findings regarding size (SIZE) are driven by recent period data. Each firm's market capitalisation at month t is divided with the average market capitalisation of the full sample at month t and values are re-calculated. Findings indicate that results remain rather similar using both scaled and un-scaled methods.

was recorded on the day. The time selected is a month before each rank period. Liu et al. (1999) employ this datatype to explore share price information and conclude that winners and losers tend to be low-priced companies.

VOLUME ($vo/nosh$) is the trading volume divided by the number of outstanding shares. Raw trading is adjusted by the number of outstanding shares, since raw trading is un-scaled. The time selected for both variables is a month before each rank period. Lee and Swaminathan (2000) show that firms with high (low) trading volume experience glamour (value) characteristics and realise low (high) returns over the following period.

BM (nta/mv) shows the book-to-market ratio. Companies with negative book-values have been excluded from the sample. SM ($wc01001/mv$) shows the net sales divided by market value. The time selected for net sales and book values is the last financial year-end result before each rank period [2] and market value is a month before each rank period. A number of studies (e.g., Fama and French, 1992; O'Shaughnessy, 1998; Beneish et al., 2001) have found that both BM and SM variables are positively related with future returns. Winners tend also to be glamour companies and losers are value firms (Liu et al., 1999).

[2] Unlike US companies, the financial year-end of the companies in the sample varies significantly. 39 percent of the companies have a financial year end December and 21 percent March. The least used month as a financial year end is November (only 1 percent of firms). A six month-gap is used to ensure that the information reported in the statements is reflected in share prices.

STDEV shows the standard deviation for each share using daily returns for a year prior to each rank period. This provides a large number of observations and a relatively stable estimate of the risk of firms throughout the year. Arena et al. (2008) find that there is a strong positive association between different measures of volatility and magnitude of momentum returns.

BETA is the aggregate coefficient betas of Dimson (1979) – one lag and one lead. The time selected is 24 monthly returns for each share before each rank period. Market returns are calculated using an equal-weighted index from the returns of the sample. A number of studies (e.g., Liu *et al.*, 1999) have found that winners and losers tend to have higher betas in relation to the remaining sample, but winners' betas are lower than those of losers.

AGE (*bdate*) indicates the age of firms as number of years from the date that Datastream offers information until assigned to a portfolio. Beneish (1999b) reports that young growth firms experience large share price movements, since they have a high risk of bankruptcy.

A number of key fundamental firm characteristics are also considered. The selected variables are far from exhaustive. MARGIN (717) shows the net profit margin, CURRENT (741) the current ratio, ROE (701) the return on common equity and ROCE (707) the return on capital employed. The time selected for those variables is the last financial year-end result before each rank period. NPROFIT (623) is a dummy variable equal to 1 if a company

has negative after tax profits at the latest financial statement before each rank period and 0 otherwise. GSALES ($wc01001$) shows the growth of sales and is motivated by Beneish (1999a) and Beneish et al. (2001). Beneish (1999a) for example reports that earnings manipulators tend to report high sales growth. In line with prior literature (e.g., Beneish et al., 2001), GSALES is estimated as sales reported at the latest financial statement before each rank period, divided by sales reported two years before ($sales_t / sales_{t-1} - 1$). [3]

It would appear that no previous study has investigated the association between these key fundamental factors and momentum profitability. A number of studies have, however, shown association between accounting information and share returns. For example, Reinganum (1988) and Beneish et al. (2001) use US data and investigate nine and 20 indicators respectively to distinguish and predict future winners and losers. Consistent with Beneish et al. (2001), extreme winner and loser performers may experience similar market-based signals, but accounting signals distinguish winners from losers.

Overall, the selection of these variables is based on previous factors that have been found to be associated with momentum and on some key fundamental factors of companies with a theoretical motivation. An alternative method could be to select as many variables as possible, allowing the final choice of

[3] The time selected for the above measures is to avoid endogeneity issues by contaminating characteristics of companies with their performances. For example, if the market capitalization of losers (winners) is collected using the rank period, losers (winners) would exhibit low (high) size simply due to the portfolio construction. The time selected for the above measures is in line with that used within the literature (e.g., Liu et al., 1999).

variables to emerge from the empirical analysis. A disadvantage with this method is that the reported model may perform well within the dataset, but poorly using an alternative dataset and thus, an out-of-sample analysis is essential to test for external validity. There may also be a statistical association between two variables when there is no theoretical explanation. Given that the objective of this study is to understand firm characteristics that drive the momentum pattern, the first option is selected. Stated differently, the selected fourteen variables may not be an exhaustive list of potential factors but they do offer a good basis to develop an insight into the sort of companies that generate the momentum pattern.

2.3. Treatment of missing data [4]

Since WW and LL firms tend to be small capitalization firms, this study follows two approaches in dealing with missing firm characteristics. The first is commonly used in accounting and finance literature: the listwise deletion approach. According to this method, researchers delete listwise companies with any missing firm characteristic and thus, the sample includes firms with complete characteristics. One of the disadvantages of this method is that it can incorrectly assume that data are missing completely at random. Small capitalization companies tend to exhibit a larger percentage of missing data in comparison to their counterpart large capitalization companies and therefore,

[4] Alison (2001) offers a comprehensive review on alternative missing data treatments. Researchers within various fields have also used alternative approaches - e.g., in political studies (King et al., 2001), in psychology (Roth et al., 1996; Roth, 2006), in clinical studies (Molenberghs and Kenward, 2007).

the listwise deletion method may generate biased parameter estimates. Another disadvantage of using the listwise deletion approach is that this may significantly reduce the sample size.

The second method used by this study in dealing with missing firm characteristics is the Expectation Maximisation (E-M) algorithm (Dempster et al., 1977) which uses the full initial sample of companies and fills-in any missing firm characteristic. The E-M algorithm is perhaps the most widely used imputation method. There are two steps that are repeated until convergence to the maximum likelihood estimates is reached. In the first step, available data are used to estimate the parameters and in the second step, the parameters are used to estimate the missing firm characteristics. Then the parameters are re-estimated using the filled-in data and this process continues until the estimates converge and so with new iterations the estimates hardly change. A large number of iterations (equal to 144) were required due to the large percentage of missing firm characteristics.

Table 1 shows the percentage of missing firm characteristic for the full and WW LL samples. This study finds that the percentage of missing values for the full sample is relatively high for some variables. For example, 28.4 percent of the volume data are missing. Using the listwise deletion method, all missing information listwise should be deleted which implies only 5,645 firm-years can be used out of the total 12,192 firm-years. This is a significant reduction in the sample. The percentage of missing data is also a bit higher for

the WW LL sample in comparison to the full sample. WW and LL tend to be small capitalization firms and thus, a greater percentage of missing information is to be expected. This study uses both approaches to deal with missing data across the study to explore the extent results may change based on the method followed.

3. Empirical findings

3.1. Momentum returns and distribution of past performance portfolios

Table 2 shows the momentum profitability found within the initial and listwise deletion samples. [5] The findings indicate that compound momentum returns (W-L) are 2.31 (1.24) percent per month in the initial (listwise deletion) sample. Profits in both samples are statistically significant at the 1 percent level and are driven by the loser companies. The difference in momentum profitability between the two samples is economically significant, but not statistically significant ($p-value = 0.14$). Momentum profits are lower using the listwise deletion sample since small capitalization firms, which tend to generate the momentum pattern, display a greater number of missing data and therefore were deleted.

Overall, the strong momentum returns found in this study are consistent with those reported in the US/UK literature (e.g., Jegadeesh and Titman, 1993; Liu

[5] To clarify, the *listwise deletion sample* includes only firms that exhibit all required firm characteristics available from Datastream, the *initial sample* includes the full list of companies with missing or not firm characteristics and the *E-M algorithm sample* includes the full list of companies with the actual (available from Datastream) and fill-in firm characteristics.

et al., 1999; Hon and Tonks, 2003; Chelley-Steeley and Siganos, 2008). In unreported results, momentum returns are strong during the sample period and profits remain strong (around 2 percent per month) in the post-2003 period. This result shows that the momentum effect holds a decade from first being reported in the literature.

It is now possible to investigate the distribution of past portfolios over the following test period by calculating the percentage of previous losers that fall in the loser, 2, 3, 4 and winner quintile portfolios over the following test period. Based on the empirical findings within momentum literature, it is expected a relationship between past and future share performance with most prior winners for example to remain in the winner portfolio in the following test period. The hypothesis is therefore that the majority of observations are in the diagonal going from upper left to the lower right.

Supporting the hypothesis, Table 3 shows that there is a tendency for a large percentage of companies to remain in the same portfolio in the succeeding period. For example, 36.88 (24.38) of the previous losers (winners) remain losers (winners) over the following period. However not all winners/losers remain in the same portfolio. For example, 15.50 percent of the previous winners performed very poorly over the next period and accordingly, 17.49 percent of the previous losers performed very well over the next period. Previous studies have analyzed the full ranking period portfolio to explore the

momentum effect (W, L) and this study focuses on the characteristics of those companies that remain in the same portfolio (WW, LL).

3.2. Univariate statistics

A univariate analysis is first undertaken to explore firm characteristics. Table 4 shows the average values of firm characteristics when the initial sample is employed. Consistent with previous studies, the 'All' column shows the characteristics for the whole previous performance portfolios. Consistent with momentum literature (e.g., Liu *et al.*, 1999; Arena *et al.*, 2008), findings indicate that W and L tend to be companies with low capitalization (SIZE), low price (PRICE) and high risk (STDEV and BETA). Consistent with Beneish (1999b), W and L tend to be young (AGE) companies. L companies also tend to exhibit poor profitability (ROE, ROCE, NPROFIT) with 27.63 percent of the loser companies reporting losses (NPROFIT). Interestingly, empirical results show that W are value companies (BM and SM) and L are growth companies, which contradicts the literature (Liu et al., 1999). In unreported results, a year-by-year analysis is undertaken showing that results are driven by the 2000-2004 bear period.

Unlike prior literature, this study further dissects the results within alternative test period portfolios. The hypothesis is that firm characteristics may vary significantly across the test period and to explore the momentum effect, researchers should focus on the portfolios that generate the W-L profitability. A parametric F-test and a non-parametric Kruskal-Wallis test are employed to

test the validity of the hypothesis. As hypothesized, horizontal values for most variables tend to change significantly in economical and statistical term. For example, firms in the loser portfolio (L) have on average market capitalization (SIZE) equal to £414 millions. However firms across from LL to LW portfolios have on average market capitalization equal to £280, £382, £556, £397 and £637 millions. Overall, these results show that this study may offer interesting results by constructing portfolios with rank and test period firm returns.

Using results from Table 4, Figure 1 portrays the position of the WW and LL firms relative to the rest of the portfolios. The scale varies from one (low) to 25 (high) and the horizontal line indicates the median portfolio. For example, LL portfolio consists of the second smallest capitalization firms out of the 25 portfolios. WW and LL firms are found to have some common characteristics, since both are small (SIZE), low-priced (PRICE) and young (AGE) companies. However, they differ significantly in relation to other variables. LL are glamour (BM), non-profitable (ROE, ROCE and NPROFIT) and high-risk (STDEV and BETA) companies. Interestingly, LL firms have the highest risk of all portfolios with a beta equal to 1.46, with a standard deviation equal to 5.20 percent and 39 percent of them reported losses. WW are instead value companies with the highest book-to-market (BM) and net sales to market ratio (SM). WW firms also have the highest trading volume (VOLUME). Overall, these results indicate that extreme winner and loser performers may

experience similar market-based signals, but accounting and fundamental signals are those that tend to distinguish winners from losers.

Panels A, B and C of Table 5 respectively show the mean values of the company characteristics for the LL, WW as well as the companies remaining once the listwise deletion and the E-M algorithm samples are employed. This explores how results may change with the use of alternative treatments of the missing data. If data were missing completely at random, the listwise deletion method would offer a sample with values near to those reported in the initial sample.

Findings show that the imputation method (in relation to the listwise deletion method) offers results much nearer to those reported in the initial sample. Using the listwise approach, small capitalization companies tend to be deleted and thus, WW and LL companies appear larger in size (SIZE) and price (PRICE) with lower risk (STDEV, BETA). Interestingly, when the listwise deletion method is employed, none of the LL companies appear to report losses (NPROFIT), while the initial sample and the sample using the imputation method show that around 39 percent of the LL companies have reported losses (NPROFIT). These results show that the listwise deletion treatment can potentially bias the results.

3.3. Multivariate statistics

Going on to use both listwise deletion and E-M algorithm samples, this section investigates whether results reported for the univariate analysis hold when using a multivariate analysis. The focus is on the characteristics of the WW and LL firms. Logit estimation was implemented using the RATS software that uses the Newton-Raphson algorithm to maximize the likelihood function (criterion is lower than 0.00001). The maximum number of iterations required for any of the models was ten. The following general form model is estimated:

$$\log[p_i/(1-p_i)] = b_0 + b_1 \ln SIZE_{it} + b_2 \ln PRICE_{it} + b_3 VOLUME_{it} + b_4 BM_{it} + b_5 SM_{it} + b_6 STDEV_{it} + b_7 BETA_{it} + b_8 AGE_{it} + b_9 MARGIN_{it} + b_{10} CURRENT_{it} + b_{11} ROE_{it} + + b_{12} ROCE_{it} + b_{13} NPROFIT_{it} + b_{14} GSALES_{it} + Ut \quad (1)$$

where b_i's show the model coefficients and x_i shows the independent variables for firm i. Four variants of this general model are estimated, each with the same independent variables to identify the probability p_i of a firm i being 1. Model 1 assigns the dependent variable equal to 1 if a company is WWLL and 0 if otherwise. This shows the characteristics of the extreme performers in comparison with the rest of the sample. Models 2 and 3 assign the dependent variable equal to 1 if a company is WW and LL respectively and 0 if otherwise. Using the extreme sample only, Model 4 assigns the dependent variable equal to 1 if a company is WW and 0 if a company is LL.

It should be noted that all the variables selected in the study are included in the Model. [6] Table 6 shows the Variance Inflation Factors (VIFs) that take into account all the explanatory variables at once, to explore potential multicollinearity among variables. Results for the E-M algorithm and listwise deletion samples are shown in Panels A and B respectively. We find that the maximum VIFs is equal to 2.65 and most VIFs are less than 2, showing that there is no evidence of multicollinearity.

Panel A of Table 7 shows results when the E-M algorithm is employed to determine the sample. Findings show that WW are small (LNSIZE), young (AGE), value (BM and SM), profitable (ROCE and NPROFIT) and high-trading volume (VOLUME) companies. It is also found that LL are small (LNSIZE), low-priced (LNPRICE), young (AGE), growth (BM), non-profitable (NPROFIT) and high risk (STDEV and BETA) companies. These results show that WW and LL companies have many common characteristics.

Using the extreme WW and LL sample only, Model 4 assigns the dependent variable equal to 1 if a company is WW and 0 if a company is LL. This analysis explores the differentiation between WW and LL firms. Results show that WW are high-priced (LNPRICE), value (BM), low-risk (STDEV and BETA), high-trading volume (VOLUME) and profitable (NPROFIT)

[6] Alternatively, models could be carried out using statistically significant variables only. This method may produce models that perform well within the particular sample, but not necessarily within other samples. In unreported results, this study also re-estimates the models using each independent variable separately and finds that signs and statistical level of coefficients tend to remain relatively robust with those reported using the multiple regressions.

companies in relation to the counterpart LL companies. Overall, this study shows that most of the results reported for the univariate analysis regarding WW and LL firm characteristics tend to hold using the multivariate analysis. [7]

Panel B of Table 7 shows the results when the listwise deletion method is employed to determine the sample. The pattern of the results is relatively similar with those found using the E-M algorithm sample. There is, however, a difference on profit (NPROFIT), standard deviation (STDEV) and growth in sales (GSALES) variables. Those estimates are biased and are presented only for comparison.

3.4 Predictive accuracy

The predictive accuracy of the estimated models above is explored by solving p_i through equation (1): $p_i = e^y / (1 + e^y)$ where $y = \hat{b}_0 + \hat{b}_1 \ln SIZE_{it} + ... + \hat{b}_{14} GSALES_{it}$. It is used the default critical values for classifying companies between the two groups (0/1), which are by construction 8, 4, 4 and 50 percent for Models 1, 2, 3 and 4 respectively. The use of default critical values, other than the optimal cut off points, minimizes the classification errors, to avoid our results to be upwards biased within our sample. Companies with p_i values above the cut off points are classified into

[7] In unreported results, this study also investigates the stability of the parameters using a year-to-year analysis. This is important, considering that a large number of companies may remain in the same portfolio in more than one year. Results show that the signs of the parameters in the models are relatively stable and as an example, WW companies appear to be young in 82.35 percent of the years (14 out of 17 years). Most of the parameters appear to exhibit the same sign in more than 70 percent of the years.

category 1 (WWLL for Model 1, WW for Model 2, LL for Model 3 and WW for Model 4) and accordingly companies with p_i values below or equal to the critical values are classified into category 0.

Table 8 shows the classification accuracy results. If the models had no predictive accuracy, results would have been equal to 50 percent. It is found that models have some predictive ability, since the maximum correct probability, among our models, is found to be equal to 76.05 percent and the minimum 53.59 percent. The classification accuracy remains at a rather similar level for both listwise and E-M algorithm sample.

It is also investigated the extent to which developed models can be used for investment purposes (Table 9). The results of the momentum strategy are shown in column (1) (these returns are taken from Table 2). The results of the one-stage strategy are shown in column 2 that uses Models 2 and 3 to predict winners and losers respectively. The results of the two-stage strategy are shown in column 3 that uses first Model 1 to identify extreme performers and then Model 4 to discriminate between winners and losers. We find that the one- and two-stage strategies, which are based solely on the models developed in this study, can generate profits. In the case of the two-stage strategy, profits are equal to 1.36 percent per month driven by the loser companies. The level of the profitability for the one- and two-stage strategies is though lower than that found in the momentum strategy.

We further explore the profitability of hybrid strategies. Hybrid I strategy buys/sells short companies that both momentum and one-stage strategy identify as expected winners and losers respectively. Accordingly, Hybrid II strategy buys/sells short firms that both momentum and two-stage strategy identify as extreme performers. We find that Hybrid I (column 4) and II (column 5) strategies can generate profits significantly higher in economical and statistical terms than those reported in the momentum strategy. Hybrid I and II strategies exhibit profits equal to 2.89 and 3.25 percent per month respectively. Interestingly, those higher returns of the hybrid strategies are driven by both winner and loser firms. Adjusting for the Three-Factor Model (Fama and French, 1993) and the Sharpe ratio, we find that this outperformance cannot be explained by risk. [8] Results remain rather robust in both listwise deletion and EM algorithm samples.

[8] Thanks to Gregory, Tharyan and Christidis (2009) that offer the three Fama and French factors within UK data (http://xfi.exeter.ac.uk/researchandpublications/portfoliosandfactors/files.php).

4. Conclusion and discussion

The momentum effect is one of the most widely published stock market anomalies showing that there is continuity in share prices. This study highlights for the first time the difference between analyzing the whole previous winner and loser companies with that of analyzing only those companies that generate the phenomenon. These are the winner/loser firms that remain to perform well/poorly in both rank and test period.

We find that momentum profitability is driven by more extreme companies than previously reported. WW and LL firms have some common characteristics, since both are small, low-priced and young companies. They differ significantly, however, when other variables are considered. LL are glamour, non-profitable and high-risk companies. WW are instead value companies with the highest book-to-market and net sales to market ratio. These results show that extreme winner and loser performers may experience similar market-based signals, but accounting and fundamental signals tend to distinguish winners from losers. Using logit analysis, models are also developed for investment purposes. We find that hybrid strategies that select winners and losers firms in line with both strategies (momentum and models developed in this study) can generate profits significantly higher than those reported solely in the momentum strategy.

This study also makes one further contribution. Within the accounting and finance field, researchers mainly use the listwise deletion approach. This study

argues that the listwise deletion approach may bias findings. The extreme winner and loser portfolios for example tend to include very small capitalization firms that would have been deleted if such method is followed. This paper employs an alternative method of that E-M algorithm which uses maximum likelihood to fill-in the missing observations and shows that the imputation method offers results much nearer to those reported in the initial sample. On this basis it would seem that accounting and finance research which has been based on the listwise deletion approach solely would benefit from taking into account this paper's findings.

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Table 1. Percentage of missing data

	SIZE	PRICE	VOLUME	BM	SM	STDEV	BETA	AGE	MARGIN	CURRENT	ROE	ROCE	NPROFIT	GSALES
WW LL	1.4	1.4	30.1	17.8	13.3	2.1	3.1	0.0	39.6	19.1	26.9	23.2	16.4	21.2
Full sample	0.9	0.9	28.4	11.8	9.3	1.2	1.9	0.0	25.2	19.2	18.3	16.1	14.4	11.3

This table shows the percentage of missing data in the full and WW LL samples. WW LL are prior winners and losers that have remained winners and losers respectively in the following test period. A one-year period has been used to define and test the performance of the winner and loser portfolios.
SIZE shows the market capitalization (£ in millions).
PRICE shows the price of companies (£ in pence).
VOLUME is the trading volume divided by the number of outstanding shares.
BM shows the book-to-market ratio.
SM shows the net sales divided by market value.
STDEV shows the standard deviation for each share.
BETA is the aggregate coefficient betas of Dimson (1979) – one lag and one lead.
AGE shows the age of firms as number of years from the date that Datastream offers information until assigned to a portfolio.
MARGIN shows the net profit margin.
CURRENT shows the current ratio.
ROE shows the return on common equity.
ROCE shows the return on capital employed.
NPROFIT is a dummy variable equal to 1 if a company has negative after tax profits at the latest financial statement and 0 otherwise.
GSALES shows the growth in sales.

Table 2. Momentum returns (%)

	Returns (Initial Sample)	Returns (Listwise deletion Sample)
L	-2.06	-0.89
W	0.26	0.67
W-L (compound)	2.31***	1.56***
Average	2.12	1.37
Median	1.90	1.61
Stdev	5.16	5.13
%>0	67.65	64.22

This table shows the momentum returns when using the initial and listwise deletion samples. Momentum profits are calculated by ranking companies on the basis of their stock market performances over the previous twelve months (rank period). The quintile portfolio with the best (worst) performance is the winner, W (loser, L) portfolio. The momentum effect is calculated on the returns of each of the equally weighted portfolios over the following twelve-month period after the rank period (test period). The difference between winner and loser portfolio returns (W-L) shows the profitability of the momentum strategy. Stdev shows standard deviation and %>0 the percentage of positive monthly W-L returns. The initial sample includes the full list of companies with missing or not firm characteristics and the listwise deletion sample includes only firms that exhibit all required firm characteristics available from Datastream.

*** Significant at the 1% level.

Table 3. Distributional analysis (%) (Initial Sample)

		Test period					
		L	2	3	4	W	Sum
Rank period	L	36.88	20.75	13.03	11.86	17.49	100
	2	19.99	23.27	19.62	19.99	17.13	100
	3	15.28	21.15	23.14	22.38	18.04	100
	4	11.88	18.79	24.97	24.35	20.00	100
	W	15.50	17.47	20.56	22.09	24.38	100

This table shows the distribution of past portfolios over the following test period. For example, it is estimated the percentage of previous losers that are in the loser, 2, 3, 4 and winner portfolios over the following test period. L and W is the loser and winner portfolio respectively.

Table 4. Firm characteristics (Initial Sample)

	Test period								Test period							
	L	2	3	4	W	All	F-test	K-W	L	2	3	4	W	All	F-test	K-W
Panel A: SIZE									Panel B: PRICE							
L	280	382	556	397	637	414	4.31***	69.56***	201	246	236	231	229	224	1.21	52.50***
2	455	1223	2363	1679	656	1289	6.85***	88.26***	268	275	342	374	272	306	1.86	60.87***
3	482	2279	2190	1563	940	1586	6.99***	89.90***	259	307	365	361	305	325	8.85***	68.77***
4	608	1181	2230	1687	920	1446	6.41***	108.37***	314	358	359	328	309	456	0.86	71.77***
W	262	620	878	906	557	666	5.45***	73.70***	193	257	274	305	233	256	7.36***	83.03***
Panel C: VOLUME									Panel D: BM							
L	0.74	0.66	0.67	0.71	0.72	0.71	0.17	13.33***	0.53	0.52	0.52	0.56	0.59	0.54	0.67	13.56***
2	0.63	0.70	0.80	0.74	0.74	0.72	2.18*	23.11***	0.56	0.59	0.64	0.59	0.67	0.61	3.46***	29.19***
3	0.69	0.75	0.94	0.84	0.90	0.89	0.68	24.61***	0.57	0.66	0.67	0.68	0.68	0.66	2.16*	16.97***
4	0.67	0.77	0.86	0.81	0.97	0.83	3.51***	19.39***	0.61	0.64	0.69	0.70	0.73	0.68	2.55**	21.22***
W	0.80	0.82	0.94	1.04	1.21	0.98	0.79	17.34***	0.58	0.74	0.70	0.72	0.78	0.71	3.13**	30.05***
Panel E: SM									Panel F: STDEV (%)							
L	1.74	1.68	1.71	1.81	2.03	1.78	1.10	14.45***	5.20	4.08	3.59	3.37	3.74	4.28	23.80***	100.32***
2	1.58	1.57	1.37	1.50	2.03	1.60	5.55***	16.13***	3.73	3.23	2.87	2.69	3.08	3.12	13.83***	69.00***
3	1.73	1.60	1.53	1.49	1.87	1.63	2.32*	6.58	3.52	2.82	2.53	2.40	2.72	2.75	13.80***	85.32***
4	1.79	1.60	1.53	1.47	2.07	1.66	5.54***	7.56	3.53	2.80	2.34	2.29	2.65	2.62	31.62***	97.93***
W	2.04	2.29	1.95	2.06	2.35	2.15	1.02	37.34***	4.78	3.60	2.95	2.78	3.54	3.45	39.03***	179.00***
Panel G: BETA									Panel H: AGE							
L	1.46	1.36	1.24	1.23	1.24	1.35			10.3	12.5	12.9	12.8	13.1	11.9	8.57***	36.05***
2	1.23	1.11	0.95	0.89	0.97	1.03			12.0	17.0	18.2	17.7	15.7	16.2	24.52***	100.56***
3	1.16	0.94	0.82	0.75	0.85	0.88			13.6	18.7	19.2	18.5	15.3	17.4	20.92***	80.50***
4	1.13	0.92	0.75	0.75	0.84	0.84			12.6	16.0	18.7	18.6	16.5	17.0	18.82***	75.92***
W	1.35	0.97	0.82	0.82	0.96	0.95			9.6	13.5	14.8	16.1	12.4	13.5	23.89***	99.18***

Panel I: MARGIN (%)									Panel J: CURRENT (%)							
L	10.66	9.32	8.04	8.10	8.96	9.31	1.66	5.65	2.35	2.40	2.66	1.98	2.26	2.34	0.61	5.54
2	8.51	8.49	14.51	10.50	10.25	10.49	1.59	15.85***	2.52	1.65	1.67	2.35	1.99	2.03	1.99*	10.58**
3	8.23	12.21	11.45	11.46	11.05	11.11	1.56	28.88***	1.98	1.69	1.55	1.51	1.59	1.65	1.91	8.29*
4	15.97	10.24	12.08	11.62	9.69	11.51	1.30	17.74***	1.82	1.73	1.53	1.45	1.76	1.63	2.24*	3.13
W	16.19	10.48	9.68	8.89	10.53	10.59	1.77	1.44	2.25	1.90	1.57	1.49	1.89	1.80	5.55***	16.52***
Panel K: ROE (%)									Panel L: ROCE (%)							
L	-19.54	-12.66	9.48	13.65	-4.66	-7.24	2.14*	23.73*	-12.84	3.64	7.77	7.38	3.72	-1.06	8.20***	33.35***
2	6.81	5.67	14.37	19.71	14.59	12.17	2.28*	7.18	7.81	6.80	9.00	12.57	9.74	9.16	0.71	5.16
3	9.77	13.86	15.59	17.77	19.26	15.57	2.97**	4.30	9.69	10.63	13.76	13.97	13.84	12.57	1.92	1.93
4	28.52	14.92	16.69	17.14	14.54	17.26	0.97	4.73	9.88	11.66	13.25	13.14	11.69	12.26	1.23	2.73
W	-10.82	11.24	12.88	8.68	10.01	7.64	2.20*	35.66***	-2.37	10.72	12.66	14.27	16.98	11.60	4.51***	31.66***
Panel M: NPROFIT (%)									Panel N: GSALES							
L	39.16	30.08	21.93	18.84	27.63	30.42			1.76	1.42	1.25	3.35	1.37	1.74	1.95*	6.33
2	27.70	16.07	12.00	10.20	17.14	16.59			18.18	1.62	1.12	1.39	1.18	4.59	1.44	44.51***
3	17.46	12.43	10.02	6.44	10.54	10.95			1.40	1.37	1.22	1.15	1.24	1.27	1.41	6.96
4	21.90	14.93	9.78	5.66	10.06	11.19			1.79	1.19	1.14	1.67	1.48	1.42	0.66	12.66**
W	34.93	19.35	11.80	10.17	17.68	17.61			2.32	1.47	1.31	1.25	1.36	1.48	2.97**	19.97***

See Table 1 for definitions of firm characteristics. This table shows portfolios' average firm characteristics that have disentangled based on share prior and test period performance. K-W is the Krusal-Wallis test. L and W is the loser and winner portfolio respectively.
* Significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

Table 5. Firm characteristics – Initial Sample vs. Listwise deletion Sample vs. E-M algorithm Sample

	SIZE	PRICE	VOLUME	BM	SM	STDEV	BETA	AGE	MARGIN	CURRENT	ROE	ROCE	NPROFIT	GSALES
Panel A: Mean values - LL														
Initial	280	201	0.74	0.53	1.74	5.20	1.46	10.3	10.66	2.35	-19.54	-12.84	39.16	1.76
Listwise deletion	540	243	0.64	0.46	1.47	3.34	1.23	14.5	10.12	1.92	27.61	17.97	0.00	1.22
E-M algorithm	276	200	0.76	0.58	1.80	5.00	1.35	11.57	13.12	2.45	-26.58	-11.65	39.28	2.03
Initial vs. Listwise	***	***				***		***			***	***	***	
Initial vs. E-M	*							***						
Panel B: Mean values - WW														
Initial	557	233	1.21	0.78	2.35	3.54	0.96	12.4	10.53	1.89	10.01	16.98	17.68	1.36
Listwise deletion	829	245	1.35	0.82	2.86	3.07	0.81	16.3	8.74	1.51	23.08	17.04	0.79	1.28
E-M algorithm	552	232	1.09	0.77	2.32	3.56	0.93	13.23	12.44	1.97	19.45	16.38	17.95	1.45
Initial vs. Listwise	***				*	**		***			**		***	
Initial vs. E-M														
Panel C: Mean values - Others														
Initial	1193	301	0.80	0.64	1.73	3.06	0.98	15.75	10.69	1.85	11.52	10.27	15.39	2.17
Listwise deletion	1649	322	0.80	0.56	1.67	2.54	0.93	18.3	8.58	1.53	25.27	16.43	0.66	1.51
E-M algorithm	1170	299	0.78	0.64	1.75	2.98	0.98	16.58	11.64	1.94	12.62	10.15	15.39	2.28
Initial vs. Listwise	***	***		***		***	***	***	***	***	***	***	***	
Initial vs. E-M	***					**		***	*					

See Table 1 for definitions of firm characteristics. Initial sample values for WW and LL firms come from Table 4. The *listwise sample* includes only firms that exhibit all required firm characteristics available from Datastream, the *initial sample* includes the full list of companies with missing or not firm characteristics and the *E-M algorithm sample* includes the full list of companies with the actual (available from Datastream) and fill-in firm characteristics.

*Significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

Table 6. Variance inflation factors

	LNSIZE	LNPRICE	VOLUME	BM	SM	STDEV	BETA	AGE	MARGIN	CURRENT	ROE	ROCE	NPROFIT	GSALES
Panel A: E-M algorithm sample														
LNSIZE		1.51	1.91	1.91	1.89	1.90	1.92	1.81	1.92	1.91	1.92	1.92	1.91	1.92
LNPRICE	1.93		2.39	2.42	2.45	2.08	2.45	2.45	2.44	2.45	2.45	2.45	2.37	2.45
VOLUME	1.06	1.04		1.06	1.06	1.04	1.06	1.06	1.06	1.06	1.06	1.06	1.06	1.06
BM	1.19	1.18	1.20		1.12	1.19	1.19	1.18	1.18	1.19	1.20	1.19	1.20	1.20
SM	1.20	1.22	1.22	1.14		1.22	1.22	1.19	1.21	1.22	1.22	1.21	1.22	1.22
STDEV	1.96	1.68	1.94	1.98	1.98		1.93	1.96	1.97	1.98	1.98	1.96	1.89	1.98
BETA	1.10	1.10	1.10	1.10	1.10	1.07		1.10	1.10	1.09	1.10	1.10	1.10	1.10
AGE	1.11	1.18	1.18	1.16	1.15	1.17	1.18		1.18	1.18	1.18	1.18	1.18	1.18
MARGIN	2.64	2.64	2.65	2.62	2.62	2.63	2.64	2.64		1.05	2.65	2.62	2.65	2.65
CURRENT	2.60	2.61	2.61	2.60	2.61	2.60	2.60	2.61	1.04		2.61	2.59	2.60	2.61
ROE	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83	1.83		1.11	1.83	1.82
ROCE	2.03	2.03	2.03	2.03	2.02	2.01	2.03	2.03	2.01	2.02	1.24		1.98	2.00
NPROFIT	1.41	1.37	1.42	1.42	1.42	1.36	1.42	1.42	1.42	1.42	1.42	1.38		1.42
GSALES	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.00	1.02	
Panel B: Listwise deletion sample														
LNSIZE		1.56	1.99	2.01	1.99	1.96	2.02	1.92	2.02	2.01	2.02	2.01	2.02	2.02
LNPRICE	1.62		2.08	2.10	2.09	1.86	2.11	2.10	2.11	2.11	2.11	2.10	2.11	2.11
VOLUME	1.05	1.05		1.06	1.06	1.05	1.07	1.06	1.07	1.07	1.07	1.06	1.07	1.06
BM	1.33	1.33	1.34		1.19	1.34	1.34	1.33	1.31	1.34	1.33	1.27	1.34	1.34
SM	1.34	1.35	1.36	1.21		1.36	1.36	1.34	1.32	1.36	1.36	1.36	1.36	1.36
STDEV	1.56	1.42	1.59	1.60	1.60		1.58	1.58	1.61	1.60	1.60	1.61	1.61	1.61
BETA	1.06	1.06	1.06	1.06	1.06	1.04		1.06	1.06	1.06	1.06	1.06	1.06	1.06
AGE	1.12	1.17	1.18	1.18	1.16	1.16	1.18		1.18	1.18	1.18	1.16	1.18	1.18
MARGIN	1.11	1.11	1.11	1.09	1.07	1.11	1.11	1.11		1.09	1.11	1.09	1.11	1.11
CURRENT	1.05	1.05	1.05	1.05	1.04	1.05	1.05	1.05	1.03		1.05	1.05	1.05	1.05
ROE	1.12	1.12	1.12	1.12	1.12	1.12	1.12	1.12	1.12	1.12		1.02	1.12	1.12

ROCE	1.25	1.26	1.26	1.20	1.26	1.26	1.26	1.24	1.23	1.26	1.15		1.26	1.26
NPROFIT	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00		1.00
GSALES	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01	

See Table 1 for definitions of firm characteristics. This table shows the variance inflation factors for the E-M algorithm and the listwise deletion samples to explore potential multicollinearity among variables. The E-M algorithm sample includes the full list of companies with the actual (available from Datastream) and fill-in firm characteristics and the listwise deletion sample includes only firms that exhibit all required firm characteristics available from Datastream. .

Table 7. Logit estimation

	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
	WWLL=1, Others=0	WW=1, Others=0	LL=1, Others=0	WW=1, LL=0 (extreme sample)	WWLL=1, Others=0	WW=1, Others=0	LL=1, Others=0	WW=1, LL=0 (extreme sample)
	Panel A: E-M algorithm sample				Panel B: Listwise deletion sample			
Number of obs	12,192	12,192	12,192	1,404	5,645	5,645	5,645	487
Constant	-0.977***	-1.972***	-1.379***	-0.59	-0.790**	-1.641***	-0.373	-2.290***
lnSIZE	-0.134***	-0.145***	-0.126***	-0.009	-0.135***	-0.136***	-0.138**	0.056
lnPrice	-0.089**	-0.011	-0.127**	0.132*	-0.192***	-0.130	-0.286***	0.213
VOLUME	0.057***	0.083***	0.002	0.064**	0.151***	0.226***	-0.129	0.426***
BM	-0.116**	0.110**	-0.495***	0.435***	-0.001	0228**	-1.165***	1.519***
SM	0.012	0.026**	0.006	0.033	0.036*	0.077***	-0.072	0.138**
STDEV	4.149***	0.071	4.591***	-3.818	3.949	0.755	6.313	-7.537
BETA	0.049*	-0.117***	0.124***	-0.248***	0.056	-0.378***	0.348***	-0.624***
AGE	-0.021***	-0.021***	-0.018***	-0.004	-0.013***	-0.011**	-0.009	-0.004
MARGIN	0.000	0.000	0.000	0.003	0.002	0.002	0.003	0.0038
CURRENT	-0.001	-0.005	0.000	-0.020	0.002	-0.013	0.006	-0.080
ROE	0.000	0.000	0.000	0.000	-0.000	-0.001	-0.000	-0.000
ROCE	0.000	0.002*	-0.001	0.004	0.003	0.005	-0.005	0.010
PROFIT	0.364***	-0.120	0.608***	-0.559***	-0.426	0.138	-29.850	32.010
GSALES	-0.007	-0.029	-0.002	-0.053	-0.545**	-0.07***	-0.095	0.298*
X^2	480***	138***	510***	167***	138***	119***	136***	114***
Pseudo-R^2	3.98%	1.14%	4.28%	11.73%	2.46%	2.16%	2.47%	22.71%

See Table 1 for definitions of firm characteristics. This table shows the results of logit regressions to differentiate firm characteristics between WW and LL firms. WW (LL) are firms that perform well (poorly) during both rank and test periods. The extreme sample includes only WW and LL firms. R^2 is equal to $1-(LogL_c/\log L)^{-(2/N)\log L_c}\cdot LogL_c$ is the base likelihood and $\log L$ is the log likelihood. This measure of fit was developed by Estrella (1998).

* Significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

Table 8: Classification accuracy (%)

	Model 1	Model 2	Model 3	Model 4
	WWLL=1, Others=0	WW=1, Others=0	LL=1, Others=0	WW=1, LL=0
Panel A: E-M algorithm sample				
Correctly classified 1	58.12	63.65	63.12	76.05
Correctly classified 0	67.18	54.99	71.03	53.59
Panel B: Listwise deletion sample				
Correctly classified 1	55.88	57.54	63.36	66.67
Correctly classified 0	62.71	68.52	67.27	75.43

This table shows the predictive accuracy of developed models in Table 7 for both E-M algorithm and listwise deletion samples. The default critical values for classifying companies between the two groups (0/1) are employed. Companies with p_i values above the cut off points are classified into category 1 (WWLL for Model 1, WW for Model 2, LL for Model 3 and WW for Model 4) and accordingly companies with p_i values below or equal to the critical values are classified into category 0.

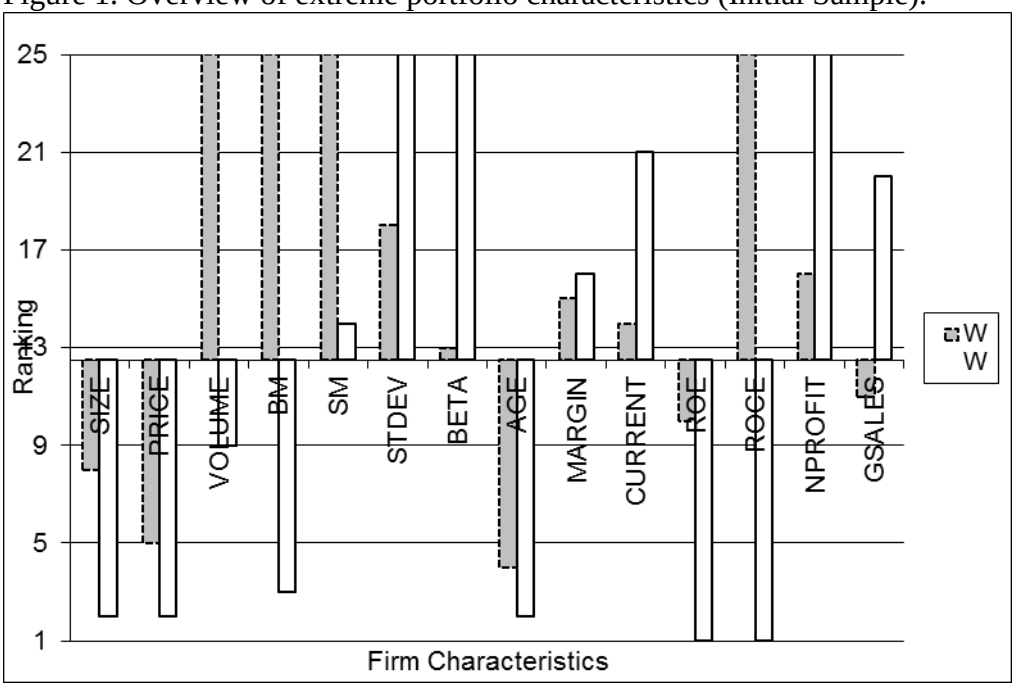
Table 9: Investment strategies (%)

	Momentum (1)	One-stage (2)	Two-stage (3)	Hybrid I (4)	Hybrid II (5)	(1) vs (4)	(1) vs (5)
Panel A: E-M algorithm sample							
Long	0.26	-0.29	0.24	0.55	0.92		
Short	-2.06	-1.08	-1.12	-2.34	-2.33		
Hedge	2.31***	0.79***	1.36***	2.89***	3.25***	0.58	0.94*
Median	1.90	0.71	1.28	3.05	3.76		
Percentage positive	67.80	68.78	68.29	72.68	72.20		
Standard deviation	5.2	2.0	3.4	5.5	5.9		
Alpha 3FF	2.53***	0.68***	1.25***	2.96***	3.30***		
Sharpe	0.45	0.40	0.40	0.53	0.55		
Panel B: Listwise deletion sample							
Long	0.67	0.21	0.42	0.76	1.31		
Short	-0.89	-0.85	-1.08	-1.63	-2.05		
Hedge	1.56***	1.06***	1.51***	2.39***	3.36***	0.83	1.80**
Median	1.61	0.85	1.00	2.35	2.43		
Percentage Positive	64.39	66.83	62.44	65.85	69.43		
Standard deviation	5.13	2.88	4.12	6.62	7.51		
Alpha 3FF	1.48***	1.06***	1.44***	2.49***	3.37***		
Sharpe	0.30	0.37	0.37	0.36	0.45		

This table compares the profitability of the momentum strategy with strategies developed in this study. We use models developed in Table 7 to generate investment strategies. The one-stage strategy uses Model 2 to predict winners and Model 3 to predict losers. The two-stage strategy uses first Model 1 to identify extreme performers and then Model 4 to discriminate between winners and losers. Hybrid I strategy uses companies that both momentum and one-stage strategies identify as potential winners and losers. Hybrid II strategy uses companies that both momentum and two-stage strategies identify as potential winners and losers. Alpha 3 FF is the alpha found when regressing returns of investment strategies with the three UK Fama and French (1993) factors.

*Significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.

Figure 1. Overview of extreme portfolio characteristics (Initial Sample).



This figure portrays the position of the WW and LL firms relative to the rest of the portfolios. There are in total 25 portfolios (5x5) and the scale varies from one (low) to 25 (high). The horizontal line indicates the median portfolio. See Table 1 for definitions of firm characteristics.