Financial statement analysis and the return reversal effect

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Abstract

This paper investigates the combined use of two investment strategies, each of which, a number of researchers believe, indicate some degree of equity market inefficiency; firstly, a strategy using financial statement variables identified by Piotroski (2000) which provide information on strength of companies that is inadequately priced in the market, and; second, the purchase of 'loser' companies, i.e. those showing the worst five-year returns companies. Financial statement variables are used to establish an overall financial strength score (L-score) for loser companies. We then test whether the market fully incorporates information contained in the financial statements of losers. Despite portfolios of losers out-performing the market in the five post-portfolio formation years, the majority of individual losers companies under-perform. We successfully differentiate between strong losers and weak losers using the L-score. Furthermore the out-performance during the test period for high L-score firms is most marked in the small firm segment, suggesting a market neglect factor. The out-performance of high L-score losers is robust to various risk tests.

1. Introduction

Considerable research documents that shares which previously experienced extreme sub-market performance over three to five years go on to produce market out-performing returns, on average. For example, Arnold and Baker (2005) show high returns to purchasing

long-term UK loser shares. That is, shares producing the lowest returns over a five year period go on to out-perform the market index by 8.9% per year on average in the following five years, over the study period 1960 - 2000.

They, and other researchers, report the average performance of each formation of the 'loser' portfolios without a more detailed breakdown. It seems reasonable to postulate that within these portfolios a high proportion of the shares continue to under-perform. This is indeed the case. We find in this paper that the overall success of the strategy of buying losers is dependent on the performance of a minority of the firms. These returns are sufficiently large so as to outweigh the poor performance of many deteriorating loser companies. We show that only 47% of loser firms earn positive market-adjusted returns during the five years following portfolio formation. On average, 7% of losers are liquidated during the five test period years, leaving 46% that survive but under-perform the market.

Given the wide variety of loser test period performance and the fact that a majority of losers under-perform it is plausible to argue *a priori* that investors could benefit by discriminating, *ex ante*, between weak and strong companies. The motivation for this paper is to answer the simple question of whether a financial statement-based heuristic can discriminate between loser firms with weak prospects and those with strong prospects. In other words, can an accounting-based fundamental analysis, when applied to a broad portfolio of loser firms, shift the distribution of returns earned by an investor?

The evidence we present shows that the market fails to fully incorporate historical financial information into prices in a timely manner. Not all loser shares are equal in terms of future returns: a stronger portfolio can be created for a loser strategy by using a simple screen

based on financial statements. We thus provide more descriptive evidence on the return reversal puzzle.

More specifically, we show, first, that the mean return earned by small-market capitalization loser shares can be increased by 16% in the twelve months following portfolio formation through the selection of financially strong losers. Second, a strategy of purchasing the financially strong small losers and shorting the weak small losers generates a 27% return in the twelve months following portfolio formation between 1981-2005. If the small firm arbitrage portfolio is maintained for 24 months the return is 80%; if it is held for 36 months, 115%. Returns to this strategy are shown to be robust across time.

Third, we find evidence supporting the predictions of behavioural models (e.g. Hong and Stein, 1999, Barberis, Schleifer and Vishny, 1998 and Daniel, Hirshleifer and Subrahmanyam, 1998). This is because the strategy is less effective for shares subject to more rapid information dissemination, i.e. large companies that tend to have a wider following among analysts. The effectiveness of financial statement analysis strategy in differentiating between strong and weak loser firms is greatest in smaller firms, that is, companies with a fewer (no) analysts following and less rapid information dissemination. Finally, we show that a plausible explanation for the above results is the failure of the market to fully recognize the high relative potential of the strong accounting-fundamentals firms to produce superior economic returns on funds invested within the business (as measured by return on capital employed over the five test period years) compared with the weak companies. Not only do weak firms display lower ROCE in the five years following portfolio formation but they are also three times more likely to be liquidated than firms showing strong accounting-fundamental signals.

2. Literature review

A convincing long-term return reversal effect has been shown in US studies (e.g. De Bondt and Thaler, 1985, 1987; Chopra, *et. al*., 1992) and in the UK market (Dissanaike, 1997 and 2002, and Arnold and Baker, 2005). Prior period extreme positive return shares (over 3 to 5 years) subsequently under perform the market, whereas those shares that perform the worst over a sequence of years then, on average, produce returns significantly greater than the market as a whole. Studies from around the world have drawn similar conclusions[i]. The phenomenon is demonstrated to be robust to various risk analyses, the influence of size and market-to-book ratio.

Another strand of research takes the perspective that the firm's fundamental values are indicated by information in financial statements. Share prices deviate at times from these, and only slowly gravitate toward fundamental values. Thus, analysis of published financial statements can discover values that are not reflected in share prices. Several papers document the market's inability to fully process the implications of various financial signals (e.g. Foster, et. al., 1984, Sloan, 1996, Michaely, et. al., 1995, Piotroski, 2000 and Hirshleifer, et. al., 2004). Multiple pieces of information available from firm's financial statements are used to predict future excess returns (Ou and Penman, 1989a, 1989b, Holthausen and Larcker, 1992, Lev and Thiagarajan, 1993, Abarbanell and Bushee, 1997, Richardson, et. al., 2003 and Fairfield, et. al., 2003). Linked to this 'predictability anomaly' may be the observation that financial analysts pay less attention to poor-performing, low-volume or small firms (McNicholls and O'Brien, 1997, and Hayes, 1998). They have a bias in recommending those with a strong recent performance (Stickel, 2000, Jegadeesh et. al.

2004). One possible explanation for this is that, on an individual basis, the typical loser share will continue to under-perform. So, despite the documented out-performance of a loser portfolio analysts may risk ridicule and loss of credibility by recommending prior period losers as most of the these recommendations will turn out to be bad.

This paper brings together these two lines of research by aggregating a range of financial signals to create a loser firm's overall signal.

3. Data, Sample and Method

3.1 Financial statement data signals

Piotroski (2000) shows that the combined use of nine selected accounting variables has greater power to discriminate between stronger and weaker firms in terms of their future returns than alternative fundamental based factors (e.g. Altman's z-score or the historical change in profitability). Thus, the financial signals we use to establish the strength of loser firms are his nine factors[ii]. These financial signals measure three areas of the company's financial position, namely profitability, financial gearing/liquidity and operating efficiency. A binary approach is taken in which a signal (e.g. rise or fall in return on capital employed last year compared with the previous year) is classified as either 'good' or 'bad', depending on the signal's implication for future share returns and profitability. If the signal is good it contributes a value of one to the overall L-score. Given that there are nine signals the maximum L-score is nine. If the signal is bad then the contribution is zero. Therefore the lowest L-score is zero. Thus we have 10 levels of aggregate financial signal strength, from 0 to 9.

In what follows year t is the year of portfolio formation.

3.1.1 Profitability signals

The level of profits and cash flow of the company provide information about its current ability to generate internal funds. Many loser firms are loss making, so any loser generating profits and/or positive cash flow is showing an ability to produce funds by operating its business. Also, it seems reasonable to assume that those firms with a positive profit trend have a greater ability to generate positive future cash flows.

The profitability signals are:

1. Return on capital employed

$$ROCE = \frac{\text{Earnings before interest and tax, t-1}}{\text{Total capital employed + short term borrowings - total intangibles, t-1}}$$

Datastream code: 707[iii]

2. Operating cash flow return on assets

CFO = (Operating profit + depreciation - change in stock and work in progress - change in debtors + change in creditors, year t-1) ÷ (Total assets employed, beginning of year t-1)

$$CFO^{iv} = \frac{\text{Datastream code: 137 + 402 – 445 – 448 + 417 (t-1)}}{\text{Datastream code: 391 (t-2)}}$$

3. ΔROCE = Year t-1 ROCE - Year t-2 ROCE

(Datastream code: 707 for each year)

4. Cash flow minus profit

ACCRUAL = (Operating profit + depreciation - change in stock and work in progress - change in debtors + change in creditors - pre-tax profit[v], t-1) ÷ (Total assets employed, beginning of year t-1)

$$\text{ACCRUAL} = \frac{\text{Datastream code: } 137 + 402 - 445 - 448 + 417 - 154 \text{ (t-1)}}{\text{Datastream code: } 391 \text{ (t-2)}}$$

If ROCE is positive the value of one is assigned, zero otherwise.

If CFO is positive the value of one is assigned, zero otherwise.

If ΔROCE is positive the value of one is assigned, zero otherwise

If ACCRUAL is positive the value of one is assigned, zero otherwise[vi]

(ΔROCE can be used for all companies, even those with negative ROCEs in the prior two years because an improving trend will give a positive value and, therefore contribute one to the aggregate L-score.)

3.1.2 Gearing, Liquidity and Source of Funds Signals

Given that many loser firms are financially constrained we assume that an increase in financial gearing, a worsening liquidity or the raising of external finance is a bad signal. The signals are:

5. Change in financial gearing

$$\Delta \text{GEAR} = \frac{\text{Total debt + pref. capital, year t-2}}{\text{Total capital employed, year t-2}} - \frac{\text{Total debt + pref. capital, year t-1}}{\text{Total capital employed, year t-1}}$$

ΔGEAR[vii] = Datastream code 731 (t-2) – Datastream 731 (t-1)

6. Change in liquidity

ΔLIQUID = Current ratio, year t-1 - Current ratio[viii], year t-2

ΔLIQUID = Datastream code 741 (t-1) – Datastream code 741[ix] (t-2)

7. Equity issues

EQ_OFFER = the absence of an issue of new shares through a right issue, open offer or placing in year t-1. Datastream code 412 shows equity issued (including share premium) for cash. To make allowance for regular small equity issues to supply shares under managerial share incentive schemes rather than significant capital raising exercises we ignore the issue of less than 2% of the overall share capital. Thus only those companies that issue shares worth more than 2% of market capitalization in the year are classified as having an equity offer.

$$\text{EQ\_OFFER} = \frac{\text{Datastream code } 412^{\text{x}} \text{ (t-1)}}{\text{Market value}^{\text{xi}}}$$

A higher level of gearing two years before portfolio formation than one year before portfolio formation (a positive ΔGEAR) is viewed as a positive signal that the company is on an improving trend, and assigned a value of one, zero otherwise.

A positive ΔLIQUID is taken as a good signal (increasing the firm's ability to service current debt obligations) and assigned a value of one, a negative ΔLIQUID is assigned a value of zero.

A firm that issues new equity (especially after large share price falls) could be signaling an inability to generate sufficient internal funds to service obligations (Myers and Majluf, 1984), therefore the absence of a rights issue, open offer or placing is assigned a value of one, zero otherwise.

3.1.3 Operating Efficiency

The signals are:

8. Change in trading margin

ΔMARGIN = Trading profit margin in year t-1 - Trading profit margin in year t-2

ΔMARGIN = Datastream code 711 (t-1) – Datastream code 711[xii] (t-2)

9. Change in asset turnover

$$\Delta TURN = \frac{\text{Total sales, year t-1}}{\text{Beginning of year t-1 total assets}} - \frac{\text{Total sales, year t-2}}{\text{Beginning of year t-2 total assets}}$$

ΔTURN = Datastream code 721 (t-1) – Datastream code 721[xiii] (t-2)

A positive ΔMARGIN signals an improvement in factor costs, a reduction in inventory costs, or a rise in the price of the product, therefore it is assigned a value of one. A negative ΔMARGIN is assigned a value of zero.

If the asset turnover ratio rises this indicates an improvement in productivity from the asset base. This may be due to either more efficient operations (sales maintained while the asset base decreases) or an increase in sales, which could signal an improvement in market conditions for the company's products. If ΔTURN is greater than zero then this factor is assigned a value of one, zero otherwise.

For all nine factors the accounting data used are for the latest financial year ending at least six months before the portfolio formation date. This is to allow for the lag between companies' financial year-ends and reporting dates (Datastream does not adjust for this lag). This ensures that financial information is available to the investor at the time of portfolio formation. All the portfolios are formed at the beginning of July each year t. Therefore, the accounting data relate to annual accounts whose year-end falls in the calendar year t-1.

There is no agreement in the literature on an optimal set of fundamental financial statement based signals. We therefore are forced to select signals on a rather ad hoc basis. However, the principles followed in Piotroski's selection are: (i) that the fundamental accounting factor be a plausible indicator of financial distress/strength, and (ii) that the signal be regularly used in the context of measuring financial strength.

3.2 Sample selection and method

We use the master index of the London Share Price Data (LSPD) to identify all UK firms with a listing on the London Stock Exchange, LSE, between 1975 and 2005. Monthly return data for every share listed on the London Stock Exchange, LSE, excluding financial companies, investment trusts and foreign companies, is taken from the LSPD. However, for calculating the market index financial companies are included. The firms on the lightly regulated markets operated by the LSE (The Alternative Investment Market, Third Market or the Unlisted Securities Market) are not "listed" and so are excluded from the analysis. Companies on OFEX and the O.T.C. market are also excluded.

All shares continuously listed for the prior five calendar years are ranked each year on the basis of their five-year buy-and-hold returns and assigned to one of five portfolios. The 20% that performed the worst over five years are allocated to the losers portfolio. The first ranking period ends at the end of June 1981, and the last one ends at the end of June 2000, a total of 20 ranking periods. Portfolios are formed at the beginning of July each year from 1981 to 2000.

Test period buy-and-hold returns for a portfolio are calculated from individual monthly share prices and dividend payments, allowing for stock splits and other capital

changes[xiv]. The returns for a portfolio are then market adjusted by an equal-weighted market index and then by a market capitalization (value) weighted market index. Arnold and Baker (2005) show that the out-performance of losers is similar when shares within the portfolio are given equal or value weights. As a result, in this study we examine the portfolio performance when the portfolio shares are equally weighted within the portfolio only.

Shares whose type of death from the LSPD database is described as liquidation (death code type 7) quotations cancelled for reasons unknown (14), receiver appointed/liquidation (16), in administration/administrative receivership (20), and cancelled assumed valueless (21), are regarded as losing all value in the delisting month. However, if there is a post-liquidation dividend this is invested equally among the remaining shares in the portfolio. By including even those companies that delist during the test period, many of which show a –100% return, we avoid survivorship bias.

If a company is deleted from the LSPD database for any of the following reasons the money received (or value of shares or other securities received) is reinvested in the portfolio on an equally weighted basis (that is, the remaining investments in the portfolio are scaled up): Acquisition/takeover/merger (5), Suspension/cancellation with shares acquired later (6), Quotation cancelled as the company becomes a private company (8 and 9), Quotation suspended (10), Voluntary liquidation (11), Change to foreign registration (12), Quotation cancelled for reason unknown, dealings under rule 163 (13), Converted into an alternative security for the same company (15), Nationalisation (18). If the amount received from these deletions is unknown then the last share value on LSPD is used as the amount available to invest in the shares remaining in the portfolio.

All companies in the loser sample must have eleven types of data: five-year prior period return, market capitalization at portfolio formation date and nine fundamental variables.

The normal service from Datastream fails to provide accounting data for most listed companies in the 1980s, and excludes many companies in the 1990s. To obtain a more complete set of data we paid for a special service that provides historic financial statement information for the majority of LSE listed companies.

Merging data on loser quintile companies from the LSPD and Datastream is achieved as follows. LSPD company numbers are cross-referenced to SEDOL codes (security identifiers assigned by the LSE). Also, Datastream codes are cross-referenced to SEDOL codes. After combining these databases by SEDOL number we found that some SEDOL numbers are used more than once, so to confirm the correct combinations we also matched by company name, previous name, date of last revision to security name, base date and end date. Despite these steps we found that some companies were still not matched. Those that remain unmatched by SEDOL number are linked by examining in LSPD and Datastream the time series unadjusted share price[xv]. The companies matched by time series adjusted share price are then also matched by company name, previous name, date of last revision to security name, base date and end date. Of the Official List companies on LSPD that are not financials, investment trusts or overseas corporations, 85% also have all the data we require available on the supplementary Datastream database in the period 1981-2005.

We are unable to use data prior to 1981 for portfolio formation because of the absence of accounting data for most listed firms prior to that (see Nagel, 2001 for a

description of the problem). Also, five years of prior period returns are needed to allocate shares to loser portfolios and LSPD provides returns for all listed companies only from 1975.

Finally, throughout this paper returns are calculated as the proportional changes in share returns over a period, except in the calculation of betas, where continuously compounded returns are used.

The number of firms in the sample grows from 519 in the first sample formation year (1981) to 637 in the last year (2000). The number of companies for whole research period (from 1981 to 2000) is 1745.

4. Test period returns for portfolios defined by five-year prior period return.

We first calculate the buy-and-hold test period returns to quintile portfolios formed on the basis of five-year rank period returns. In Panel A of Table 1 these returns are market-adjusted by an equal-weighted market index constructed using all listed companies except investment trusts and overseas companies. In Panel B the returns are market adjusted by a market index with the same constituents, but they are value-weighted. We report the average results over the 20 test periods for each of the quintile portfolios. Table 1 shows the now familiar inverse relation between the past and subsequent returns.

Table 1 Average market-adjusted buy-and-hold test period returns for quintile portfolios formed on the basis of five-year rank period buy-and-hold returns.

London Stock Exchange listed UK shares with a continuous listing for five years are ranked and assigned to quintiles annually on the basis of their returns over five year periods to end June 1981 and all subsequent Junes to 2000. Starting at the beginning of July each year 1981 to 2000 average market-adjusted returns for shares within an equal-weighted quintile portfolio are calculated for periods of 1, 2, 3, 4 and 5 years post-formation. In Panel A an equal-weighted market index including all listed shares except investment trusts and overseas companies is used to adjust returns. In Panel B a market-capitalisation weighted market index including all listed shares except investment trusts and overseas companies is used to adjust returns. The returns in the ranking period are raw returns with no market adjustment. All numbers presented are averages over the 20 test periods computed for corresponding portfolios.

Panel A Equal-weighted market index portfolio

Portfolio	Rank period (5-year) Buy-and-hold return	Months after portfolio formation 12	24	36	48	60
1(loser)	-0.2882	0.0883	0.2455	0.4232	0.5618	0.6524
1 sample t-test		3.10	3.60	4.84	5.27	5.06
2	0.4968	0.0104	0.0829	0.1695	0.2825	0.3758
1 sample t-test		0.68	3.75	4.21	4.46	4.88
3	1.1985	0.0003	-0.0037	-0.0058	0.0115	0.0163
1 sample t-test		0.02	-0.15	-0.19	0.27	0.36
4	2.1853	-0.0237	-0.0583	-0.0756	-0.1208	-0.1342
1 sample t-test		-1.42	-2.20	-2.89	-3.19	-2.82
5(winner)	6.5729	-0.0324	-0.1041	-0.1941	-0.2924	-0.3321
1 sample t-test		-1.75	-3.92	-4.42	-4.46	-3.78
Loser minus winner (L-W)		0.1207	0.3496	0.6173	0.8542	0.9845
Paired two sample t-test		2.98	4.13	5.20	5.51	5.36

Panel B Value-weighted market index portfolio

Portfolio	Rank period (5-year) Buy-and-hold return	Months after portfolio formation 12	24	36	48	60
1(loser)	-0.2882	0.1237	0.3386	0.5867	0.8025	0.9435
1 sample t-test		2.16	2.78	3.52	3.59	3.39
2	0.4968	0.0457	0.1759	0.3329	0.5233	0.6669
1 sample t-test		1.49	2.46	2.80	2.82	2.81
3	1.1985	0.0357	0.0894	0.1576	0.2522	0.3074
1 sample t-test		1.19	1.40	1.64	1.81	1.75
4	2.1853	0.0117	0.0348	0.0878	0.1200	0.1569
1 sample t-test		0.47	0.75	1.02	0.97	0.99
5(winner)	6.5729	0.0030	-0.0110	-0.0307	-0.0517	-0.0410
1 sample t-test		0.11	-0.24	-0.48	-0.67	-0.34
Loser minus winner (L-W)		0.1207	0.3496	0.6173	0.8542	0.9845
Paired two sample t-test		2.98	4.13	5.20	5.51	5.36

Note: a figure of 0.0767 indicates a return of 7.67%

We find that the loser portfolio out-performs the equal-weighted market index by 65% over five years, or 10.5% per year. In contrast, the prior period winners under-perform

equal-weighted market index in the subsequent five years by 33%. When the larger firms in the market index are given greater weight the out-performance of the loser quintile is shown to be even larger at 94% over five years. The difference in performance for the losers relative to the winners at 98% is very close to the L-W five-year return of 100% shown in the Arnold and Baker's (2005) decile-based study, which examined performance over the longer period 1960 – 2002.

Figure 1 shows the average cumulative market-adjusted returns month-by-month for the five portfolios. Clearly, the return reversal effect kicks in fairly soon after portfolio formation and continues throughout the next five years. Also, from very early on the ranking of relative performance is the exact reverse of the five years beforehand, with portfolios 1 (prior period losers) and 2 placed first and second, and 4 and 5 (prior period winners) placed last.

Figure 1. Cumulative market-adjusted returns for each quintile over the 60 month test period – equal-weighted market index

LSE listed UK stocks are ranked and assigned to quintiles annually on the basis of their returns over five year periods to end of June 1981 and all subsequent Junes to 2000. Cumulative equal-weighted average residual returns for shares month-by-month in the post-formation period are calculated. An equal-weighted market index including all listed UK shares except investment trusts is used to adjust returns. All results presented are averages over the 20 rank periods computed for corresponding portfolios.
Note that a figure of, say, 0.20 should be interpreted as a market-adjusted return of 20%

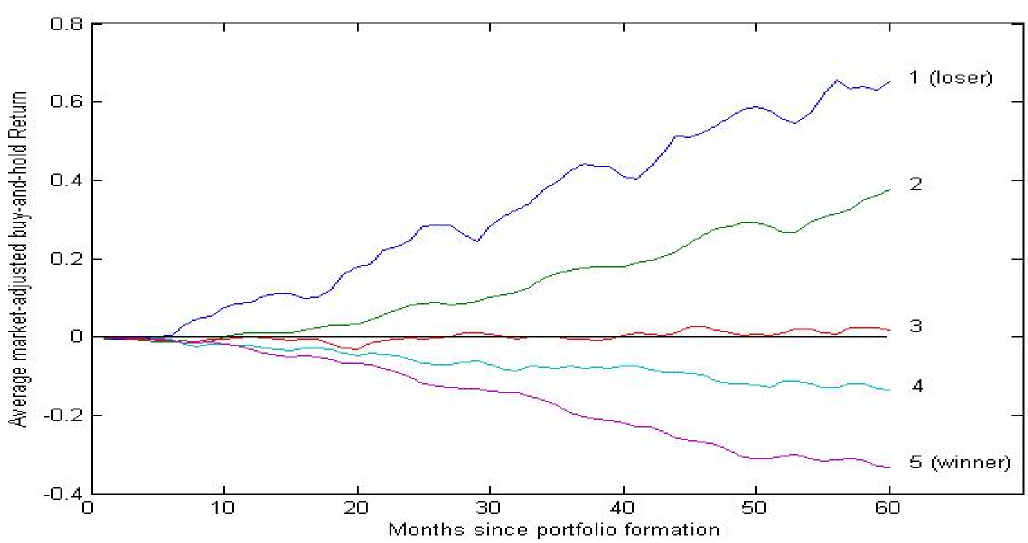


Figure 2 is constructed in the same manner as figure 1 except that the market adjustment is made using a value weighted index.

Figure 2 Cumulative market-adjusted returns for each quintile over the 60 month test period – value-weighted market index

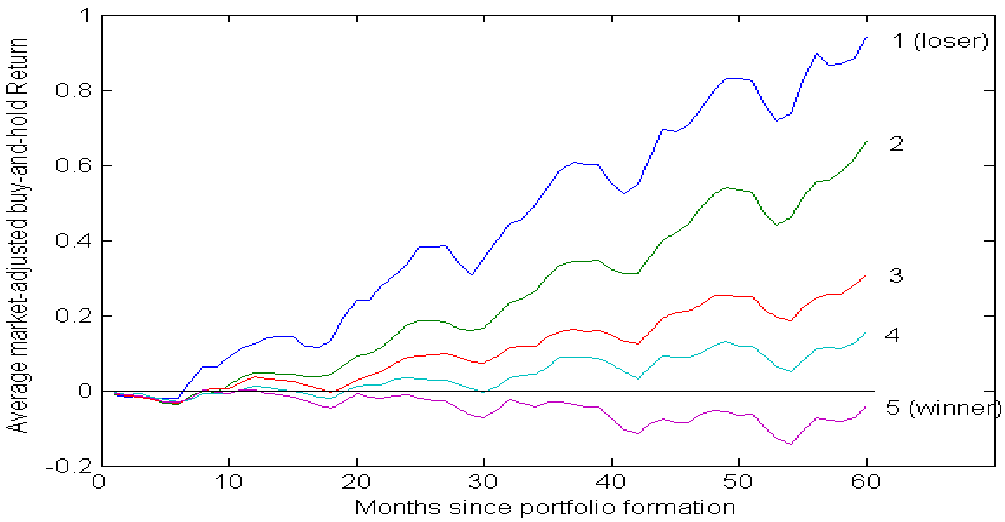


Table 2 shows the characteristics of the loser firms – those in the lowest prior-period return quintile. In a number of cases there are extreme values causing a distortion in the standard deviation (and the mean). Therefore, following the calculation of the normal standard deviation – shown in the fourth column – we also calculate a standard deviation when all those values more than four standard deviations from the mean are excluded. This is our adjusted standard deviation, shown in the fifth column.

Table 2. Characteristics of loser firms (3,170 firms-year observations between 1981 and 2000)

Variable	Mean	Median	Standard deviation	Adjusted standard deviation	Proportion with positive signal
Market cap(£m)	72.47	11.00	286.33	134.75	n/a
ROCE	0.13	0.09	2.55	0.42	0.77
CFO	0.19	0.15	1.64	0.52	0.79
Δ ROCE	0.02	(0.01)	2.77	0.57	0.45
ACCRUAL	0.19	0.12	1.95	0.54	0.77
Δ GEAR	1.01	(0.01)	59.29	2.93	0.43
Δ LIQUID	(0.01)	(0.02)	0.77	0.47	0.44
EQ_OFFER	n/a	n/a	n/a	n/a	0.85
Δ MARGIN	(0.02)	(0.00)	2.78	0.21	0.44
Δ TURN	0.00	0.00	0.29	0.06	0.53

Losers tend to be very small companies with a median market capitalization of only £11m. However, there is a high degree of variability around that median figure, with some large market capitalization firms in the sample. Before the deduction of interest and tax, over three-quarters of the losers display a positive profit or cash flow. Considering that these firms have lost on average 29% of value over the previous 5 years it is perhaps surprising that the median operating ROCE is as high as 9% and the median operating cash flow as a percentage of total assets as high as 15%. Under one-half of the losers produced an improving trend in ROCE in the recent past, but 77% produced greater operating cash flows than operating profits (with a median twelve percentage point difference).

Most loser firms displayed a deteriorating capital gearing position, but as many as 43% did show some improvement. The figures for the changes in the current ratio are similar. A mere 15% of the sample engaged in an issue of shares accounting for more than 2% of market capitalization in the year prior to portfolio formation. Change in operating profit margin was generally in a negative direction, but 44% of losers produced an improving trading margin position. Roughly one-half of firms showed a deteriorating asset turnover.

The overall picture is of a heterogeneous group of companies in terms of financial statement fundamental variables.

Table 3 shows the average returns to losers following allocation to 10 portfolios defined by financial statement factors. At the beginning of each July L-scores are calculated for the loser quintile shares based on accounting data for year t-1. The market-adjusted returns on those portfolios containing companies having the same L-score are calculated for the following 12, 24, 36, 48 and 60 months. The averages across all L-score portfolios formed between 1981 and 2000 are shown. We also classify firms with the lowest L-scores (0, 1 and 2) as *Low L-score firms* expecting them to display the worst subsequent return performance. Firms receiving the highest L-scores, of 7, 8 and 9, thus showing the strongest fundamental signals, are classified as *High L-score firms*. These are expected to produce better subsequent return performance than either the Low L-score firms or the all loser firm portfolio, given the strength of their fundamental signals.

Table 3. Test period buy-and-hold market-adjusted returns to a loser strategy based on fundamental accounting variable signals

Shares are initially allocated to quintiles on the basis of prior five-year returns, as in table 1. At the beginning of July 1981 to 2000 the shares in the loser quintile are then examined on the basis of the nine fundamental accounting factors. Companies scoring a 1 for all nine factors are placed into the L-score portfolio 9. Those with no positive signals are placed into the L-score portfolio '0', and so on. Buy-and-hold returns extending up to 60 months post-formation are calculated after adjustment for the value-weighted market index. Shares within each L-score portfolio are equally weighted. The market index is constructed using all companies in the LSPD except investment trusts and overseas companies, and is not confined to the loser shares – shares are market-capitalisation weighted. The high L-score and low L-score portfolios are constructed by combining all companies in L-score portfolios 0, 1 and 2 (for low L-score) and 7, 8 and 9 (for high L-score) and then calculating average market adjusted returns for the portfolio formation, which is then averaged over 20 years.

	Number of Companies		Months after portfolio formation					Per cent positive after	
	total	average	12	24	36	48	60	36 months	60 months
All loser	3170	158.5	0.1237	0.3386	0.5867	0.8025	0.9435	47.73%	46.92%
L-score									
9	156	7.8	0.2762	0.5935	0.9560	1.2227	1.4287	53.43%	56.01%
8	338	16.9	0.1155	0.4078	0.5961	0.8640	1.1053	54.45%	51.82%
7	470	23.5	0.1481	0.3428	0.5619	0.7851	1.0708	52.47%	50.36%
6	598	29.9	0.1359	0.4229	0.5661	0.7285	0.8271	47.67%	47.13%
5	628	31.4	0.1287	0.2936	0.4747	0.8236	0.9012	45.88%	48.53%
4	514	25.7	0.1359	0.3337	0.5122	0.4952	0.6402	47.83%	43.28%
3	282	14.1	0.0903	0.4457	1.6975	2.0518	2.1657	40.06%	40.01%
2	152	7.6	0.0712	0.2090	0.7514	0.4900	0.6001	34.79%	34.00%
1	36	1.8	0.1046	0.2375	0.3379	0.5122	0.8145	31.94%	15.74%
0	4	0.2	-0.2657	0.1998	-0.0905	-0.0818	-0.9359	33.33%	33.33%
High L-score(7,8,9)	962	48.1	0.1505	0.3799	0.5997	0.8581	1.0853	53.03%	51.47%
Low L-score (0,1,2)	192	9.6	0.0744	0.2144	0.6144	0.4543	0.6174	34.17%	30.52%
High-All loser			0.0268	0.0413	0.0130	0.0555	0.1418		
Paired two sample t-test			1.10	0.72	0.13	0.43	0.96		
High-Low			0.0762	0.1655	-0.0148	0.4038	0.4679		
Paired two sample t-test			0.8	0.68	-0.03	1.09	1.14		

Table 3 shows an imperfect, but distinct, pattern, with the highest returns occurring in the higher L-score portfolios, and the lowest returns in the low L-score portfolios. Generally, we find the L-score portfolio performance is ranked in the expected order with L-score portfolio 9 performing the best and L-score 0 the worst, and 4, 5 and 6 somewhere in the middle. However, L-score portfolio 3 is an exception to this pattern after the second holding year. When the details of this portfolio were investigated it was found that one company bought in 1981 for portfolio 3 produced a return over three years of 11,800%, thus raising the average significantly for the first three years – the company was taken over in 1984. If this outlier is removed the five year market-adjusted returns for L-score 3 portfolio falls to 98%, lower than that on portfolio 7.

The majority (53%) of the High L-score firms produce positive market adjusted returns, whereas only around one-third of the Low L-score firms manage to outperform the market capitalization market index (34% over three years and 31% over five).

The overall impression is that L-score level has some bearing on future portfolio performance. When we examine the difference between the High L-score portfolio and the performance of the All-losers portfolio we find a positive result, for example, over five years, on average, those firms in L-score categories 7, 8 or 9 produce returns 108.5% above the market, compared with 94.3% on average for the quintiles of losers. However, we do not find this to be statistically significant. Also, the difference in returns between the High L-score and Low L-score is statistically insignificant.

Figure 3 shows the average cumulative market-adjusted returns for the ten L-score portfolios. It is clear that generally the higher L-score firms out-perform the market and the lower L-score throughout a five-year holding period. If the L-score 3 portfolio is adjusted by

removing that one extraordinary firm (out of 282) then the five-year performances would be far more orderly – but not perfect, given that L-score portfolio 1 out-performs L-score portfolio 2, and L-score 5 performs slightly better than 6 – see figure 4.

Figure 3. Cumulative market-adjusted returns to loser shares classified by L-scores

Residual buy-and-hold returns are calculated after deduction of a value-weighted market index – as in table 3. Shares within an L-score portfolio are equally weighted. The results presented are an average of the 20 portfolio formations. (No outliers removed)

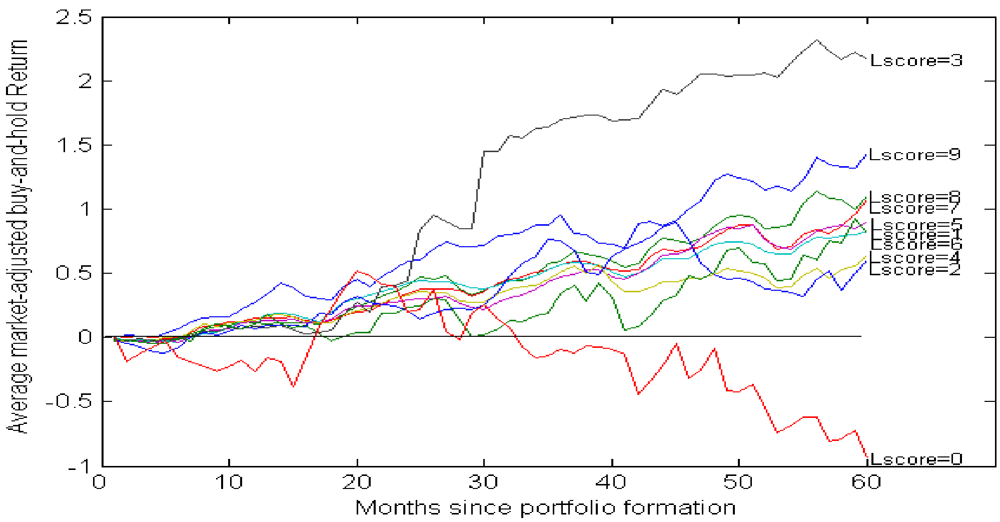
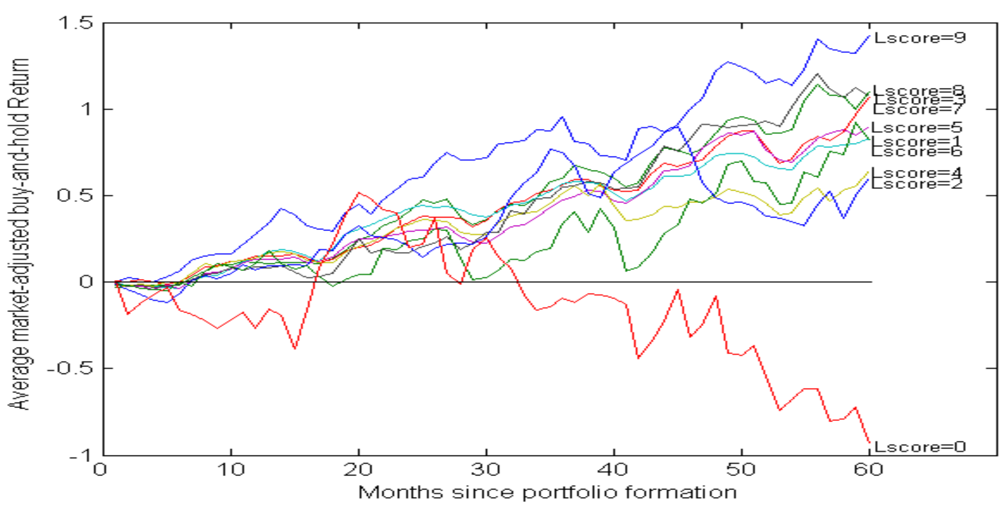


Figure 4. Cumulative market-adjusted returns to loser shares classified by L-scores – One outlier in group L-score = 3 is deleted



5. The effectiveness of the financial-statement data strategy in small, medium and large company shares

Arnold and Baker (2005) established the return reversal effect to be independent of the size effect in UK shares. An interesting question to consider is whether the abnormal return to

losers ranked high by accounting fundamentals is stronger or weaker in smaller firms. *A priori* we postulate that smaller companies with a tendency to generate less investor, analyst and press attention are more vulnerable to mis-pricing with regard to their fundamental accounting characteristics than large, widely followed, companies.

At the end of June each year 1981 to 2000 all companies in the LSPD except financials, investment trusts and overseas companies are arrayed by market capitalization and then allocated to one of three size categories: smallest 30%, medium-sized 40% and the largest 30%. Within each size cohort companies are arrayed on the basis of prior five-year returns and allocated to quintiles. Those companies in the loser quintiles are then ranked by L-score. The market-adjusted returns of each of these L-score loser portfolios over the subsequent five years are calculated. The results are shown in Table 4.

The first key observation from Table 4 is that the returns to losers depends very much on the size of firm: The small losers produce a five-year return 136% above the market; the medium sized losers out-perform the market by 61%, and; the large firm losers, while still out-performing, do so by a mere 42% over five years. This, again, indicates a strong small firm effect also evident in the Arnold and Baker (2005) study. Interestingly, the percentage of losers that produce positive returns over three or five years is in the reverse order to what one might expect given the average post-formation performances: only 44% of small firm out-perform the market index over three years, whereas 47% of medium-sized firms and 49% of large firms do. It would seem that the small firm portfolios rely to an extraordinary extent on the return performance of a minority of firms. An investor in a small firm loser strategy would need to cope with witnessing 56% of companies in the portfolio under-performing the market. The investor in a large loser portfolio would need the psychological fortitude to

withstand a 'mere' 51% being 'failures' (as defined by under performance of a market capitalization weighted index) over three or five years.

There is the possibility of lowering the failure rate by investing in companies with high L-scores. For example, by investing only in companies with L-scores of nine the failure rate falls to 40% for small firms, 37 % for medium-sized firms and 45% for large firms over three years. On the other hand, investing in low L-score firms results in a very high failure rate. For example, investing in the Low L-score category (L-scores of 0, 1 and 2) leads to only 25% of small losers out-performing over five years (22% for medium-sized firms and 45% for large). The pattern in the final two columns is clear: a raising of L-scores raises the proportion of firms the beat the market.

We observe that small loser High L-score companies (L-scores of 7, 8 and 9 combined) out-perform small loser Low L-score (L-scores of 0, 1 and 2 combined) companies by a statistically significant 27% over one year, 80% over two years, 115% over three years and 110% over four years. The medium-sized firms show a slightly greater L-score response, with the High L-score firms outperforming the Low L-score firms by a statistically significant 30% over one post-formation year, 65% over two, 99% over three and 122% over four years, 119% over five years. In the large firm group we observe a strong response to L-score ranking (e.g. High-Low out-performance is 97% over five years), but this it less than for small and medium-sized firms. However, these results are inhibited by the small number of large firms showing L-scores of two or less. Despite this, the evidence showing that the highest gains are from fundamental analysis for small and medium-sized companies provides some indication that the greatest information gains rest with those shares

given least attention by institutional fund managers or analysts. However, there remain information gains with respect to L-scores for the large firms.

Table 4. Average test period market-adjusted buy-and-hold returns to losers based on fundamental financial statement characteristics and size of company.

Shares in the market index are value-weighted and it comprises all LSPD shares except investment trusts and overseas companies.

Panel A Small companies

	Number of Companies		Months after portfolio formation					Per cent positive after	
	total	average	12	24	36	48	60	36 months	60 months
All small losers	966	48.3	0.1610	0.4520	0.8275	1.1822	1.3616	44.14%	42.76%
L-score									
9	34.5	1.7	0.9380	1.5307	2.4980	1.8156	2.0748	59.89%	53.78%
8	104	5.2	0.1994	0.5279	0.5398	0.6942	1.1137	48.24%	46.21%
7	118	5.9	0.2677	0.6247	1.1201	1.3720	1.7659	57.76%	52.39%
6	154	7.7	0.1586	0.3553	0.4758	0.6630	0.6084	40.46%	41.97%
5	172	8.6	0.1964	0.3808	0.4889	1.3160	1.1480	37.66%	42.67%
4	164	8.2	0.1091	0.3004	0.5231	0.6864	0.8614	46.61%	41.99%
3	118	5.9	-0.0322	0.9719	3.6040	4.1547	4.3140	41.79%	38.67%
2	76	3.8	0.0269	-0.1117	-0.0759	0.3007	1.0514	28.81%	30.33%
1	22.4	1.1	0.1383	0.0761	0.2721	0.5941	0.9526	34.52%	16.67%
0	2	0.1	-0.5211	-0.4955	-1.0861	-1.0972	-1.8086	0.00%	0.00%
High L-score (7,8,9)	260	13.0	0.3236	0.7334	1.0774	1.3265	1.8293	51.96%	50.02%
Low L-score (0,1,2)	100	5.0	0.0492	-0.0748	-0.0761	0.2291	0.8354	28.33%	25.40%
High - All small loser			0.1626	0.2814	0.2499	0.1443	0.4677		
Paired two sample t-test			2.27	1.17	0.76	0.40	1.11		
High - Low			0.2744	0.8082	1.1535	1.0974	0.9939		
Paired two sample t-test			1.95	2.53	3.39	2.02	1.05		

PANEL B Medium-sized firms

	Number of Companies		Months after portfolio formation					Per cent positive after	
	total	average	12	24	36	48	60	36 months	60 months
All medium losers	1292	64.6	0.0551	0.1809	0.3018	0.4497	0.6065	46.84%	45.94%
L-score									
9	72	3.6	0.1628	0.4320	0.7154	0.9111	0.9832	63.24%	60.26%
8	154	8.1	0.0107	0.1842	0.2958	0.6041	0.7420	51.23%	54.41%
7	218	10.9	0.0850	0.2439	0.4184	0.6146	0.7344	50.99%	50.80%
6	261	13.1	0.0174	0.1189	0.2509	0.4484	0.7114	45.94%	47.11%
5	269	13.5	0.0875	0.2708	0.3823	0.5804	0.8037	45.07%	44.06%
4	201	10.1	0.0861	0.2019	0.2209	0.3346	0.4876	47.56%	43.71%
3	83	4.2	-0.0041	-0.0891	0.0623	-0.0316	-0.0869	43.47%	39.30%
2	29	1.5	-0.2711	-0.4159	-0.5436	-0.5092	-0.3714	22.22%	23.33%
1	5	0.3	-0.1558	-0.3034	-0.5087	-0.6998	-0.8341	0.00%	0.00%
0	0	0.0							
High L-score (7,8,9)	444	22.2	0.0707	0.2260	0.3885	0.6098	0.7349	52.09%	51.62%
Low L-score (0,1,2)	34	1.7	-0.2296	-0.3856	-0.5239	-0.5196	-0.4096	20.83%	21.88%
High - All medium losers			0.0156	0.0451	0.0867	0.1601	0.1283		
Paired two sample t-test			0.82	1.43	1.55	3.02	1.80		
High-Low			0.2954	0.6478	0.9939	1.2211	1.1919		
Paired two sample t-test			3.84	5.50	5.60	5.96	4.81		

PANEL C Large firms

	Number of Companies		Months after portfolio formation					Per cent positive after	
	total	average	12	24	36	48	60	36 months	60 months
All large losers	965	48.25	0.0057	0.0584	0.1464	0.2775	0.4195	49.02%	49.40%
L-score									
9	55.0	2.8	-0.0203	0.0340	0.1331	0.6449	0.5363	54.63%	56.33%
8	106.0	5.3	0.0857	0.1241	0.3082	0.5016	0.6311	53.78%	52.61%
7	181.0	9.1	0.0313	0.0487	0.1010	0.2081	0.2680	43.59%	48.29%
6	215.0	10.8	0.0111	0.1191	0.2421	0.4572	0.7126	50.64%	48.71%
5	231.0	11.6	-0.0234	0.0147	0.1306	0.2514	0.3465	49.87%	48.09%
4	127.0	6.4	-0.0538	-0.0889	-0.1045	-0.0501	0.1604	37.47%	36.72%
3	38.0	1.9	-0.0129	0.0065	0.0135	0.0999	-0.0851	38.21%	36.92%
2	12.0	0.6	-0.0472	0.1201	-0.1381	-0.4822	-0.4112	40.48%	45.24%
1	0.0	0.0							
0	0.0	0.0							
High L-score (7,8,9)	342	17.1	0.0266	0.0658	0.1690	0.3575	0.4640	49.26%	52.16%
Low L-score (0,1,2)	12	0.6	-0.0472	0.120056	-0.13809	-0.48217	-0.41121	40.48%	45.24%
High - All large loser			0.0209	0.0074	0.0226	0.0800	0.0445		
Paired two sample t-test			1.12	0.26	0.80	1.43	0.51		
High - Low			0.1145	0.0156	0.3844	0.9768	0.9745		
Paired two sample t-test			0.65	0.07	1.67	2.70	2.23		

6. Risk

In attempting a risk explanation for the results we have a difficulty. The shares that out-perform tend to be those with the smallest amount of *ex ante* financial and operating risk as measured by the financial statement performance signals. Nevertheless, it is important to examine the risk of these portfolios when risk is defined in alternative ways. We consider five alternative risk measures.

The first two risk measures are beta and standard deviation. These are presented for each of the L-score portfolios in Table 5. For each portfolio we have 20x12 monthly observations on returns in the first year following formation. We also compute the corresponding monthly returns on a value-weighted market portfolio comprising all UK listed shares (excluding investment trusts). The risk-free interest rate is taken as the 30-day Treasury rate. Hence we can calculate beta and standard deviation. Beta for the first post-portfolio formation year is calculated from the following formulae:

$$r_{pt} - r_{ft} = \alpha_p + \beta_p (r_{mt} - r_{ft}) + e_t \quad (1)$$

$$r_{Ht} - r_{Lt} = \alpha_{H\text{-}L} + \beta_{H\text{-}L} (r_{mt} - r_{ft}) + e_t \quad (2)$$

Where all returns are continually compounded, and:

r_{mt} is the monthly return on the value weighted market portfolio comprising all listed UK stocks (excluding investment trusts) in month t,

r_{pt} is the return on the equally weighted portfolio in the test period month,

r_{ft} is the risk-free rate of return in month t,

β_p is the portfolio beta,

H and L represent the High L-score (shares with an L-score of 7, 8 or 9) and the Low L-score (shares with an L-score of 0, 1 or 2) portfolios respectively.

Parallel analyses are conducted for each of the test period years.

Table 5 Betas and Standard Deviations for L-score Loser Portfolios

All LSE UK listed shares are ranked and allocated to prior period return quintiles each June from 1981 to 2000. The loser quintile shares are then sorted on L-scores and allocated to 10 portfolios. In the first test period year following L-score portfolio formation we observe the raw monthly returns of the portfolio relative to the Treasury Bill rate and the return on a value-weighted market portfolio relative to the (30 day) Treasury Bill rate. The regressions are based on all the monthly observations for a portfolio, drawing on all 20 portfolio formations, thus 20 x 12 monthly observations are used. The analysis is repeated for each of the test years. Using the 20 formation periods, we also compute the standard deviation of returns in the year after formation and in each of the other test years. An arbitrage portfolio (High-Low, H-L) is constructed by subtracting the test period monthly return for the High L-score shares from the return on the Low L-score shares for that month.

$r_{pt} - r_{ft} = \alpha_p + \beta_p (r_{mt} - r_{ft}) + e$

$r_{Ht} - r_{Lt} = \alpha_{H\text{-}L} + \beta_{H\text{-}L} (r_{mt} - r_{ft}) + e_t$

Test year after formation	L-score portfolio	Alpha	Beta	Standard deviation
1	9	0.0162	0.7710	0.0941
1	8	0.0079	0.8860	0.0682
1	7	0.0105	0.8400	0.0650
1	6	0.0094	0.8300	0.0683
1	5	0.0075	0.9180	0.0724
1	4	0.0097	0.8570	0.0880
1	3	0.0057	0.8740	0.0905
1	2	0.0040	0.9530	0.1264
1	1	0.0070	1.1000	0.1535
1	0	-0.0175	1.3000	0.1789
1	High - Low	0.0067	-0.0700	0.0937
2	9	0.0085	0.9230	0.0884
2	8	0.0138	0.7750	0.0690
2	7	0.0087	0.9470	0.0667
2	6	0.0116	0.8380	0.0762
2	5	0.0079	0.8640	0.0662
2	4	0.0069	0.8940	0.0688
2	3	0.0101	1.1200	0.1514
2	2	0.0063	0.9090	0.1226
2	1	-0.0044	1.2400	0.1478
2	0	0.0723	3.6400	0.4355
2	High - Low	0.0030	-0.1620	0.1024
3	9	0.0104	0.8030	0.0787
3	8	0.0072	0.7890	0.0734
3	7	0.0068	0.9100	0.0656

3	6	0.0036	0.7760	0.0535
3	5	0.0048	0.9010	0.0634
3	4	0.0044	0.9640	0.0680
3	3	0.0171	0.9780	0.1295
3	2	0.0040	0.9630	0.1077
3	1	-0.0017	0.7370	0.1711
3	0	-0.0054	0.9990	0.1889
3	High - Low	0.0035	-0.0650	0.0808
4	9	0.0128	1.0000	0.1522
4	8	0.0090	0.7850	0.0735
4	7	0.0021	0.8680	0.0684
4	6	0.0041	0.8610	0.0612
4	5	0.0074	0.9460	0.0659
4	4	-0.0006	0.8680	0.0671
4	3	0.0067	1.0100	0.0990
4	2	0.0007	0.9390	0.1052
4	1	0.0144	0.7840	0.1656
4	0	0.0471	-1.3800	0.2795
4	High - Low	0.0040	-0.0460	0.0883
5	9	0.0002	0.7700	0.0782
5	8	0.0030	0.9030	0.0852
5	7	0.0041	0.9120	0.0644
5	6	0.0014	0.8980	0.0579
5	5	0.0004	0.8550	0.0584
5	4	0.0045	0.7910	0.0676
5	3	-0.0040	0.9150	0.0940
5	2	0.0125	1.0000	0.1202
5	1	-0.0055	1.0700	0.1454
5	0	-0.0060	-0.3910	0.1567
5	High - Low	-0.0047	-0.1520	0.0984

An alpha return of 0.0162 should be interpreted as 1.62% per month

In Table 5 for the first four years following portfolio formation the High L-score portfolios tend to display lower betas than Low L-score portfolios, while their alphas are higher and positive. The overall impression is that the higher L-score portfolios do not have

raised beta levels, and the alphas are greater for the higher L-scores. Nor do the higher L-score portfolios display greater risk as measured by standard deviation.

We also examine the potential for High L-score firms to perform poorly over periods when the stock market is in short-term decline or the economy is in recession or growing slowly. It is conceivable that when there are large declines in the stock market index over a period of a month the returns on the High L-score portfolios fall to an exaggerated extent, showing them to be more risky than both the market and the Low L-score portfolios. Also it may be the case that when quarterly real GDP declines the loser portfolios suffer more than other shares.

Thus an investor with a time horizon measured in weeks or months might be concerned about these kinds of intra-year vulnerability to events. To test the risk of portfolios over short periods we observe returns on the High L-score portfolios (portfolios of L-scores of 7, 8 and 9 are combined) and Low L-score portfolios (combining L-scores of 0, 1 and 2), as well as the market portfolio during each of the 288 months from July 1981 to June 2005. These months are placed into four categories:

- The 50 months when the value-weighted market index return was at its worst ('W_{50}')
- The other 45 months when the value-weighted market index fell ('N_{45}')
- The 50 months with the highest value-weighted market index returns ('B_{50}')
- The other 143 months when the value-weighted market portfolio rose ('P_{143}')

Each of the 60 test months for each of the 20 portfolio formations are allocated to one of the four categories. The raw (not market adjusted) returns for each of the portfolios falling in a particular month are observed. For any one month between July 1981 and June 2005 the maximum number of portfolios held is five, but this can fall to as low as one in 1981 and in

2005. There are 288 possible observations months and 20x60 = 1200 monthly returns observable for those months amounting to an average of 4.17 observed returns per month.

A similar analysis is conducted for the worst and the best quarters as measured by real GDP growth. Quarterly real GDP data are obtained from Datastream. The 96 quarters are allocated to the following categories:

- The 24 poorest real GDP growth quarters (‘W_{24}’)
- The next 24 lowest real GDP growth quarters (‘L_{24}’)
- The 24 best real GDP growth quarters (‘B_{24}’)
- The next 24 highest real GDP growth quarters (‘H_{24}’)

The returns for each of 60 months for each portfolio are allocated to one of the four categories depending on the real GDP growth in the relevant quarter. The monthly portfolio returns falling in a real GDP category are averaged for all months in that category.

Panel A of Table 6 presents the performance of portfolios in various months as defined by the extent of the rise or fall in the market index that month. The average difference in returns between the High L-score portfolio and Low L-score portfolio for each state is also reported along with t-statistics for the test that the difference of returns is equal to zero. The results show that High L-score shares out-perform Low L-score shares in the worst states of the market by a statistically significant 1.48% per month. This evidence does not support the view that High L-score firms are on average riskier than Low L-score firms[xvi].

Panel B of Table 6 provides information on returns in various states of the world as defined by real GDP growth in the quarter. The results do not indicate that High L-score shares perform worse than Low L-score shares in poor GDP growth periods.

Overall the evidence in Table 6 fails to support a conventional asset pricing equilibrium in which the higher returns on the High L-score portfolio are compensation for the under-performance in bad-states-of-the-world risk – it would seem that the High L-score strategy does not expose investors to greater downside risk.

Table 6. Performance of Losers Grouped by L-scores in Best and Worst Times

Panel A: All the months from July 1981 to June 2005 are divided into four categories: the 50 months when the market index return was at its worst (‘W_{50}’); the other 45 months when the market index return was negative (‘N_{45}’); the 50 months with the highest market index returns (‘B_{50}’); the other 143 months when the market portfolio gave a positive return (‘P_{143}’). A value-weighted market index comprising all the UK listed shares except investment trusts is used to measure market returns. At the beginning of July 1981 and all Julys to 2000 all loser quintile shares are allocated to one of ten portfolios on the basis of their L-scores. The average monthly returns of the shares in L-score portfolios 7, 8 and 9 (‘High L-score’) and in L-score portfolios 0, 1 and 2 (‘Low L-score’) in each of the subsequent 60 months are observed. The results presented are the average monthly returns for the portfolios over the W_{50} , N_{45} , P_{143} and B_{50} months. The t-statistic tests the hypothesis that the difference in returns between the High L-score and the Low L-score portfolios is equal to zero.

Panel B: This is constructed in a similar manner to panel A except that the states are defined in terms of the best and worst quarters for GDP growth. The 96 quarters from July 1981 to June 2005 are divided into 4 sets: the 24 poorest real GDP growth quarters (‘W_{24}’); the next 24 lowest real GDP growth quarters (‘L_{24}’); the 24 best real GDP growth quarters (‘B_{24}’); the next 24 highest real GDP growth quarters (‘H_{24}’). The High L-score portfolio contains the equally weighted highest ranking shares based on L-scores of 7 or above. The Low L-score portfolio contains the equally weighted lowest ranking shares based on L-scores of 2 and below. The market portfolio contains all UK listed shares except investment trusts, which are value weighted in the index. The results presented are the monthly returns for the portfolios over the W_{24} , L_{24} , B_{24} and H_{24} quarters. The t-statistic tests the hypothesis that the difference in returns between the loser and winner portfolios is equal to zero.

Panel A: Portfolio returns across best and worst stock market return months (average monthly returns)

	High L-score	Low L-score	Market index	High-Low	Paired 2 sample t-test
W_{50}	-0.0464	-0.0613	-0.0581	0.0148	3.09
N_{45}	0.0019	0.0033	-0.0089	-0.0014	-0.21
P_{143}	0.0314	0.0332	0.0228	-0.0019	-0.51
B_{50}	0.0625	0.0606	0.0700	0.0019	0.38

Panel B: Portfolio returns across best and worst GDP quarters (average monthly returns)

	High L-score	Low L-score	GDP	High-Low	Paired 2 sample t-test
W_{24}	0.0101	0.0025	-0.0003	0.0076	1.49
L_{24}	0.0207	0.0133	0.0053	0.0074	1.40
H_{24}	0.0129	0.0104	0.0081	0.0025	0.57
B_{24}	0.0299	0.0392	0.0132	-0.0092	-1.45

Note: a figure of 0.0625 for High L-score, Low L-score and market means a monthly return of 6.25%, a figure of 0.0132 for GDP means 1.32% change quarter on quarter.

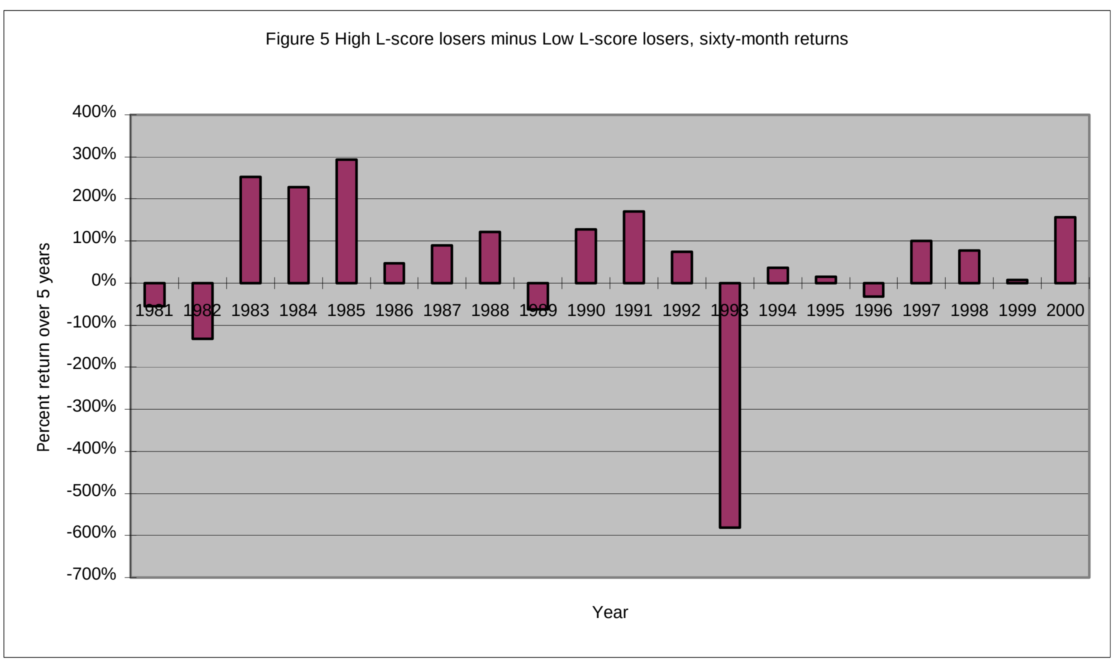
Of great interest to researchers and practitioners alike is the whether there are long periods when the High L-score strategy fails to pay-off. While recognizing the superior performance on average over 20 portfolio formations investors may still be reluctant to

commit funds if they feel that there is a high probability of a sequence of years when below market returns will be delivered. Many investors are not prepared to accept even two consecutive years of under performance, regardless of the out-performance over decades. Financial economists, in order to comment on implications of the evidence for the debate on the pricing efficiency of the LSE, need to know whether High L-score shares under-perform Low L-score shares with some regularity.

Figure 5 shows the performance for each of the 20 High-Low portfolios separately over five-test period years. There are five occasions when the High-Low strategy produces a negative return over the five years following portfolio formation. Thus in three quarters of cases the strategy performed well, but when it performs badly the arbitrageur would lose a substantial amount.

Figure 5. Market-adjusted buy-and-hold five-year test period returns for High L-score losers minus Low L-score losers strategies for each of the twenty portfolio formations.

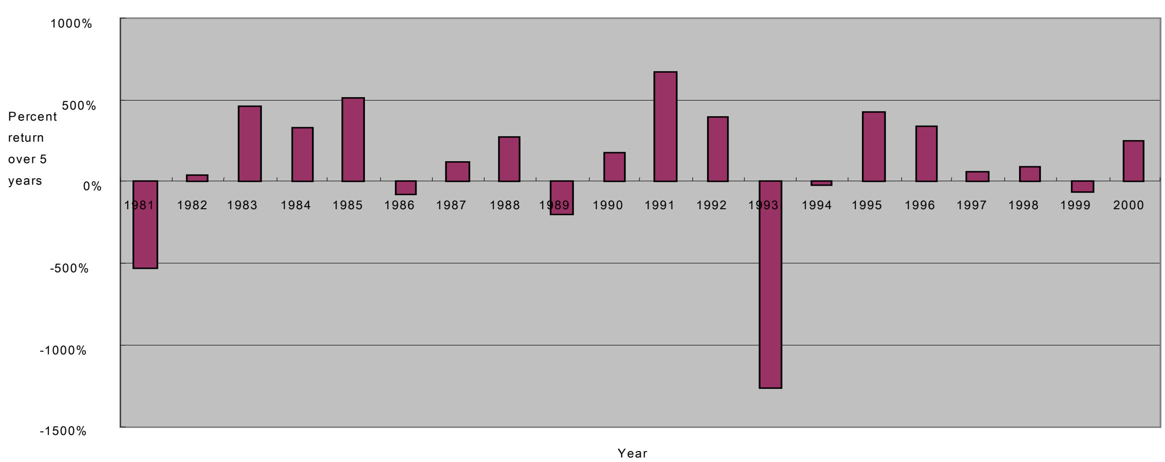
The five-year test period returns for each loser-winner strategy are assigned to the year of formation.



On further investigation it was found that in the 1993 portfolio formation one of the companies in the Low L-score portfolio produces a 5,048% return if bought and held for five years. If this company is deleted from the Low L-score portfolio, the five-year market-adjusted return for this portfolio decreases from 492% to 41%. Thus, the return for High minus Low L-score portfolio return changes from -581% to -129% (the market adjusted return for the High L-score is –88%), still a substantial amount, but not quite so worrying. The High L-score portfolio formed in 1993 actually gave a positive absolute (not market-adjusted return) over the subsequent five years of 48%, but the market rose by an extraordinary amount in the five years to July 1998.

In a similar reliability analysis for the smallest 30% of companies the High L-score minus Low L-score results for each portfolio formation again show that the majority of portfolio formations result in returns outperforming the market index – see in figure 6.

Figure 6. Small market capitalisation analysis: Market-adjusted buy-and-hold five-year test period returns for High L-score losers minus Low L-score losers strategies for sixty month returns.



Again, the extraordinary result for the 1993 formation is largely due to the one company in the small Low L-score portfolio making a 5,048% return. On deleting this company from the

Low L-score portfolio, the five-year market-adjusted return for this portfolio decreases from 1,234% to 315%. Thus, the return for High minus Low L-score portfolio return changes from -1264% into -345%.

Forming arbitrage portfolios over long periods is frequently impossible or prohibitively expensive, therefore investors are interested in the reliability of a long-only strategy – i.e. buying High L-score losers. Table 7 shows the number of occasions when the L-score loser portfolios produced negative market-adjusted returns over five years for the full sample of losers and for the small market capitalization losers. For the All-loser portfolios we find that in only 10% of cases (2 out of 20) does the High L-score portfolio (containing companies with L-scores of 7, 8 and 9) under-perform the value-weighted market index over the five-year holding period. However, the High minus Low arbitrage portfolio under-performs five times out of 20. The last two lines show that the small firm performance is less reliable than for the All-losers; for example, an investor buying small High L-score losers would under perform the market is three years out of ten.

While the small High L-score firms show an overall positive performance it must be acknowledged that investors in a strategy of buying these shares would have to accept the possibility that around one-third of the time the returns would not match those of the market. However, the results for low L-score firms show this strategy to be much less reliable. Holding the low L-score portfolios (0, 1 and 2) would result in sub-market performance in about two-thirds of cases for both All-losers and for small firms. The overall strong positive performance for higher L-score portfolios and the low negative return exposure vis-à-vis lower L-score portfolios casts doubt on a risk-based explanation for the return differences.

Table 7. Number of occasions when L-score portfolios produce negative market-adjusted returns when portfolios are held for five years

	Panel A. All loser companies	**Panel B. Small companies**
L-score		
9	5 out of 20 formations	7 out of 15 formations
8	4 out of 20 formations	8 out of 20 formations
7	6 out of 20 formations	7 out of 20 formations
6	4 out of 20 formations	11 out of 20 formations
5	7 out of 20 formations	10 out of 20 formations
4	9 out of 20 formations	11 out of 20 formations
3	8 out of 20 formations	9 out of 20 formations
2	12 out of 20 formations	13 out of 20 formations
1	14 out of 20 formations	10 out of 14 formations
0	2 out of 3 formations	2 out of 2 formations
High-Low	5 out of 20 formations	6 out of 20 formations
High (9,8,7) portfolio	2 out of 20 formations	6 out of 20 formations

(In some years there is no company in some of L-score portfolio in specific formations. For example, for all loser companies, portfolio L-score = 0 has companies in only 3 formations)

7. Does the L-score predict future company performance?

Evidence on the process underlying the success of the financial statement analysis investment strategy is presented in this section. We consider whether the L-score predicts the future economic performance of the firm or the liquidation rate. Thus, we examine whether the L-score strategy captures systematic errors in market expectations about future earning performance. Table 8 shows the relationship between the loser L-score and the future return on capital employed and the proportion of the portfolio of loser firms liquidated over the subsequent five years.

Earlier in the paper (Table 2) we showed that in year t-1 the mean ROCE for losers is 13%. Panel A of Table 8 shows that in the two years after formation this rate is at least maintained. However, the trend ceases after the second test year and ROCE declines to below the pre-formation rate. Panel A also shows a generally positive relation between L-

score and future profitability in the post-formation years. (There is an outlier in the Low L-score portfolio. One of the companies included in 1996 has an extremely high ROCE of 2,021%, which pushes the ROCE of the Low L-score portfolio in 1996 to 511%. If this company is deleted from the Low L-score portfolio the ROCE in 1996 decreases to 0.07 or 7%, and the average ROCE for Low L-score portfolio for 20 formation will be -0.0187 or – 1.87%, thus allowing third year to fall in with the general pattern of larger post-formation ROCE's for firms with higher L-scores).

Panel B reports the proportion of loser firms that liquidate conditional on the L-score. A strong negative relation between a company's *ex ante* financial strength (L-score) and the incidence of liquidation is shown. The relationship is nearly monotonic across L-score portfolios when held for five years. (Note: all companies in L-score portfolio 0 merged, none were liquidated).

To the extent that the ROCE levels and liquidation rates shown in Table 8 are not expected and priced by investors, a large portion of the market-adjusted returns earned by the High L-score firms over the Low L-score firms could be explained.

Table 8 strongly suggests that L-scores can successfully discriminate between strong and weak future firm performance. The results contradict the common notions of risk. The portfolios of the healthiest firms yield both higher returns and better subsequent financial performance than the most financial distressed firms. The evidence does not support Fama and French's (1993) claim that abnormally high returns are related to financial distress. The evidence does, however, support the view that the market is slow to incorporate information concerning the financial strength of the high L-score firms.

Table 8. Test period economic performance and liquidation rate of loser companies grouped by L-scores

Panel A. Return on Capital Employed

	Average number of firms	Average (mean) ROCE after formation				
		Year 1	Year 2	Year 3	Year 4	Year 5
All loser firms	158.5	0.1463	0.1938	0.0967	0.0959	0.1156
L-score portfolios						
9	7.8	0.1546	0.1370	0.1773	0.2586	0.2648
8	16.9	0.1494	0.0946	0.0612	0.1422	0.1585
7	23.5	0.1345	0.1172	0.0874	0.1392	0.1254
6	29.9	0.1740	0.1231	-0.0208	0.1481	0.0375
5	31.4	0.4315	0.1552	0.1447	0.0724	0.0608
4	25.7	0.1070	0.1376	0.0756	0.0863	0.1107
3	14.1	-0.1475	1.0734	0.2403	-0.0113	0.1310
2	7.6	-0.3195	-0.0855	0.2188	-0.0314	-0.0630
1	2.0	-0.2025	0.3249	-0.0108	0.0438	0.0613
0	1.3	-0.1520	-0.5432	-0.1677	-0.2051	0.0097
High L-score (7,8,9)	48.1	0.1445	0.1132	0.0911	0.1573	0.1589
Low L-score (0,1,2)	9.6	-0.3057	-0.0377	0.2332	-0.0061	0.0506
High-Low		0.4502	0.1507	-0.1420	0.1635	0.1083
Two sample t-statistic		6.1	1.38	-0.52	1.61	0.54

Panel B. Proportion of firms liquidated since portfolio formation

By end of year	Year 1	Year 2	Year 3	Year 4	Year 5
All loser firms	0.69%	2.63%	4.36%	5.81%	7.10%
l-score portfolios					
9	0.56%	1.11%	1.11%	1.42%	1.98%
8	0.00%	0.94%	1.78%	3.47%	4.28%
7	0.29%	1.28%	2.04%	3.38%	4.77%
6	0.55%	2.51%	4.09%	5.41%	6.58%
5	0.75%	3.16%	5.27%	7.06%	8.10%
4	1.28%	3.17%	5.78%	7.17%	7.78%
3	0.75%	6.67%	10.17%	12.25%	14.37%
2	2.36%	4.38%	6.48%	8.31%	10.80%
1	0.00%	1.85%	8.80%	8.80%	17.13%
0	0.00%	0.00%	0.00%	0.00%	0.00%
High l-score (7,8,9)	0.23%	1.17%	1.88%	3.16%	4.27%
Low l-score (0,1,2)	1.62%	3.46%	6.84%	8.42%	11.45%
High-low	-1.39%	-2.29%	-4.96%	-5.26%	-7.18%
Two sample t-statistic	-1.26	-1.27	-2.07	-1.98	-2.66

The difference in liquidation rate between the high and low L-score firms is tested using a t-test statistic from a binomial test.

8. Conclusions

We find that a simple accounting-based fundamental analysis strategy, when applied to a broad sample of shares displaying very poor prior five-year total returns, shifts the distribution of returns earned by the investor. The magnitude of the abnormal returns is large. More specifically, we find that small loser High L-score shares produce statistically significant superior returns to (i) the returns for the complete portfolio of loser shares, and; (ii) to the small loser Low L-score shares.

Many practitioners hold the view that a firm's fundamental value is indicated by information in financial statements and that share prices, at times, deviate from these 'intrinsic values', particular in the more neglected areas of the market, e.g. loser companies, small companies. Then, as deviant prices eventually move toward fundamental values, investment strategies that use financial strength indicators to concentrate fund resources in loser firms with brighter prospects produce abnormally high returns. This paper provides supporting evidence for this view. We find that the annual mean return to a portfolio of loser shares can be increased by at least 16% through the selection of only those losers with a high ranking on financial strength factors.

Furthermore, the L-score strategy appears to be robust across time and to changes in size of firm, although the effect is most pronounced in smaller companies. The risk of the High L-score firms is lower than the risk of the Low L-score, as judged by all the ways in which we measure risk.

A positive relation between the L-score and the future company ROCE performance and a negative relation between the L-score and liquidation probability reinforces the indication that the market under-reacts to historical financial statement information.

One factor not yet discussed is transaction costs. On investigation of the practicalities of implementing a small-firm High L-score loser long only strategy it was discovered that firms with a history of return declines, especially small firms, tend to exhibit very high bid-offer spreads. Some firms within the the quintile of loser firms included in the FTSE Fledgling index and the FTSE All-Aim index show an offer price twice the bid price. A 100% bid-offer spread would result in a large proportion of the advantage of this strategy being eliminated. However, the average spread was a more manageable 20% or so. This remains relatively expensive, but must be considered in the context of market-index adjusted returns of 107% over three year and 133% over four years for small market capitalization loser firms with L-scores of 7 or above (see table 4). It is also possible to select only those firms with bid-offer spreads of less than 10% (but we do not know whether this will result in biasing the performance – an issue to be addressed in a future paper). Other transaction cost (Stamp duty, broker fees) are estimated to be around 1 – 2%, but this can be spread over a number of years.

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[i] For example: Baytas and Cakici (1999) who found return reversal in six countries, Schiereck, De Bondt and Weber (1999) and Külpman (2002) in German shares, Mun, Vasconcellos and Kish (2000) for Canada and the US, Da Costa, (1994) for Brazil, Ahmad and Hussain (2001) for Malaysia, Fung (1999) for Hong Kong, Wang et al. (2004) for Shanghai and Shenzhen. (However, Brailsford (1992) failed to find return reversal in the Australia equity market)

[ii] Our financial statement factors do not always equate exactly to those of Piotroski due to differences in the way Datastream and Compustat database (used by Piotroski in his US study) define particular accounting items. However, we have matched the items as closely as possible.

[iii] Datastream code 707: Return on capital employed (%)
Earnings before interest and tax divided by total capital employed plus short-term borrowings minus total intangibles.

$$707 = \frac{157 + 153 + 622 + 170}{322 + 309 - 344} \times 100$$

157: Pre-Tax Profit (including associates) - adjusted for exceptional items
153: Total interest charges
322: Total Capital Employed
309: Borrowings Repayable Within 1 Year
344: Total Intangibles
622: Associates after tax profits
170: Associates total tax

[iv] Datastream code 137: Operating profit – adjusted: This is net profit derived from normal activities of the company after depreciation and operating provisions, 137 = 993 + 981
993: Operating profit
981: Adjustments to operating profit (This shows the total of all items that have been excluded from the published operating profit. This will include items of an exceptional nature, which do not form part of a company's normal trading activities.)
402: Depreciation relating to tangible fixed assets

445: Change in stock and work in progress: This is the change in stock, net of advances on work in progress, where applicable. For cash flow, it does not include the effect of acquisitions. A minus sign indicates a decrease in the stocks.
448: This shows the increase or decrease in total debtors and equivalent during the year. For cash flow, it does not include the effect of acquisitions. A minus sign indicates a decrease in debtors.
417: Change in creditors: This shows the increase or decrease in creditors during the year. A minus sign indicates a decrease in creditors in the balance sheet. Sometimes described by the company as creditors & provisions.
391: Total assets employed: Defined as the sum of tangible fixed assets, intangible assets, investments (including associates), other assets, total stocks & WIP, total debtors and equivalent, cash and cash equivalents, minus current liabilities.

[v] Datastream code 154: Pre-tax profit: The pre-tax profits as disclosed by the company.

[vi] It has been shown (e.g. Sloan, 1996) that when profits are greater than cash flow from operations this may indicate earnings being pushed up (managed) by positive accrual adjustment. This is a bad signal for future profitability and returns. This measure is used even if cash flow and/or profits are negative

[vii]Datastream code 731: Capital gearing (%): Preference capital plus total debt divided by total capital employed plus short term borrowings minus total intangibles.

$$731 = \frac{306 + 1301}{322 + 309 - 344} x100$$

where:
306: Preference capital
309: Borrowings repayable within 1 year
1301: Total debt
322: Total capital employed
344: Total intangibles

[viii] This ratio of total current assets divided by total current liabilities is called Working capital ratio in Datastream

[ix] Datastream code 741: Working capital ratio: Total current assets divided by total current liabilities.

[x] Datastream code 412: Equity issued for cash: This shows ordinary shares including share premium issued during the year for cash - if possible the amount will be gross of expenses. The cash proceeds of issues of equity shares. Gross amounts are entered here - comprising share capital & premium of ordinary issues.

[xi] Monthly market values are read from A4, Archive file LSPD 2005. Market value on 30 June for each company is used.

[xii] Datastream code 711: Trading profit margin (%). This shows operating profit before depreciation/provisions as a percentage of sales. 711 = (135 / 104) * 100
where:
135: profit before provisions-adjusted
104: total sales

[xiii] Datastream code 721: Turnover/assets employed. This is the ratio of sales to assets employed.
721=104 / (339 + 356 + 359 + 390 + 309)
where:
104: total sales
339: total fixed assets-net
356: total investments (including associates)
359: other assets

390: net current assets
309: borrowing repayable within 1 year

[xiv] The buy-and-hold approach has an advantage over the cumulative abnormal return (CAR) approach because it reflects a realistic strategy available to a long term investor who would suffer from the high transaction costs implicitly assumed by the monthly rebalancing in the CAR method. It seems reasonable to judge the success of the contrarian strategy on the basis of the one-off decision to buy or sell stocks on portfolio formation. The CAR method biases the measurement of rank-period returns and thus affects the composition of the winner and loser portfolios (Dissanaike, 1994). Conrad and Kaul (1993) show that CAR is flawed in that it spuriously inflates the return to the arbitrage portfolio, "Apart from being conceptually consistent with the notion of long term overreaction this measure [buy-and-hold] greatly reduces the statistical biases in previous cumulative performance measures" (p. 40). Barber and Lyon (1997) and Schierick *et. al*. (1999) note that buy-and-hold returns avoid biases in test statistics that result from the summation of monthly excess returns . Also, the buy-and-hold method provides a sharper distinction between portfolios when classifying firms (Loughran and Ritter, 1996). It is less prone to the problems created by infrequent trading. However, one disadvantage with the buy-and-hold method is that the weight accorded to securities that have risen by more than the average within the portfolio will, over time, increase; this could reduce diversification.

Note that we do not rebalance the portfolio at the end of each test period year thus giving each share an equal weight within the portfolio at the start of each of the five holding years. Rebalancing would incur significant transaction costs.

[xv] The price is the closing price which has not been historically adjusted for bonus and rights issues

[xvi] Both High L-score and Low L-scores portfolios out-perform the market index in most states of the market in this analysis. This is largely because the market index used is value weighted, whereas the L-score portfolio shares are equally weighted, giving a greater proportional weight to small companies.