The Profitability of Momentum Trading Strategies in the Irish Equity Market

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Abstract:
We examine the profitability of momentum based trading strategies in the Irish equity market between 1988 and 2007. We investigate a range of trading strategies over alternative backward looking ranking periods and forward looking holding horizons as well as for alternative size momentum portfolios. We find that returns to momentum based strategies are highly non-normally distributed giving rise to concern about the validity of inferences based on standard statistical tests of their abnormal performance. We therefore apply a bootstrap procedure to construct nonparametric p-values for the portfolio performance measures. Overall, we find very little evidence that momentum based trading strategies would have yielded an abnormal risk adjusted return over the period. The Irish equity market appears to be quite efficient in this respect.

Keywords : momentum, trading strategies, equity returns

JEL Classification: G11, G14.

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1. Introduction

Momentum based investment strategies involve holding a portfolio of assets where each period the portfolio holdings are decided by a simple rule of buying past 'winner' assets and selling past 'loser' assets (from among the universe of assets available for selection). The strategy attempts to capture a momentum effect in the price movements of the underlying assets over consecutive time periods. Momentum based trading strategies are of obvious interest to investors as they may provide an abnormal return at relatively low cost. First, the strategy can be constructed to be low (even zero) cost where short positions fund long positions. Second, it is simple to implement as it does not require extensive research into asset selection[1].

The existence of profitable momentum strategies among, for example, equity mutual funds is well documented for the US (Jegadeesh and Titman 2001, 1993) while Fletcher and Forbes (2002) report evidence that a substantial proportion of UK mutual funds also attempt to capture a momentum effect. In general, however, momentum effects are an under-explored phenomena outside of the US equity market. In this study we examine the profitability of equity based momentum strategies in the Irish market. The Irish market is an interesting case because of its comparatively low liquidity and high concentration of stock ownership which may permit momentum effects to persist at least in the short term. Furthermore, smaller markets have in the past been found to be less efficient. Studies of momentum investment strategies are also of general interest to researchers because findings of abnormal returns would typically be in breach of the efficient market hypothesis. However, it should be noted, that in the fund performance literature momentum risk factors are now widely specified in regression models, where the intercept is a measure of stock selection skill, in order to control for performance attributable to momentum effects which do not require 'skill', *per se*, on the part of the fund manager to capture.

We examine the profitability of momentum trading strategies in the Irish equity market by simulating and evaluating several different momentum portfolios based on alternative size portfolios, ranking periods (used to select equities) and holding periods. We examine the period February 1988 to December 2006. A recent paper by O' Donnell and Baur (2009) also examines momentum trading strategies in the Irish case. Over a similar sample period the paper fails to find evidence of profitable strategies, although some abnormal returns are found during certain sub-periods. We extend the

[1] Of course, transactions costs incurred will be related to the degree of portfolio turnover but clearly a portfolio manager has some discretion here.

O' Donnell and Baur (2009) analysis by examining alternative size momentum portfolios and also by specifically investigating the effects of non-normality in the momentum portfolio returns.

The study proceeds as follows: the next section briefly outlines some of the key findings from previous studies of momentum strategies, section 3 describes the data and methodology used in this study, section 4 describes our empirical findings while section 5 concludes.

2. Review of the Literature

Momentum trading has been widely examined in the literature for a number of alternative markets with variations across studies in factors such as, *inter alia*, the length of historical horizons used to select stocks, holding periods lengths, sample periods and momentum portfolio sizes. For example, Rouwenhourst (1998) found that momentum effects exist in European markets, Moskowitz and Grinblatt (1999) found momentum effects across industry-sorted portfolios, and Grundy and Martin (2001) found that momentum strategies have been consistently profitable in the United States since the 1920s. There was some focus on relative strength strategies (that buy past winners and sell past losers) in early literature, most notably Levy (1967). However, as Levy arrived at this trading rule after investigating 68 different trading rules, it was believed that his result could be attributed to selection bias (Jegadeesh and Titman 1993:66).

Jegadeesh and Titman (1993) is a seminal paper in the area of momentum strategies. Using data from 1965 to 1989 the methodology involves selecting stocks based on their returns over the past 1, 2, 3 or 4 quarters and holding stocks for periods varying from 1 to 4 quarters. Specifically, securities are ranked in ascending order at the beginning of each period. Based on these rankings, ten equally weighted decile portfolios are formed. In each period the strategy buys the top 'winner' portfolio and sells the bottom 'loser' portfolio, holding this position for *h* periods. The authors show that stock returns exhibit momentum behaviour at intermediate horizons. They find that a strategy that uses a 6 month historical ranking period can earn profits of about 1% per month for the following year, after which the returns begin to dissipate. Their results indicate that these profits can be attributed to delayed stock price reactions to firm-specific information, not common factors. That the strategy is profitable in the medium-term but unprofitable in the longer term is seen as evidence that the theories of investors either overreacting (in the case of contrarian strategies) or underreacting (in the case of relative strength strategies) to information are too simplistic. Instead, the authors deduce that investors who buy past winners and sell past losers move market prices from their long-term value temporarily, with a reversal after about a year. An alternative deduction is that the market underreacts to information about the short-term prospects of firms, which tend to be more ambiguous.

The results of Jegadeesh and Titman (1993) prompted a variety of interpretations ranging from explanations of market inefficiency, compensation for risk and data mining. Conrad and Kaul (1998) argue that the apparent momentum arises because of cross-sectional variation in expected returns in adjacent time periods and is simply a compensation for risk. In direct contrast, others such as Daniel, Hirshleifer and Subrahmanyam (1998), Barberis, Shleifer and Vishny (1998) and Hong and Stein (1999) present behavioural models (see Barberis and Thaler 2003 for expanded survey) which argue that the momentum effect arises because of a delayed over-reaction to information that pushes the prices of winners (losers) above (below) their long term values and in subsequent periods the returns of losers should exceed that of winners as prices re-adjust to the over-reaction. Hence such models predict that in the 'postholding' period returns to a momentum strategy should be negative.

Jegadeesh and Titman (2001) evaluate the various explanations for the profitability of momentum trading strategies identified in the literature following their 1993 study. The authors offer evidence to refute the criticism that the momentum anomaly is a product of data mining by demonstrating that profitable momentum strategies persisted in the 1990s after initially being identified in their earlier study of the 1980s. Jegadeesh and Titman (2001) do indeed find evidence that the performance of a momentum portfolio in the postholding period (13 to 60 months) is negative as predicted by Daniel et al (1998) and others above.

While the bulk of the extant momentum literature relates to the US market, Rouwenhorst (1998) is a comprehensive study of the European market, using data from twelve countries; Austria, Belgium, Denmark, France, Germany, Italy, The Netherlands, Norway, Spain, Sweden, Switzerland and the United Kingdom. Employing a similar procedure to that of Jegadeesh and Titman (1993), the paper finds the strategy to be as profitable using European stock prices as it is using US stock prices, yielding approximately 1.16% per month for the following year with reversal thereafter. However, Rouwenhorst (1998) notes that an international momentum strategy may not be well diversified. A dominant performance by one country will subsequently cause the winner portfolio to be overweight that country. In examining this further the paper constructs momentum portfolios that weight by ranking stocks based on past performance relative only to stocks listed in the same country. However, momentum portfolio returns using this revised strategy remain highly profitable at 0.93% per month suggesting that individual country momentum does not explain the success of the European wide strategy. However, the Rouwenhorst (1998) results do show a variation in excess returns (‘winner’ portfolio minus ‘loser’ portfolio) across European countries. Although momentum effects are present in all countries, the strongest profits were experienced by Spain, followed by The Netherlands, Belgium and Denmark. Sweden is the only country that doesn’t experience significant profits in this period, with portfolios earning 0.16% excess returns per month.

Moskowitz and Greenblatt (1999) question whether the apparent profitability of momentum strategies arises because of industry effects. They formulate a momentum strategy based on returns of different industries and test it using stock prices from 1963 to 1985 on the HYSE, AMEX and NASDAQ indices. They also test the individual stock price momentum strategy used by Jegadeesh and Titman (1993) in order to compare the two strategies. They report that momentum returns exist in industry-based portfolios which are more profitable than individual stock price momentum strategies claiming that much of the profit derived from the latter is eroded after controlling for industry effects. Of course, the further implication here is that momentum portfolios are not well diversified, as winners and losers are from the same industry, hence momentum returns may be a compensation for risk and not a market inefficiency.

Jegadeesh and Titman (1993) also investigated the hypothesis that stock prices overreact to information in an extension of the contrarian strategies developed by De Bondt and Thaler (1985, 1987). Contrarian strategies involve buying (selling) stocks that have been performing poorly (well) in recent months. DeBondt and Thaler (1985) explore the consequences of people’s tendencies to overreact to information such as unexpected or dramatic news events. They find that people tend to emphasise recent information too much and under-weight previous information. As a result of investor overreaction, they believed it was possible that stock prices might temporarily depart from their fundamental values. If this is the case, buying past losers would be a more profitable strategy than buying past winners. Their results showed that forming portfolios of past ‘losers’ reaped exceptionally large January returns as far as five years on. Their conclusion was that stocks that experienced extreme long term gains or losses tended to undergo systematic price reversals. DeBondt and Thaler (1987) form portfolios of the most extreme losers and winners as measured by excess cumulative returns over successive five year formation periods. Their results showed that the loser portfolio outperforms the winner portfolio by an average of 31.9% over the following five year test period. In order to reconcile the findings that both contrarian strategies and momentum strategies are profitable, even though they consist of taking opposite actions, Jegadeesh and Titman (1993) considered different time horizons. Contrarian strategies are found to be profitable using returns over the very long term (3 to 5 years) or over the very short term (1 week to 1 month). Relative strength strategies base their selection on price movements over the medium horizon (3 to 12 months).

The Irish case has been examined recently by O' Donnell and Baur (2009). Over the period 1984 to 2007 the authors examine momentum portfolios (winner minus loser) as well as winner and loser portfolios separately. Over the full sample period the authors find no evidence of profitable momentum strategies although some evidence is found examining alternative sub-periods of high, low and negative market growth. First, however, O' Donnell and Baur (2009) form momentum portfolios comprising the top and bottom third of stocks. In our paper, we look further into alternative size portfolios to identify possible profitable momentum strategies among the more extreme winner and loser stocks. Second, O' Donnell and Baur report standard statistical tests of risk adjusted return. However, we find that portfolios of winners and loser stocks are both highly non-normally distributed and serially correlated – so much so that questions arise as to the validity of the standard statistical tests such as t-tests. To examine the robustness of the O' Donnell and Baur conclusions we apply a bootstrap procedure in our paper and derive non-parametric p-values in our statistical tests.

As past findings have been found to be sensitive to using different ranking and holding period lengths, the analysis in this paper is conducted testing alternative time horizons in this regard as well as alternative size momentum portfolios in order to capture these dynamics and examine the robustness of results.

In a related area of the literature, the question of momentum effects also arises in fund performance evaluation. As this is somewhat tangential to the focus of this study, we do not propose to discuss it in detail here. Instead, we very briefly refer the interested reader to some important contributions to the area. Carhart (1997) demonstrates, *inter alia*, that momentum effects explain around half of the cross-sectional spread between the top and bottom decile portfolios of mutual funds ranked by performance. Chen, Jegadeesh and Wermers (2000) examines the *past* returns of the *current* constituent stock holdings of winning and losing funds and finds that stocks currently held by winning funds have higher past returns, or momentum, than stocks held by losing funds. The raw returns of the winning funds go on to outperform the returns of losing funds for the subsequent two quarters. The risk adjusted returns of winning funds go on to outperform those of losing funds for the subsequent quarter. Grinblat and Titman (1992) and Hendricks, Patel and Zeckhauser (1993) report some evidence that the source of the fund performance persistence found in their studies lies in a momentum effect in the fund's stock holdings rather than in persistent stock picking ability on the part of the fund manager.

A summary of the main findings from the momentum strategy literature is presented in Table 1. There is some variability in these findings due to variations in country/index, historical horizons, holding periods and the type of strategy examined as indicated. All studies find momentum strategies to be profitable to some degree. The majority of the investigations have been carried out on US data, with very little research on European indices.

[Table 1 Here]

3. Data and Methodology

To construct momentum portfolios, at month *t* we rank all stocks in ascending order of raw return based on a past period of *r* months. Based on these rankings two equally weighted portfolios, each of size *s*, are formed. The winner (loser) portfolio comprises the top (bottom) performing stocks. The strategy involves buying (selling) the winner (loser) portfolio and holding for *h* months. The momentum portfolio return between time *t* and *t+1* is the return on the winning portfolio minus the return on the losing portfolio over this holding period. This is then carried out recursively monthly to generate a time series of returns. In this study, we examine momentum portfolios for alternative values of r = 3,6,11, h = 1, 3, 6 and s = top/bottom 30% of stocks, top/bottom 10% of stocks and top/bottom 5 stocks. We then test for abnormal performance in the momentum portfolio by estimating the risk adjusted return, α_i, in the least squares regression of the CAPM as follows:

(1) $$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + \varepsilon_{it}$$

where R_{it} is the return on portfolio *i*, R_{mt} is the return on a market factor mimicking portfolio, R_{ft} is a risk free rate. A statistically significant positive value of alpha is taken to indicate superior performance in the momentum trading strategy. Here, R_{mt} is the returns on the ISEQ index while R_{ft} is proxied by the one-month interbank rate. Our entire analysis is conducted on monthly returns.

Our data set which covers the period February 1988 to December 2006 includes all stocks listed on the ISEQ index. This also includes all de-listed and dead stocks over the period. Therefore, portfolios of past winners and losers are calculated at each time *t* based on the full set of stocks that were available to fund managers at *that* time historically and *not* just based on the historical time series of stocks that exist at the end of the sample period. This avoids the possible problem of survivorship bias. If a stock drops out of the database during a holding period the portfolio is rebalanced to be equally weighted across all the remaining stocks.

Our investigation of momentum trading profitability extends that of O' Donnell and Baur (2009) in two key respects. First, we find that all the momentum portfolios demonstrate returns which are highly non-normally distributed potentially invalidating the inferences from standard statistical tests such as t-tests in (1). Therefore, we apply a bootstrap procedure to generate nonparametric p-values for the performance estimates of each of the momentum portfolios. To do this, the performance measurement model is first estimated by OLS. The estimated coefficients and OLS residuals, $\hat{\alpha}_i$, $\hat{\beta}_i$ and $\hat{\varepsilon}_{it}$ are saved. In the next step a random sample of residuals of size T_i is drawn (with replacement) from $\hat{\varepsilon}_{it}$. Using the estimated factor loadings from step one and the original chronological ordering of R_{mt} and setting $\hat{\alpha}_i$ = 0 under the null hypothesis of no abnormal performance, bootstrap simulated returns, $\tilde{R}_{it}$, are constructed. By construction, this bootstrapped or simulated portfolio return has 'true' abnormal performance of zero. Using these bootstrap fitted returns, the performance measurement model is re-estimated and a bootstrap estimate of abnormal performance under the imposed null hypothesis is obtained, denoted $\tilde{\alpha}_i$. This $\tilde{\alpha}_i$ represents random sampling variation around a true value of zero. This simulation process is repeated B = 1,000 times. The 1,000 values of $\tilde{\alpha}_i$ represent the nonparametric distribution of $\hat{\alpha}_i$ under the null hypothesis. We can then examine where the OLS estimate of $\hat{\alpha}_i$ lies relative to the distribution of $\tilde{\alpha}_i$ to determine a nonparametric p-value for $\hat{\alpha}_i$ which makes no prior assumptions regarding the normality of returns. So, for example, a p-value = 0.10 indicates that only 10% of the values of $\tilde{\alpha}_i$ are greater than $\hat{\alpha}_i$ suggesting that there is only a 10% chance of observing the estimated value of $\hat{\alpha}_i$ where the 'true' value of α_i is zero. We can also use the t-statistic of alpha as a measure of abnormal performance. The t-statistic has the advantage that it controls for the standard error and may therefore give a more reliable estimate of abnormal performance relative to $\hat{\alpha}_i$. The same bootstrap procedure as above can be used to generate $t_{\tilde{\alpha}_i}$ and hence the nonparametric distribution of the t-statistic of $\hat{\alpha}_i$, denoted $t_{\hat{\alpha}_i}$, under the null hypothesis. In this study we report the nonparametric p-values of $t_{\hat{\alpha}_i}$. Furthermore, in the calculation of all t-statistics in this study we use New-West serial correlation and heteroscedasticity adjusted standard errors.

Second, the O' Donnell and Baur (2009) study investigates momentum portfolios comprising the top and bottom third of stocks. One concern is that such large portfolios may disguise profitable momentum based strategies among more extreme winner and loser stocks, e.g. top and bottom 10% of stocks or, say, top and bottom 5 stocks. One advantage of these latter cases is that the pursuit of the momentum strategy may involve lower transactions costs on the part of the fund in rebalancing the fund holdings each period. In this study we also report findings for momentum trading strategies based on the top/bottom 10% and top/bottom 5 stocks.

In the next section we report our findings.

4. Empirical Results

Our main findings are presented in Table 2 which shows results for the full sample period 1988:2 – 2006:12. Performance estimates are reported for momentum based portfolios for alternative ranking and holding periods as indicated in each column. E.g., the column headed "3 - 1" refers to a past ranking period of 3 months and a holding period of 1 month etc. Results are also reported for alternative size momentum portfolios including top 30% minus bottom 30%, top 10% minus bottom 10% and top 5 minus bottom 5 stocks as indicated. 'Alpha' is the risk adjusted monthly percentage return from the OLS estimation of Equation (1) while 't-alpha' is the corresponding t-statistic (Newey-West adjusted for serial correlation and heteroscedasticity).

[Table 2 Here]

From the t-statistics it is clear that none of the momentum portfolios yielded statistically significant positive returns (at the 5% significance level) over the full period and indeed in several cases returns are negative. Table 2 also shows results of tests of the normality of the regression residuals. Here, we report the Jarque-Bera test statistic, JB ~ $\chi^2_{df=2}$. The χ^2 critical value at 5% significance is 5.99. It is immediately evident that in the case of all portfolios the null hypothesis of normally distributed residuals is strongly rejected. In turn this suggests that the alpha estimates are also non-normally distributed thus potentially questioning the reliability of findings based on t-tests. This motivates our use of the bootstrap procedure to generate non-parametric p- values in order to investigate the robustness of momentum findings. In Table 2, these p-values are denoted as 'Bootstrap p-value'. The p-values, all greater than 0.05, indicate that none of the momentum portfolios yield positive and statistically significant returns at 5% significance (or even at the 10% significance level).

The full set of results in Table 2 lead us to conclude that, over the full sample period, momentum trading strategies did not yield a positive risk adjusted return in the Irish equity market. This finding is remarkably robust to alternative ranking windows and holding periods as well as to alternative size momentum portfolios. It also proves robust to alternative statistical testing methodologies which account for the finding of non-normally distributed returns data. These overall findings are qualitatively similar to those of O' Donnell and Baur (2009).

However, O' Donnell and Baur (2009) go on to explore the profitability of momentum portfolios separately during periods of low versus high growth in the stock market and report evidence of abnormal returns in the latter but not the former. It is in this analysis that we find that results are somewhat sensitive to the (i) non-normality issue, (ii) size of momentum portfolios and (iii) ranking and holding windows. Table 3 presents findings for the later relatively high stock market growth period of 1995:9 – 2006:12 (dates chosen for consistency of comparison with O' Donnell and Baur

(2009))[2]. The upper panel of Table 3 shows results for the largest momentum portfolios of the top minus bottom 30% of ranked stocks. Here, according to the standard t-statistics, two of the momentum portfolios yield a positive and significant abnormal return at the 10% significance level, i.e. portfolios of '11-3' and '11-6' ranking and holding periods. However, examining the non-parametric p-values of the t-statistics from the bootstrap procedure we find that four of the portfolios are profitable at 10% significance. This is, the parametric t-tests and the more robustly estimated non-parametric p-values from the bootstrap procedure give conflicting inferences regarding the profitability of some the momentum trading strategies - highlighting the potential for non-normality in financial data to invalidate the findings of many standard statistical tests.

[Table 3 Here]

From Table 3, we find that one of the smaller momentum portfolios (top 10% minus bottom 10%) with 3-6 ranking/holding period yields a positive and significant abnormal return at 10% significance. However, all other portfolios regardless of size or holding and ranking periods yield insignificant (and sometimes negative) returns by both the standard t-tests and the non-parametric p-values.

There are some further surprises in the results. First, the finding that profitable momentum strategies are more prevalent among larger rather than smaller portfolios suggests that the momentum effect is not driven by the extreme winner and loser stocks but instead is driven by those slightly further inside the tail of the cross-section distribution of stock returns. Alternatively, there is more noise among the more extreme winner and loser stock returns which does not persist, even in the short term. Second, momentum is stronger among portfolios of longer ranking and holding windows. That a longer ranking period provides a more reliable ranking of stocks in the momentum strategy is intuitive but one might have expected that in an efficient market the momentum effect in stocks would dissipate quickly and hence would be better captured by shorter rather than longer holding periods.

Overall, the findings in Table 2 strongly suggest that momentum based trading strategies in the Irish equity market failed to yield abnormal returns over the longer

[2] We do not present results for the earlier lower growth period as, similar to Table 2, they consistently show no significant return to momentum trading across all portfolios.

sample period under investigation. Results presented in Table 3 do show some evidence of momentum trading profitability but highlight the sensitivity of results to non-normality, momentum portfolio sizes and ranking and holding period lengths. In any case, these abnormal returns are found only in conditions of relatively high market growth. As these conditions are comparatively rare and their persistence unreliable, our overall analysis finds against the existence of abnormal returns from momentum based equity trading in the Irish market.

5. Conclusion

This study examines the profitability of momentum based trading strategies in the Irish equity market between 1988 and 2007. Investigating a range of trading strategies over alternative backward looking ranking periods and forward looking holding horizons as well as for alternative size momentum portfolios, we find that returns to momentum based strategies are highly non-normally distributed giving rise to concern about the validity of inferences based on standard statistical tests. We apply a bootstrap procedure to construct nonparametric p-values for the momentum portfolio performance measures. Overall, we find very little evidence that momentum based trading strategies would have yielded an abnormal risk adjusted return over the period. Our overall results are qualitatively similar to those of O' Donnell and Baur (2009) but contribute to this literature by highlighting that (i) the non-normality of stock returns, particularly in the tails of the cross-sectional distribution, must be considered if robust inferences are to be drawn from this type of study and (ii) the most extreme winner and loser stock returns appear to be noisy and detract from rather than drive profitable momentum portfolios where these exist at all.

Table 1: Summary of International Findings from Momentum Studies

Author and Year	Momentum Strategy	Country/Index	Sample Period	Historical Horizon (Months)	Holding Period (Months)	Profits
Jegadeesh and Titman (1993)	Individual Stock Price	USA: NYSE and AMEX	1965 - 1989	6, 9, 12	3,6,9,12	Around 1% per month for following year. Unprofitable under 1 month and over 1 year.
Rouwenhorst (1998)	Individual Stock Price	12 European countries	1978 - 1995	6	3, 6, 9, 12	Around 1% per month for following year with reversal thereafter.
Jegadeesh and Titman (2001)	Individual Stock Price	USA: NYSE, AMEX, NASDAQ	1990 – 1998	6	3, 6, 9, 12	Around 1% per month for following year. Unprofitable under 1 month and over 1 year.
Grundy and Martin (2001)	Individual Stock Price	USA: NYSE and AMEX	1926 - 1995	6	1	0.44% per month
George and Hwang (2004)	Individual Stock Price	USA: CRSP	1963 – 2001	6	6	0.48% per month
Marshall and Cahane (2005)	Individual Stock Price	Australian Stock Exchange (ASX)	1990 – 2003	6	6	0.59% per month

Moskowitz and Grinblatt (1999)	Industry	USA: NYSE, AMEX and NASDAQ	1963 - 1995	6-12	1- 36	1% per month for following year. Strongest at 1 month horizon. Unprofitable after a year.
George and Hwang (2004)	Industry	USA: CRSP	1963 – 2001	6	6	0.45% per month
Marshall and Cahane (2005)	Industry	Australian Stock Exchange (ASX)	1990 – 2003	6	6	0.16% per month
George and Hwang (2004)	52-week high	USA: CRSP	1963 - 2001	12	6	0.45% per month without a reversal after a year.
Marshall and Cahane (2005)	52-week high	Australian Stock Exchange (ASX)	1990 – 2003	12	6	2.14% per month

Table 2: The Profitability of Momentum Trading Strategies – Full Sample Period

Table 2 presents performance estimates for momentum based portfolios for alternative ranking and holding periods as indicated in each column over the full sample period 1988:2 – 2006:12. E.g., "3 - 1" refers to a past ranking period of 3 months and a holding period of 1 month. Alpha is the portfolio performance measure from the OLS estimation of Equation (1). In addition, we report the Jarque-Bera normality test statistic, JB ~ $\chi^2_{df=2}$. The table also reports the bootstrapped p-value of the t-statistic of alpha as described in Section 3. All t-statistics are based on New-West serial correlation and heteroscedasticity adjusted standard errors. Performance estimates and associated test statistics are shown for momentum portfolios comprising the top/bottom 30% of stocks, top/bottom 10% of stocks and top/bottom 5 stocks as indicated.

	3 - 1	**6 - 1**	**11 - 1**	**3 - 3**	**6 - 3**	**11 - 3**	**3 - 6**	**6 - 6**	**11 - 6**
Top 30% – Bottom 30%									
Alpha	0.172	0.227	0.105	0.349	0.176	0.207	-0.402	0.164	-0.032
t-alpha	0.543	0.604	0.248	1.051	0.460	0.485	-1.094	0.431	-0.073
JB Normality Statistic	30.54	385.12	348.14	58.19	282.19	375.70	239.30	301.38	539.02
Bootstrap p-value	0.360	0.260	0.460	0.180	0.350	0.260	0.850	0.380	0.550
Top 10% – Bottom 10%									
Alpha	-0.222	-0.030	-1.115	0.401	-0.149	-0.547	-0.637	-0.354	-1.695
t-alpha	-0.296	-0.034	-1.206	0.521	-0.172	-0.584	-0.751	-0.396	-1.190
JB Normality Statistic	259.62	676.22	1384.22	318.12	798.08	1402.52	846.86	773.38	1400.66
Bootstrap p-value	0.580	0.590	0.890	0.280	0.540	0.730	0.790	0.650	0.880
Top 5 – Bottom 5									
Alpha	-1.287	-0.935	-0.952	0.234	-0.616	-0.027	-1.447	-1.537	-1.936
t-alpha	-1.017	-0.584	-0.678	0.181	-0.405	-0.018	-0.965	-0.950	-1.021
JB Normality Statistic	410.24	1652.22	1114.38	402.59	2032.11	1608.63	889.94	2039.36	1746.81
Bootstrap p-value	0.850	0.660	0.750	0.440	0.610	0.460	0.810	0.790	0.880

Table 3: The Profitability of Momentum Trading Strategies – High Stock Market Growth

Table 3 presents performance estimates for momentum based portfolios for alternative ranking and holding periods as indicated in each column. Results are reported for the later sample period of relatively high stock growth from 1995:2. E.g., “3 - 1” refers to a past ranking period of 3 months and a holding period of 1 month. Alpha is the portfolio performance measure from the OLS estimation of Equation (1). In addition, we report the Jarque-Bera normality test statistic, JB ~ $\chi^2_{df=2}$. The table also reports the bootstrapped p-value of the t-statistic of alpha as described in Section 3. All t-statistics are based on New-West serial correlation and heteroscedasticity adjusted standard errors. Performance estimates and associated test statistics are shown for momentum portfolios comprising the top/bottom 30% of stocks, top/bottom 10% of stocks and top/bottom 5 stocks as indicated.

	3 - 1	**6 - 1**	**11 - 1**	**3 - 3**	**6 - 3**	**11 - 3**	**3 - 6**	**6 - 6**	**11 - 6**
Top 30% – Bottom 30%									
Alpha	-0.048	0.346	0.418	0.282	0.374	0.546	-0.011	0.309	0.545
t-alpha	-0.136	1.022	1.173	0.790	1.118	1.562	-0.037	0.945	1.592
JB Normality Statistic	0.157	10.749	0.517	17.862	46.176	0.763	25.512	18.015	9.676
Bootstrap p-value	0.600	0.140	0.160	0.140	0.060	0.060	0.470	0.070	0.080
Top 10% – Bottom 10%									
Alpha	-0.863	0.013	-0.233	0.101	0.326	0.273	0.834	0.524	-0.163
t-alpha	-1.227	0.019	-0.349	0.142	0.493	0.413	1.348	0.814	-0.273
JB Normality Statistic	16.967	13.807	13.351	25.193	27.081	4.397	66.494	47.552	6.186
Bootstrap p-value	0.860	0.510	0.590	0.470	0.230	0.320	0.100	0.270	0.600
Top 5 – Bottom 5									
Alpha	-2.003	-1.220	-0.682	-0.256	0.117	0.320	0.698	-0.941	0.248
t-alpha	-1.201	-1.010	-0.594	-0.195	0.099	0.268	0.518	-0.784	0.191
JB Normality Statistic	51.768	10.100	6.248	120.056	12.682	13.489	165.182	13.243	33.743
Bootstrap p-value	0.880	0.810	0.640	0.610	0.480	0.380	0.330	0.850	0.410

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