Momentum profits in alternative stock market structures

Patricia Chelley-Steeley*

Antonios Siganos**

* Reader in Finance, Aston Business School, Birmingham, B4 7ET, UK

** Corresponding author; Antonios Siganos, Lecturer in Finance, Department of Accounting and Finance, 73 Southpark Avenue, University of Glasgow, Glasgow, G12 8LE, Scotland, E-mail: **a.siganos@accfin.gla.ac.uk**

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Abstract

The aim of this study is to examine the relationship between momentum profitability and the stock market trading mechanism and is motivated by recent changes to the trading systems that have taken place on the London Stock Exchange. Since 1975 the London stock market has employed three different trading systems: a floor based system, a computerized dealer system called SEAQ and the automated auction system SETS. Since each new trading system has reduced the level of execution costs, one might expect, a-priori, the magnitude of momentum profits to decline with each amendment to the trading system. However, the opposite empirical result is found showing that shares trading on the automated system generate higher momentum profits than those trading on the floor system and companies trading on the SETS system display greater momentum profitability than those trading on SEAQ. Our empirical results concur with the theoretical findings of the trader's hesitation model of Du (2002) and the empirical findings of Arena et al. (2005).

JEL classifications: G14; G15

Keywords: Momentum; SETS; SEAQ

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1. Introduction

The momentum strategy describes the tendency for return performance to persist in the medium term. The pioneering work of Jegadeesh and Titman (1993) on the US market showed that by buying winners and selling short losers an abnormal monthly return of approximately 1 percent could be achieved. Extent evidence now exists in support of the momentum strategy for the US (e.g., Jegadeesh and Titman, 2001), the UK (e.g., Hon and Tonks, 2003), and a global range of stock markets (e.g., Griffin et al., 2003).

A number of studies have examined whether the momentum strategy enjoys significant profitability after transaction costs. Lesmond et al. (2004) reported that the momentum returns found by Jegadeesh and Titman (1993, 2001) and Hong et al. (2000) disappear after adjusting for transaction costs, since both winner and loser portfolios tend to include high transaction cost shares, such as small capitalisation and illiquid shares. Chen and Stanzl (2002) and Korajzyk and Sadka (2004) examined the price impact cost of following the momentum strategy. Chen and Stanzl, for instance, reported that the maximal fund size possible to exploit the momentum strategy is $44.2 million when value-weighted portfolios were formed.

A significant number of studies have also considered the potential reasons for momentum, but no clear consensus has emerged. Ang et al (2001) argued that the contents of the winner portfolio are characterized by more downside risk. The higher returns displayed by winners is compensation for this additional amount of risk investors would be exposed to when falling market arise. The importance of risk as a potential explanation for momentum contrasts with the findings of Fama and French (1996) and Liu et al (1999). After controlling for the risk inherent in the three-factor model of Fama and French (1993), both papers showed that momentum profitability does not diminish.

Behavioral models have suggested that momentum is caused by the underreaction of stock prices to new information. Barberis et al (1998) developed a model in which investors underreact to information about earnings. Du (2002) argued that investors can be characterized by high or low levels of confidence. Underreaction arises when investors with low confidence are slow to make decisions. Delays in acting upon information cause the effects of new information to persist inducing a continuation pattern in returns.

Momentum profits have also been found to be influenced by firm level characteristics. Lee and Swaminathan (2000) showed that firms with high trading volume have higher momentum than firms with low trading volume. Moskowitz and Grinblatt (1999) found that momentum is related to a firm's industry. Momentum also appears to be related to firm size (Hong et al., 2000) and to glamour features (Gregory et al., 2001).

In this paper, we suggest that the size of UK momentum profits can be influenced by the stock market trading system. The London Stock Exchange (LSE) has employed three trading systems since 1975. Until the reforms of Big Bang in 1986 the LSE employed a single capacity floor based trading system. From 1986 onwards the London exchange adopted a computerized dealing system called SEAQ. Since

1997 equities with the highest turnover on the LSE have been able to trade on an automated trading system that has been operating in parallel to SEAQ.

One may expect, a priori, that the level of momentum profits declines with each amendment to the trading system. With the introduction of each new system, a reduction of the transaction costs was occurred (e.g, Naik and Yadav, 1999; Tonks and Webb, 1991). A move to the computerized system SEAQ and then to SETS would have therefore made momentum trading progressively more attractive after the microstructure changes made by the LSE. Furthermore, the increased transparency and ease of trading associated with the new systems would have made momentum trading more attractive to non-institutional traders.

However, when we measure momentum profits in the period prior to and subsequent to the introduction of SEAQ, it is found that share trading in the post-Big Bang period generates higher continuation profits than trading in the pre-deregulation floor period. This is robust to the employment of a sub-sample of firms and to a range of adjustment tests. We also examine the momentum profits generated from trading on SETS and find that shares trading on the SETS system provide higher continuation profits than those trading on SEAQ. The difference in momentum profits between the two structures widens significantly after considering share market values. Our empirical results concur with the theoretical findings of the trader's hesitation model of Du (2002) and the empirical findings of Arena et al. (2005).

The remainder of this paper is set out as follows. Section 2 describes the trading systems. Section 3 explains the data and how it has been utilized. Section 4 measures momentum in different market structures and Section 5 concludes the paper.

2. Trading systems

Prior to Big Bang in 1986 the LSE utilized a floor based trading system that employed jobbers and brokers with single capacity. In response to dissatisfaction with the ability of floor based trading to encourage competition, cope with rising trade sizes and an increasing trend towards the internationalization of capital markets (Thomas, 1989), a major overhaul of the LSE trading system took place on 27th of October 1986. These changes saw the introduction of a dual capacity electronic dealer system called SEAQ.

In response to competition from order driven systems on other exchanges that offer lower trading costs, the LSE introduced SETS on 20th of October 1997. All FTSE100 stocks and since March 1998 some additional companies from the FTSE250 index, have been traded in an auction system. In contrast to SEAQ, SETS is a fully automated order driven system. SETS opens with a batch auction and allows continuous trading until the market closes.

Our examination of the link between momentum and trading activity is motivated by a range of studies that have shown that the trading mechanism can exert a strong influence on stock returns. In particular, a number of studies have reported a link between stock market structures and volatility. Chelley-Steeley (2005), for example, showed that both the opening and closing returns of FTSE100 shares experienced a significant increase in volatility since the introduction of the SETS mechanism. Tonks and Webb (1991) documented a substantial increase of volatility in UK shares in the post-automation period. Arena et al. (2005), Balsara and Zheng (2006) and Fang et al. (2003) argued that there exists a strong positive association between different measures of volatility and magnitude of momentum returns. Since shares displayed higher volatility when traded on the post-Big Bang period and on the SETS system, and higher volatility appears to imply stronger momentum returns, we predict that shares trading on the automated and the SETS systems generate higher momentum profits than those trading on the floor and dealer systems respectively. These predictions are in line with our empirical findings.

Trading systems also influence the relative trading activities of institutional and small investors. Institutions seem to prefer to use floor rather than automated systems, since on the floor of a stock market large investors can observe the investment strategies followed by traders who have inside information. Institutional traders also tend to prefer dealer systems that provide better liquidity for large trades, while retail investors tend to prefer auction mechanisms that are associated with lower transaction costs (e.g., de Jong et al., 1995). Du (2002) argued that investor behavior contributes to the scale of momentum profits, since the level of investor confidence influences the decision making speed of investors. This suggests that trading mechanisms more favorable to a particular investor type will encourage either fast decisions about equity (little momentum) or slow decisions (high momentum). Since large (small) investors appear to prefer floor and dealer (automated and auction) systems, the Du (2002) model, to some extent, predicts that shares trading on the automated and the SETS systems generate higher momentum profits than those trading on the floor and dealer systems respectively. Once more these predictions correspond with our empirical results.

3. Data and methodology

Monthly return information for all UK companies listed on the Master Index File of the London Share Price Database (LSPD) between October 1975 and October 2001 were utilized in this study. The sample period focused in the post-1975 period because LSPD includes all British companies listed on the LSE after 1975. This provided information on over 6,000 firms. This constituted our main sample. Our second sample was the accounting sub-sample. This was drawn from the main sample but required from each firm accounting information on annual market value and book-to-market. This information was available from Datastream for over 2,000 of the companies. Our SETS sample reflected the 150 stocks that according to the LSE have traded on SETS. This sample extended from October 1997 to October 2001.

To calculate momentum profitability, each company was ranked on the basis of its stock market performance over the previous six months. We then placed each security into one of ten equally sized portfolios. The winner portfolio (W) contained the best performing decile of securities and the loser portfolio (L) contained the worst performing decile of securities[1]. One month was skipped to avoid potential market frictions identified by Jegadeesh (1990) and in the following six-month period, the returns of each of the equal weighted portfolios were calculated. This procedure was repeated for each non-overlapping six-month period. The difference

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[1] Tables 1 and 7 and Fig. 1 use additional definitions of winner and loser portfolios as a robustness test. When using three portfolios, winners and losers each comprised 30 percent of the sample and when using five portfolios, winners and losers each included 20 percent of the sample.

between winner and loser portfolio returns (W-L) showed the profitability of the momentum strategy.

This study then investigated whether bull and bear markets can account for our empirical results. Market states have differed during the pre- and post-Big Bang periods and Cooper et al. (2004), using US data, and Siganos and Chelley-Steeley (2006), using UK data, reported that momentum profitability varies significantly following bull and bear markets. Two states were separated. The bull state was when the average market return (FTSE-All Share) was non-negative six months before the test period, and the bear state was when the average market return was negative six months before the test period. Since 1975 the UK stock market has experienced a strong upward trend and therefore a much larger number of periods were bull. In particular, 76 percent of the periods identified as bull during the floor sub-period and 68 percent during the automated sub-period.

The importance of controlling for firm size was highlighted by Zarowin (1990) in a study of long term overreaction as matching winners and losers on the basis of firm size caused evidence of overreaction to disappear. We applied a matching process similar to Daniel and Titman (1997) that was found to explain overreaction by Nagel (2001). Securities were first sorted into three groups based on their market capitalization. Companies in each size-sorted group were further divided into three additional groups based on their book-to-market. All this provided nine portfolios. The returns of these nine size-book-to-market portfolios were calculated over the test period as:

$$R_{it}^{CH} = R_{it} - R_{t}^{CH} \tag{1}$$

where R_{it}^{CH} is the characteristic-adjusted return on security i in month t, R_{it} is the return on security i in month t, and R_t^{CH} is the return on a size-book-to-market matched portfolio in month t. To undertake this procedure, book and market values were required. Since LSPD does not provide book values, our smaller accounting sub-sample was utilized for this analysis.

This study also controlled for risk based on the Capital Asset Pricing Model. We calculated the aggregate coefficient betas of Dimson (1979) to overcome the problem of infrequent trading that conventional betas exhibit. We estimated regressions of portfolio returns against lagging, contemporaneous and leading market returns. The aggregate coefficient betas were determined by the number of leads and lags that are statistically significant.

$$R_{p,t} - R_{f,t} = a_p + \sum_{k=-n}^{n} \beta_p (R_{m,k,t} - R_{f,k,t}) + e_{i,t} \qquad (2)$$

where $R_{p,t}$ is the return of portfolio p in month t, $R_{f,t}$ is the one-month Treasury Bill rate in month t, and $R_{m,t}$ is the return of the proxy market (FTSE All-Share) in month t. The aggregate coefficient beta was the sum of betas with different leads and lags. Four lags and two leads were analyzed for the loser portfolio and four lags and four leads for the winner portfolio.

We further defined risk based on the three-factor model (Fama and French, 1993). Liu et al. (1999) reported that after controlling for the three-factor model, momentum profits are lower than when only beta adjustments are made. This suggests that the three-factor model captures the momentum gains better than CAPM. We estimated the following regression:

$$R_{p,t} - R_{f,t} = a_p + \beta_p (R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + e_{p,t} \quad (3)$$

where $R_{p,t}$ is the return of portfolio p in month t, $R_{f,t}$ is the one-month Treasury Bill rate in month t, and $R_{m,t}$ is the return of the proxy market (FTSE All-Share) in month t. We generated nine portfolios; shares were sorted into three groups based on the market value and then, each size-sorted portfolio was divided further into three portfolios based on the book-to-market ratios. SMB_t (Small Minus Big) shows the portfolio that buys the three small size portfolios and sells short the three big size portfolios. HML_t (High Minus Low) shows the portfolio that buys the three high book-to-market portfolios and sells short the three low book-to-market portfolios.

4. Empirical findings

4.1. Momentum profits in floor and automated systems

Preliminary analysis yields the first evidence that there is a tendency for stronger momentum returns during the automated sub-period. Fig. 1 plots the continuation gains generated on the LSE. The interruption of the lines in 1987 arises because we miss one test period at the time of the Big Bang. Fig. 2 shows the structure of momentum returns in floor and automated sub-periods. It is found that winners outperform the losers by more than 2 percent per month in 39 percent of observations during the automated sub-period and only in 19 percent of observations during the floor sub-period. The momentum strategy generates losses only in 18 percent of observations during the automated sub-period, but in 33 percent of observations during the floor sub-period.

Table 1 shows that in the period before Big Bang monthly momentum profits are 0.41 percent when three portfolios are studied (Panel A), 0.50 percent when five portfolios are employed (Panel B) and 0.73 percent when ten portfolios are examined (Panel C). These returns are largely attributable to the performance of the winner portfolio. Post-Big Bang, monthly continuation payoffs are 1.38 (three portfolios), 1.69 (five portfolios) and 2.14 percent (ten portfolios). Automated share trading appears to generate significantly larger momentum returns than shares trading on the floor based system. The difference in monthly momentum profits between automated and floor based trading is 0.97 (t-statistic=2.42) percent using three portfolios, 1.19 (t-statistic=2.50) percent examining five portfolios and 1.41 (t-statistic=2.38) percent studying ten portfolios. In unreported results, we also find that the momentum portfolio achieves a Sharpe ratio equal to 0.44 (0.85) before (after) Big Bang and the Mann-Whitney non-parametric test provides identical findings to those generated when a parametric test is employed.

Panel A of Table 2 shows that when the accounting sub-sample is employed, findings are rather identical to those reported for the full sample. The correlation on momentum profits between the full sample and the accounting sub-sample is strong with a Pearson correlation equal to 0.63. During the automated period, market values tended to rise and book-to-market ratios fall. However, changes in size and book-to-market cannot explain differences in momentum across the two periods. The winner portfolio is characterized by higher market values in all samples. The arbitrage portfolio in the post-Big Bang period includes larger capitalization companies than its counterpart arbitrage portfolio in the pre-Big Bang period. In addition, the winner portfolio tends to include shares with lower book-to-market ratios than the loser portfolio, indicating that winners tend to be glamour stocks and losers value equities.

As a robustness test, this study also examines the momentum profitability that the same shares generate in both structures by analyzing companies that have return information for the duration of the whole sample period. Only 266 shares fulfill that condition. Panel B of Table 2 demonstrates that the automated sub-period still provides higher monthly momentum profits than the floor sub-period.

As a control, Panel C of Table 2 examines the magnitude of momentum profits pre and post-October 1986 when US data are used[2]. Unlike with the LSE, there have been no major changes in the trading mechanisms of US stock exchanges between 1975 and 2001; therefore, no major change in the magnitude of momentum profitability is expected. Indeed, we find that US momentum returns were 1.40 percent per month during the pre-October 1986 period and 1.28 percent per month during the post-October 1986 period. The difference in momentum gains between the two subperiods is neither statistically significant at the 10 percent level nor economically significant. Interestingly, momentum profits are stronger in the UK than in the US post-October 1986 and smaller pre-October 1986. The distinctive pattern of momentum profits in the UK strengthens our arguments that it is changes to the trading system that are influencing the size of momentum profits over the period we study.

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[2] We obtained the equal-weighted monthly US momentum returns from October 1975 to October 2001 from Kenneth French's website (we thank Kenneth French for making those data freely available). Like our study those momentum returns were calculated using deciles to define the winner and loser portfolios and unlike our study t-12 to t-2 months were used to form the portfolios.

The strong UK momentum returns reported in the post-Big Bang period concur with Agyei-Ampomah (2006). Agyei-Ampomah used UK data over the 1988-2003 period and investigated the profitability of the momentum strategy after transaction cost. Using deciles to define the winner and loser portfolios, he reported that the representative momentum strategy (6x6) produces strong momentum gains of 33.72 percent per annum. This level of profitability, which is even stronger than the one reported in the present study, reflects pre-transaction cost trading and is largely driven by the loser portfolio (L=-24.96 percent per annum).

This study next examines whether the momentum returns post-Big Bang remain strong after controlling for various factors that may account for our empirical results. Table 3 shows the magnitude of momentum returns prior to and subsequent to Big Bang following bear (Panel A) and bull (Panel B) markets. It is found that momentum profits are stronger over the automated sub-period even when we consider for bull and bear conditions. For example, following bear markets the monthly momentum returns are 3.68 (0.57) percent post- (pre-) Big Bang.

Table 4 shows the size and book-to-market adjusted portfolio returns. It is found that after controlling for size and book-to-market ratios, momentum profits decrease, especially when the automated system was in operation. Nevertheless continuation profits are economically and statistically significant at the 1 percent level using the entire period and abnormal returns are still much larger in the post-Big Bang period.

Table 5 shows the portfolio aggregate betas. The winner portfolio displays lower aggregate betas than its counterpart loser portfolio. This study also shows that portfolios in the automated period tend to have higher betas, but the beta of the arbitrage portfolio (β_{W-L}) is –0.22 for the automated period and 0.31 for the floor period. Therefore, the arbitrage portfolio generates higher performance and experiences lower risk during the automated period. In unreported results, we further calculate the aggregate betas of the arbitrage portfolio examining alternative lags and leads. When applying up to three lags and three leads, the beta of the arbitrage portfolio is always positive during the floor sub-period and negative during the automated sub-period.

Table 6 shows the sensitivities and the intercept of the three-factor model (Fama and French, 1993) for the loser portfolio (Panel A), the winner portfolio (Panel B) and the arbitrage portfolio (Panel C). In unreported results, the Variance Inflation Factor for explanatory variables is around one, indicating that there is no problem with multicollinearity. The alpha of the model demonstrates the abnormal profits that remained after considering the three factors. When market efficiency holds, alpha should be equal to zero. Findings show that the three-factor model cannot explain the differences across the two sub-periods. Continuation payoffs remain at 1.64 percent per month during the period of automation, but lower at 0.80 percent per month during the floor period. Using the Chow (1960) test[3], this study further investigated whether the parameters of the three-factor model for the W-L portfolio are statistically different before and after Big Bang. It is found that $F = 4.21$ and

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[3] $F = \dfrac{(RSS_T - RSS_1 - RSS_2)/(K+1)}{(RSS_1 + RSS_2)/(N_1 + N_2 - 2K - 2)}$ where N_i is the number of observations in sample i, RSS_i is the residual sum of squares for sample i and K is the number of independent variables. Reject the null hypothesis of equality in parameters between the two sets of data if $F > F_C$ where F_C is the critical value for $(K+1)$ numerator and $(N_1 + N_2 - 2K - 2)$ denominator degrees of freedom.

therefore, the null hypothesis (Ho: $a_{W-L,floor} = a_{W-L,automated}$, $\beta_{W-L,floor} = \beta_{W-L,automated}$, $s_{W-L,floor} = s_{W-L,automated}$ and $h_{W-L,floor} = h_{W-L,automated}$) was rejected at the 1 percent level, showing that the coefficients of the model for the momentum portfolio are significantly different between the two sets of data.

4.2. Momentum profits in dealer and auction systems [4]

Table 7 reports that the magnitude of continuation profits is different when comparing quote-driven and order-driven mechanisms. It is found that monthly momentum profits for shares trading on the SETS mechanism are 1.20 percent when three portfolios are examined, 2.01 percent when five portfolios are studied and 2.94 percent when ten portfolios are employed. These abnormal returns are driven by the loser portfolio and are significantly higher than those reported by shares trading on other systems between 1975 and 2001. Since auction mechanisms tend to generate lower execution costs than dealer systems (e.g., Huang and Stoll, 1996), the difference in the profitability of momentum profits generated by the two mechanisms is even greater than revealed by our data.

Since the auction and dealer systems operate in parallel, we can compare directly the magnitude of profits from the two systems for the same periods. These simple controls were not possible when making comparisons of the automated and floor based periods. It is found that stocks trading on SETS system generate roughly comparable momentum profits to those shares traded on the SEAQ.

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[4] Full adjustment tests were not undertaken in this section, since the SETS sample includes a small number of companies to generate a large number of portfolios.

Companies trading on SETS and SEAQ are, however, essentially different. Large companies trade on SETS and smaller companies on SEAQ. As shown by Hong et al. (2000), there exists a negative relationship between size and momentum profitability and since companies trading on SETS are the largest on the LSE, we would anticipate them to generate lower momentum profits. To adjust for size, momentum profits were calculated for the 150 largest companies (by market value) that have been trading on the SEAQ dealer system, as these will be most similar to those trading on SETS. It is found that the largest 150 shares trading on the SEAQ mechanism generate significantly lower continuation profits than their counterpart companies trading on SETS when five or ten portfolios are formed. In unreported results, the momentum portfolio (using deciles) achieves a Sharpe ratio equal to 0.46 for shares trading on the SETS system and 0.15 for the largest 150 shares trading on the SEAQ.

We further calculated the continuation profits generated by the stocks on the SETS in the previous four years (1994-1997) when they were traded on the SEAQ system. It is shown that the SETS stocks generate significantly lower returns when they were traded on the dealer system between 1994 and 1997, while the full sample demonstrates strong profits.

5. Conclusions

This study found that momentum profits are significant when we use all listed companies on the LSE (over 6000 shares), a sub-sample of 2000 shares with additional accounting information, the SETS sample of 150 shares and a small number of 266 stocks with complete return information from 1975 to 2001. It was further documented that momentum profits persist after controlling for size, book-to-market and risk as defined by the CAPM and the three-factor model. These suggested that the momentum effect persists on the LSE using various data sets and after controlling for various factors that might influence share returns.

This study also studied the impact that the trading system might have on momentum profits and is the first time this issue has been examined. The motivation to examine this field stems from the influence that different stock market structures have on stock returns. When momentum profits were measured in the period prior to and subsequent to the introduction of SEAQ, it was found that shares trading in the post-Big Bang period generate higher continuation profits than trading in the pre-deregulation floor period. When we examined the momentum profits generated from trading on SETS, it was shown that shares trading on the SETS system provide higher continuation profits than those trading on SEAQ. The difference in momentum profits between the two structures widens significantly after taking into consideration share market values. Our empirical results concur with the theoretical findings of the trader's hesitation model of Du (2002) and the empirical findings of Arena et al. (2005).

References

Agyei-Ampomah, S., 2006. The post-cost profitability of momentum trading strategies: further evidence from the UK. European Financial Management (forthcoming).

Ang, A., Chen, J., Xing, Y., 2001. Downside risk and the momentum effect, working paper.

Arena, M., Haggard, S., Yan, X., 2005. Price momentum and idiosyncratic volatility, working paper.

Balsara, N., Zheng, L., 2006. Profiting from past winners and losers. Journal of Asset Management 6, 329-344.

Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. Journal of Financial Economics 49, 307-343.

Chelley-Steeley, P., 2005. Noise and the trading system: the case of SETS. European Financial Management 3, 389-424.

Chen, Z., Stanzl, W., 2002. Price impact costs and the limit to arbitrage, working paper.

Chow, G., 1960. Tests of equality between sets of coefficients in two linear regressions. Econometrica 28, 591-605.

Cooper, M. J., Gutierrez, J. R., Hameed, A., 2004. Market states and momentum. Journal of Finance 59, 1345-1365.

Daniel, K. D., Titman, S., 1997. Evidence on the characteristics of cross-sectional variance in common stock returns. Journal of Finance 52, 1681-1714.

De Jong, F., Nijman, T., Roell, A., 1995. A comparison of the cost of trading French shares on the Paris Bourse and on SEAQ International. European Economic Review 39, 1277-1301.

Dimson, E., 1979. Risk measurement when shares are subject to infrequent trading. Journal of Financial Economics 7, 197-226.

Du, J., 2002. Heterogeneity in investor confidence and asset market under- and overreaction, working paper.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3-56.

Fama, E. F., French, K. R., 1996. Multifactor explanations of asset pricing anomalies. Journal of Finance 51, 55-84.

Fang, Y., Wada, S., Moody, J., 2003. Stock returns: momentum, volatility and interest rates. IEEE Press.

Gregory, A., Harris, R. D. F., Michou, M., 2001. An analysis of contrarian investment strategies in the UK. Journal of Business Finance and Accounting 28, 1193-1228.

Griffin, J. M., Ji, S., Martin, J. S., 2003. Momentum investing and business cycle risk: evidence from pole to pole. Journal of Finance 58, 2515-2547.

Hon, M., Tonks, I., 2003. Momentum in the UK stock market. Journal of Multinational Financial Management 13, 43-70.

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

Hong, H., Lim, T., Stein, J. C., 2000. Bad news travels slowly: size, analyst coverage and the profitability of momentum strategies. Journal of Finance 55, 265-295.

Huang, R. D., Stoll, H. R., 1996. Dealer versus auction markets: a paired comparison of execution costs on NASDAQ and the NYSE. Journal of Financial Economics 41, 313-357.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. Journal of Finance 45, 881-898.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. Journal of Finance 48, 65-91.

Jegadeesh, N., Titman, S., 2001. Profitability of momentum strategies: an evaluation of alternative explanations. Journal of Finance 56, 699-720.

Korajczyk, R. E., Sadka, R., 2004. Are momentum profits robust to trading costs?. Journal of Finance 59, 1039-1082.

Lee, C. M., Swaminathan, B., 2000. Price momentum and trading volume. Journal of Finance 55, 2017-2069.

Lesmond, D., Schill, M., Zhou, C., 2004. The illusory nature of momentum profits. Journal of Financial Economics 71, 349-380.

Liu, W., Strong, N., Xu, X., 1999. The profitability of momentum investing. Journal of Business Finance and Accounting 26, 1043-1091.

Moskowitz, T. J., Grinblatt, M., 1999. Do industries explain momentum?. Journal of Finance 54, 1249-1290.

Naik, N. Y., Yadav, P. K., 1999. The effects of market reform on trading costs of public investors: evidence from the London Stock Exchange, working paper.

Nagel, S., 2001. Is it overreaction? The performance of value and momentum strategies at long horizons, working paper.

Shen, Q., Szakmary, A., Sharma, S., 2005. Momentum and contrarian strategies in international stock markets: further evidence. Journal of Multinational Financial Management 15, 235-255.

Siganos, A., Chelley-Steeley, P., 2006. Momentum profits following bull and bear markets. Journal of Asset Management 6, 381-388.

Taylor, N., Van Dijk, D., Franses, P. H., Lucas, A., 2000. SETS, arbitrage activity and stock price dynamics. Journal of Banking and Finance 24, 1289-1306.

Thomas, W. A., 1989. *The securities market*. Philip Allan.

Tonks, I., Webb, D., 1991. Big Bang, working paper.

Zarowin, P., 1990. Size, seasonality and stock market overreaction. Journal of Financial and Quantitative Analysis 25, 113-125.

Table 1

Momentum profits in floor and automated systems

	Entire period	Floor sub-period	Automated sub-period
Panel A: 3 portfolios			
L	0.17%	1.40%	-0.74%
2	0.99%	1.79%	0.41%
W	1.13%	1.80%	0.64%
W-L	0.96%***	0.41%*	1.38%***
Panel B: 5 portfolios			
L	-0.01%	1.32%	-1.00%
2	0.70%	1.62%	0.03%
3	1.01%	1.84%	0.41%
4	1.07%	1.78%	0.56%
W	1.17%	1.82%	0.69%
W-L	1.18%***	0.50%*	1.69%***
Panel C: 10 portfolios			
L	-0.34%	1.15%	-1.44%
2	0.31%	1.49%	-0.55%
3	0.54%	1.56%	-0.21%
4	0.86%	1.68%	0.26%
5	1.01%	1.88%	0.37%
6	1.00%	1.79%	0.43%
7	1.08%	1.78%	0.57%
8	1.07%	1.77%	0.56%
9	1.14%	1.76%	0.69%
W	1.19%	1.87%	0.70%
W-L	1.53%***	0.73%*	2.14%***

Each company was ranked on the basis of its stock market performance over the previous six months. We then placed each security into one of ten equally sized portfolios. The winner portfolio (W) contained the best performing decile of securities and the loser portfolio (L) contained the worst performing decile of securities. When using three portfolios, winners and losers each comprised 30 percent of the sample and when using five portfolios, winners and losers each included 20 percent of the sample. One month was skipped to avoid potential market frictions identified by Jegadeesh (1990) and in the following six-month period, the returns of each of the equal weighted portfolios were calculated. This procedure was repeated for each non-overlapping six-month period. The difference between winner and loser portfolio returns (W-L) showed the profitability of the momentum strategy. *, ** and *** show significance at the 10, 5 and 1 percent level for the W-L respectively.

Table 2

Employing different datasets

		Entire period	Floor sub-period	Automated sub-period
Panel A: Accounting sub-sample				
L		-0.19%	1.24%	-1.22%
W		1.28%	2.20%	0.62%
W-L		1.47%***	0.96%**	1.84%***
L	size	232.40	55.76	395.96
	B/M	1.86	2.58	1.18
W	size	501.36	70.87	870.36
	B/M	0.98	1.45	0.59
W-L	size	268.96	14.45	504.62
	B/M	-0.87	-1.17	-0.60
Panel B: 266 shares				
L		0.58%	1.81%	-0.30%
W		1.47%	2.16%	0.97%
W-L		0.89%***	0.35%	1.28%***
Panel C: Obtaining US momentum returns by Kenneth French's website				
L		0.90	1.26	0.63
W		2.23	2.67	1.91
W-L		1.33***	1.40***	1.28**

Panel A shows the momentum profitability when the accounting sub-sample is employed. Panel B shows the momentum profitability that the same shares generate in both structures by analyzing companies that have return information for the duration of the whole sample period. Only 266 shares fulfill that condition. Panel C uses the equal-weighted monthly US momentum returns from October 1975 to October 2001 from Kenneth French's website. Like our study those momentum returns were calculated using deciles to define the winner and loser portfolios and unlike our study t-12 to t-2 months were used to form the portfolios. *, ** and *** show significance at the 10, 5 and 1 percent level for the W-L respectively.

Table 3

Adjusting for bull and bear markets

	Entire Period	Floor sub-period	Automated sub-period
Panel A: Bear state			
L	-1.66%	0.42%	-2.90%
W	0.90%	0.99%	0.78%
W-L	2.57%***	0.57%	3.68%***
Panel B: Bull state			
L	0.19%	1.38%	-0.74%
W	1.31%	2.15%	0.66%
W-L	1.12%***	0.77%*	1.41%***

The bull state (Panel B) was when the average market return (FTSE-All Share) was non-negative six months before the test period, and the bear state (Panel A) was when the average market return was negative six months before the test period. 76 percent of the periods identified as bull during the floor sub-period and 68 percent during the automated sub-period. *, ** and *** show significance at the 10, 5 and 1 percent level for the W-L respectively.

Table 4

Size and book-to-market adjustment

	Entire period	Floor sub-period	Automated sub-period
L	-0.61%	-0.36%	-0.79%
W	0.38%	0.38%	0.39%
W-L	0.99%***	0.74%*	1.18%***

Securities were first sorted into three groups based on their market capitalization. Companies in each size-sorted group were further divided into three additional groups based on their book-to-market. All this provided nine portfolios. The returns of these nine size-book-to-market portfolios were calculated over the test period as: $R_{it}^{CH} = R_{it} - R_{t}^{CH}$ where R_{it}^{CH} is the characteristic-adjusted return on security i in month t, R_{it} is the return on security i in month t, and R_{t}^{CH} is the return on a size-book-to-market matched portfolio in month t. To undertake this procedure, book and market values were required. Since LSPD does not provide book values, our smaller accounting sub-sample was utilized for this analysis. *, ** and *** show significance at the 10, 5 and 1 percent level for the W-L respectively.

Table 5

Aggregate betas

	Entire period	Floor sub-period	Automated sub-period
L	1.51	0.91	1.81
W	1.42	1.22	1.59
W-L	-0.09	0.31	-0.22

We estimated regressions of portfolio returns against lagging, contemporaneous and leading market returns. The aggregate coefficient betas were determined by the number of leads and lags that are statistically significant. $R_{p,t} - R_{f,t} = a_p + \sum_{k=-n}^{n} \beta_p (R_{m,k,t} - R_{f,k,t}) + e_{i,t}$ where $R_{p,t}$ is the return of portfolio p in month t, $R_{f,t}$ is the one-month Treasury Bill rate in month t, and $R_{m,t}$ is the return of the proxy market (FTSE All-Share) in month t. The aggregate coefficient beta was the sum of betas with different leads and lags. Four lags and two leads were analyzed for the loser portfolio and four lags and four leads for the winner portfolio.

Table 6

Controlling for risk with the three-factor model

	Entire period	Floor sub-period	Automated sub-period
Panel A: L			
a_p	-1.26%	1.51%	-1.08%
β_p	1.28	1.20	1.37
s_p	0.87	1.07	0.69
h_p	-0.18	0.09	-0.23
$adj-R^2$	0.52	0.70	0.48
F	108	97	54
Panel B: W			
a_p	0.00%	2.30%	0.56%
β_p	0.98	1.04	0.91
s_p	0.59	0.69	0.52
h_p	-0.35	-0.06	-0.45
$adj-R^2$	0.51	0.76	0.41
F	104	133	41
Panel C: W-L			
a_p	1.26%***	0.80%**	1.64%***
β_p	-0.30***	-0.16*	-0.46***
s_p	-0.28***	-0.37***	-0.18
h_p	-0.17**	-0.15	-0.22**
$adj-R^2$	0.09	0.06	0.14
F	10***	3.87**	10***

We estimated the following regression: $R_{p,t} - R_{f,t} = a_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + e_{p,t}$ where $R_{p,t}$ is the return of portfolio p in month t, $R_{f,t}$ is the one-month Treasury Bill rate in month t, and $R_{m,t}$ is the return of the proxy market (FTSE All-Share) in month t. We generated nine portfolios; shares were sorted into three groups based on the market value and then, each size-sorted portfolio was divided further into three portfolios based on the book-to-market ratios. SMB_t (Small Minus Big) shows the portfolio that buys the three small size portfolios and sells short the three big size portfolios. HML_t (High Minus Low) shows the portfolio that buys the three high book-to-market portfolios and sells short the three low book-to-market portfolios. *, ** and *** show significance at the 10, 5 and 1 percent level for the W-L respectively.

Table 7

Momentum profits in dealer and auction systems

	SETS auction system (1997-2001)	Dealer system (1975-2001)	Dealer system (1997-2001)	150 largest SEAQ shares (1997-2001)	SETS stocks (1994-1997)	Full sample (1994-1997)
Panel A: 3 portfolios						
L	-0.79%	0.17%	-1.66%	-1.37%	1.42%	-0.29%
W	0.41%	1.13%	-0.22%	-0.11%	1.85%	1.02%
W-L	1.20%	0.96%***	1.45%	1.25%	0.43%	1.31%***
Panel B: 5 portfolios						
L	-1.14%	-0.04%	-2.17%	-1.99%	1.52%	-0.53%
W	0.88%	1.15%	-0.33%	-0.70%	2.06%	1.12%
W-L	2.01%	1.19%***	1.85%	1.29%	0.54%	1.65%***
Panel C: 10 portfolios						
L	-2.07%	-0.35%	-2.79%	-2.38%	1.90%	-0.86%
W	0.86%	1.18%	-0.34%	-1.30%	3.01%	1.12%
W-L	2.94%	1.53%***	2.45%*	1.08%	1.10%	1.98%***

*, **, and ***, significant at the 10, 5 and 1 percent level for the W-L respectively.

Fig. 1. Momentum profits in floor and automated sub-periods

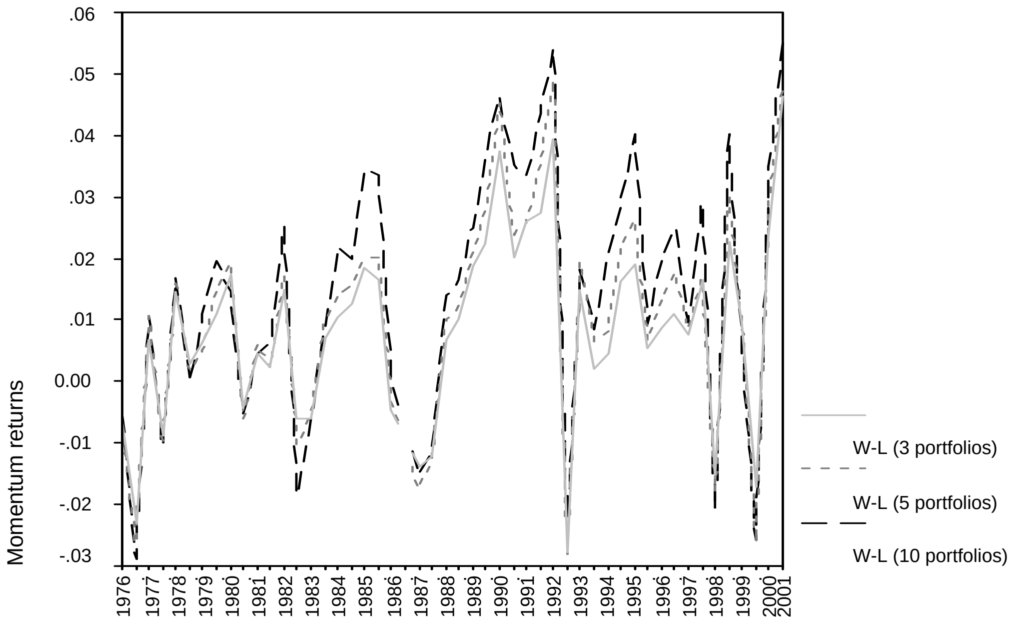

Fig. 2. Structure of momentum returns in floor and automated sub-periods