# Momentum Profits in Alternative Stock Market Structures

by

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## Abstract

This study examines the validity of the gradual diffusion model of Hong and Stein (1999). Since 1975 the London stock market has employed three different trading systems: a floor based system, a computerised dealer system called SEAQ and the automated auction SETS system. We find that after the introduction of the computerised dealer system, the diffusion of information was faster across investors, but SEAQ momentum profits are stronger than when the floor based system operated. We also report that companies trading on the SETS auction system, in which share prices adjust faster to news, display greater momentum profitability than shares trading on SEAQ. These findings contradict to the theoretical results of the model.



**Keywords:** momentum effect, trading system, SEAQ, SETS.

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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 per cent could be achieved. Extensive evidence now exists in support of the momentum strategy for the US (e.g., Moskowitz and Grinblatt, 1999; Jegadeesh and Titman, 2001), for the UK (e.g., Liu et al., 1999; Hon and Tonks, 2003) and for a global range of stock markets (e.g., Griffin et al., 2003; Rouwenhorst, 1998).

A significant number of studies have considered the potential reasons for momentum, but no clear consensus has emerged. One of the most significant studies is that by Hong and Stein (1999)[1] who developed a model based on two rational

[1] Some other significant studies that have explained momentum are the followings: Ang et al (2001) documented that the contents of the winner portfolio are characterised 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. Barberis et al (1998) developed a model in which investors underreact to information about earnings. Du (2002) argued that investors can be characterised 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) reported that firms with high trading volume have higher momentum than firms with low trading volume. Moskowitz and Grinblatt (1999) showed that momentum is related to a firm’s industry.

agents; newswatchers and momentum traders. Newswatchers observe some private information, but fail to be aware of the information that other investors have. When the private information of investors becomes public, prices adjust to new information and the momentum effect emerges. Therefore, the continuation hypothesis stems from the gradual expansion of information among investors.

Hong et al. (2000), using US data, and Doukas and McKnight (2005), using information from 13 European countries, tested the validity of the Hong and Stein (1999). They found empirical support for the model as stocks exhibit higher momentum profits if information spreads slowly amongst investors: continuation profits are higher for smaller capitalisation shares and for securities with lower levels of analyst coverage.

The novelty of this study is that it investigates the possible influence that an alternative influence of information diffusion has on momentum profitability. Since 1975 the London stock market has employed three different trading systems: a floor based system, a computerised dealer system called SEAQ and an automated auction system called SETS. The characteristics of each system allow information to diffuse to prices at different rates.

With the introduction of the SEAQ mechanism on 27$^{th}$ October 1986, information disseminated widely and rapidly throughout the investor community with the Teletext Output Price Information Computer (TOPIC) network. The adoption of recent technological advances in computing and telecommunications allowed face-to-face trading on the floor of the exchange to be replaced by telephone and electronic trading on the screen system. The Hong and Stein model would predict that since the post-Big Bang period is characterised by faster diffusion of information among investors, the magnitude of momentum profits should be lower after 1986.

With the introduction of the SETS on 20th October 1997, all FTSE 100 stocks, and later some additional shares from FTSE 250, have traded in a fully automated electronic auction system. Taylor et al. (2000) show that since the introduction of the SETS, both FTSE100 spot and futures prices adapt quicker to shocks. Chelley-Steeley (2003) demonstrated that cross-listed shares adjust to their fundamental news more quickly when they trade on the Paris Bourse auction market than when they trade on the SEAQ International dealer system. The Hong and Stein model would predict that shares traded on the SETS auction system, in which share prices adjust more quickly to news, would generate lower momentum profits than shares traded on the SEAQ dealer mechanism.

We report findings against the theoretical results of the model. First, we find that after the introduction of the computerised dealer system, SEAQ momentum profits are higher than when the floor based system operated. These results persist after controlling for size, book-to-market and risk as defined by the CAPM and the three-factor model. Second, we report that shares trading on the SETS order-driven system demonstrate larger momentum profits than shares trading on the SEAQ quote-driven system. The difference in momentum profits between the two structures increases significantly after considering for size differences.

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 utilised. Sections 4 and 5 measure momentum in different market structures. Section 6 provides the conclusions.

## 2. TRADING SYSTEMS

Prior to Big Bang in 1986 the London Stock Exchange utilised 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 internationalisation of capital markets (Thomas, 1989), a major overhaul of the London Stock Exchange trading system took place on 27$^{th}$ 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 20$^{th}$ of October 1997. 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. Unlike SEAQ, all orders are visible on SETS and no reporting delays are allowed enhancing both pre-trade and post-trade transparency.

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 (e.g., Huang and Stoll, 1996). In particular, the trading system plays an important part in determining trading activity. In their examination of changes to the trading system on the Singapore stock exchange, Naidu and Rozeff (1994) documented a strong relationship between the trading system and trading activity. As shown by Lee and Swaminathan (2000) a positive relationship between trading volume and momentum profits can be expected. We predict that automated markets, which tend to have higher trading volume, are likely to give rise to higher momentum profits than floor based systems.

Trading systems also influence the relative trading activities of institutional and small investors. The lower costs associated with auction mechanisms favour retail investors (e.g., Pagano and Roell, 1996; de Jong et al., 1995; Pagano, 1997), while market making facilities tend to attract large scale institutional trading (e.g., Pagano and Roell, 1996; Pagano, 1997). Du (2002) argued that investor behaviour contributes to the scale of momentum profits. The level of investor confidence influences the decision making speed of investors. This suggests that trading mechanisms that are more favourable to a particular investor type will encourage either fast decisions about equity (little momentum) or slow decisions (high momentum).

It has also been shown that the trading system can influence informational efficiency. Auction systems are generally more transparent (Pagano and Roell, 1996) and this may influence the rate of information diffusion. Since transparency is notably higher in auction systems such as SETS and Hong and Stein (1999) have argued that the rate of information diffusion influences momentum profits, we should expect a relationship between momentum and the type of trading system.

## 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 are utilised in this study. The sample period focuses on the post-1975 period because LSPD only includes all British companies listed on the LSE after 1975. In all this provides information on over 6,000 firms where the number of firms analysed in any given year ranges from 1,489 to 2,444 and constitutes our *main sample*. Our second sample is the *accounting sub-sample*. This is drawn from the main sample but requires from each firm accounting information on annual market value and book-to-market ratios. This information is available from Datastream for over 2,000 of the companies where the number of companies examined in any given year varies from 442 to 1,143. Our *SETS sample* reflects the 150 stocks that according to the London Stock Exchange[2] have traded on SETS. This sample extends from October 1997 to October 2001.

To calculate momentum profitability, we rank each company on the basis of their stock market performance over the previous six months. We then place each security into one of ten equally sized portfolios. The winner portfolio contains the best performing decile of securities and the loser portfolio contains the worst performing decile of securities[3]. We skip one month to avoid potential market frictions identified by Jegadeesh (1990). We calculate the returns of each of the equally weighted portfolios over the following six-month period. This procedure is repeated for each non-overlapping six-month period. We omit the first six months after the Big Bang to prevent our results from reflecting an initial adjustment.

We focus on the difference between winner and loser portfolio returns W-L. Table 1 provides the results of the momentum strategy employed for deciles, quintiles and triciles. Past winners (W) outperform prior losers (L) over the test period by 0.96 per cent per month when three portfolios are used (Panel A), 1.18 per cent when five portfolios are examined (Panel B) and 1.53 per cent per month when ten

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[2] http://www.londonstockexchange.com/en-gb/products/membershiptrading/tradingservices/sets.htm

[3] We also define winners and losers using three and five portfolios that include respectively the top and bottom 30 and 20 per cent of shares.

portfolios are employed (Panel C). A monotonic relationship exists between the size of momentum profits and prior performance. The magnitude of momentum profits reported is comparable with the results found by other studies employing international and UK data (e.g., Griffin et al., 2003).

## 4. MOMENTUM PROFITS IN FLOOR AND AUTOMATED TRADING SYSTEMS

### *(i) Initial Findings*

Table 1 shows that in the period before Big Bang monthly momentum profits are 0.41 per cent when three portfolios are studied (Panel A), 0.50 per cent when five portfolios are employed (Panel B) and 0.73 per cent 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 per cent (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) per cent using three portfolios, 1.19 (t-statistic=2.50) per cent examining five portfolios and 1.41 (t-statistic=2.38) per cent studying ten portfolios[4].

Figure 1 plots the continuation gains generated on the LSE and shows that most of the momentum profits associated with the automated sub-period come from the

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[4] In unreported results, the Mann-Whitney non-parametric test provides identical findings to those generated when a parametric test is employed.

1990-1993 period. The interruption of the lines in 1987 arises because we miss one test period at the time of the Big Bang.

The stronger trading volume displayed after the Big Bang (Tonks and Webb, 1991) might explain the higher momentum profits after 1986. Lee and Swaminathan (2000) reported that a positive relationship between trading volume and momentum profits holds and therefore, the automated market, which tend to have higher trading volume, is likely to give rise to higher momentum profits than the floor based system[5].

Asymmetry in the magnitude of momentum profits across the different time periods concurs with the results of Hon and Tonks (2003). They documented that momentum strategies were profitable between 1955 and 1996, but unprofitable between 1955 and 1976. We contradict Liu et al. (1999) who suggested that momentum profitability remained approximately the same between 1977-1987 and 1988-1998 [6].

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[5] We do not incorporate trading volume into our analysis, since Datastream does not provide trading volume data for shares before 1987.

[6] Liu et al. (1999) examined share returns from Datastream rather than LSPD returns which might explain the difference. Chakrabarty and Trzcinka (2004) reported that the use of TAQ rather than CRSP share returns can influence significantly the size of momentum profits, since databases set different criteria for listing/de-listing firms.

*(ii) Using Different Datasets*

Panel A of Table 2 shows that when the accounting sub-sample is employed, findings are identical to those reported for the full sample as shown earlier in Table 1[7]. The correlation on momentum profits between the full sample and the accounting sub-sample is strong with a Pearson correlation equals to 0.63.

Panel A of Table 2 further shows that 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 characterised by higher market values in all samples. The arbitrage portfolio in the post-Big Bang period includes larger capitalisation companies than its counterpart arbitrage portfolio in the pre-Big Bang period. This finding suggests that after controlling for size, the difference in momentum gains before and after Big Bang should be even larger. In addition, the winner portfolio tends to include shares with lower book-to-market ratios than the loser portfolio. This result is consistent with Liu et al. (1999) and indicates that winners tend to be glamour stocks and losers value equities.

We also examine the momentum profitability that the same shares generate in both structures by analysing companies that have return information for the duration of the whole sample period. Only 266 shares fulfil that condition. Panel B of Table 2 demonstrates that the automated sub-period still provides higher monthly

[7] Hereafter, we restrict only to the 10-portfolio analysis and to the winner and loser portfolio returns due to space consideration.

momentum profits than the floor sub-period[8]. The correlation on momentum profits between the full sample (accounting sub-sample) and this sub-sample is strong with a Pearson rank correlation equals to 0.72 (0.60).

*(iii) Controlling for Size and Book-to-Market*

A large number of studies have highlighted the influence that size and book-to-market can have on share returns (e.g., Banz, 1981; Fama and French, 1992). 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.

As a robustness test, we investigate whether changes in the book-to-market ratios across the two sub-periods can account for our results. To test this assertion, we apply a matching process similar to Daniel and Titman (1997) that was found to explain overreaction by Nagel (2001).

Securities are first sorted into three groups based on their market capitalisation. Companies in each size-sorted group are further divided into three additional groups based on their book-to-market ratios. In all this provides nine portfolios. We calculate the returns of these nine size-book-to-market portfolios over the test period. The performance of each security in the test period is calculated as:

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

[8] Consistent with Hong et al. (2000), who reported a negative association between size and momentum profitability, shares used in this sub-sample expected to generate relatively low momentum profits.

where $R_{it}^{CH}$ is the characteristic-adjusted return on security $i$ during 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, we require book and market values. Since LSPD does not provide book values, we must utilise our smaller accounting sub-sample for this analysis.

Table 3 shows the size and book-to-market adjusted portfolio returns. We find 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 significant using the entire period and abnormal returns are still much larger in the post-Big Bang period. This finding suggests that profits in the automated and floor-based system cannot be fully attributable to firm characteristics. The difference in momentum profitability between the two sub-periods remains significant, although smaller than that obtained from unadjusted returns. Therefore, size and book-to-market cannot explain the difference in momentum gains generated before and after Big Bang.

*(iv)Risk Adjustments*

Initially, this study controls for risk based on the Capital Asset Pricing Model. We calculate the aggregate coefficient betas of Dimson (1979) to overcome the problem of infrequent trading that conventional betas exhibit. We estimate regressions of rank period portfolio returns against lagging, matching and leading market returns.

The aggregate coefficient betas are determined by the number of leads and lags that are statistically significant[9].

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

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 is the sum of betas with different leads and lags.

Table 4 shows the portfolio aggregate betas. The winner portfolio displays lower aggregate betas than its counterpart loser portfolio. We also find that portfolios in the automated period tend to have higher betas, but the beta of the arbitrage portfolio ($\beta_{W-L}$) is –0.22 for the automated period and 0.31 for the floor period. This result suggests that the arbitrage portfolio generates higher performance and experiences lower risk during the automated period[10].

The three-factor model of Fama and French (1993) shows that beta, size and book-to-market should be taken into account when measuring risk-adjusted returns. Liu et al. (1999) reported that after controlling for the three-factor model, momentum

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[9] For example, four lags and two leads analysed for the loser portfolio and four lags and four leads for the winner portfolio.

[10] We extend the investigation and calculate the aggregate betas of the arbitrage portfolio examining alternative lags and leads (Table 5). 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.

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 estimate the following regression:

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

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 generate nine portfolios; shares are sorted into three groups based on the market value and then, each size-sorted portfolio 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.

Table 6 shows the sensitivities and the intercept of the model for the loser portfolio (Panel A), the winner portfolio (Panel B) and the arbitrage portfolio (Panel C). 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 per cent per month during the period of automation, but lower at 0.80 per cent per month during the floor period. Consistent with Liu et al. (1999) and Fama and French (1996), the negative sensitivities to all three Fama and French factors and the relatively low adjusted R-squared values reinforce the inability of the model to capture momentum.

## 5. MOMENTUM PROFITS IN DEALER AND AUCTION TRADING SYSTEMS

This section tests whether shares trading in dealer and auction systems generate different momentum profits. Table 7 reports that the magnitude of continuation profits is different when comparing quote-driven and order-driven mechanisms. We find that monthly momentum profits for shares trading on the SETS mechanism are 1.20 per cent when three portfolios are examined, 2.01 per cent when five portfolios are studied and 2.94 per cent 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[11].

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. We find that stocks trading on SETS system generate almost identical momentum profits to those shares traded on the SEAQ.

Companies trading on SETS and SEAQ are, however, 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

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[11] Shares trading on the SETS auction system experience relatively high volatility (Chelley-Steeley, 2002), which might be associated with the difference in momentum profits between auction and dealer systems.

them to generate lower momentum profits. To adjust for size, we calculate momentum profits 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. Table 7 shows that the largest 150 shares trading on the SEAQ mechanism generate significantly lower continuation profits than their counterpart companies trading on SETS.

We further calculate 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. Table 7 reports 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[12].

## 6. CONCLUSIONS

We 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. We 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 findings suggested that the momentum effect persists on the LSE using various data sets and after controlling for various factors influence share returns.

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[12] Full risk adjustment tests have not been undertaken, since the SETS sample includes a very small number of companies. For example, if the size and book-to-market adjustment was undertaken, we should have generated nine portfolios with each portfolio including only 17 shares.

We 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. This study reported findings that contradict the gradual diffusion model of Hong and Stein (1999) showing that the validity of the model is fragile to the interpretation of the concept. Hong et al. (2000) and Doukas and McKnight (2005) associated the speed of information that flows among investors with the size and the analyst coverage of companies, while this study with alternative stock market trading mechanisms generating contradictory results.

When we measured momentum profits in the period prior to and subsequent to the introduction of SEAQ, we found that shares trading in the post-Big Bang period, when a faster diffusion of information among investors holds, generate higher continuation profits than trading in the pre-deregulation floor period. This finding is robust to the employment of a sub-sample of firms and to a range of risk adjustment tests.

When we examined the momentum profits generated from trading on SETS, we found that shares trading on the SETS order-driven system, in which share prices adjust more quickly to news, 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.

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**Table 1**
Momentum Profits in Floor and Automated Systems

| | Entire Period (1975-2001) | Floor Period (1975-1986) | Automated Period (1987-2001) |
|---|---|---|---|
| Panel A: 3 Portfolios | | | |
| L | 0.17% | 1.40% | -0.74% |
| | (0.54) | (3.96) | (-1.63) |
| 2 | 0.99% | 1.79% | 0.41% |
| | (5.57) | (7.52) | (1.66) |
| W | 1.13% | 1.80% | 0.64% |
| | (5.51) | (6.73) | (2.16) |
| W-L | 0.96% | 0.41% | 1.38% |
| | (2.58) | (0.92) | (2.55) |
| Panel B: 5 Portfolios | | | |
| L | -0.01% | 1.32% | -1.00% |
| | (-0.04) | (3.46) | (-1.96) |
| 2 | 0.70% | 1.62% | 0.03% |
| | (3.21) | (5.81) | (0.09) |
| 3 | 1.01% | 1.84% | 0.41% |
| | (5.54) | (7.95) | (1.56) |
| 4 | 1.07% | 1.78% | 0.56% |
| | (6.13) | (6.97) | (2.36) |
| W | 1.17% | 1.82% | 0.69% |
| | (5.27) | (6.77) | (2.08) |
| W-L | 1.18% | 0.50% | 1.69% |
| | (2.86) | (1.07) | (2.78) |
| Panel C: 10 Portfolios | | | |
| L | -0.34% | 1.15% | -1.44% |
| | (-0.82) | (2.63) | (-2.39) |
| 2 | 0.31% | 1.49% | -0.55% |
| | (1.05) | (4.28) | (-1.30) |
| 3 | 0.54% | 1.56% | -0.21% |
| | (2.15) | (5.00) | (-0.60) |
| 4 | 0.86% | 1.68% | 0.26% |
| | (4.47) | (6.57) | (0.97) |
| 5 | 1.01% | 1.88% | 0.37% |
| | (5.53) | (8.23) | (1.44) |
| 6 | 1.00% | 1.79% | 0.43% |
| | (5.34) | (7.44) | (1.58) |
| 7 | 1.08% | 1.78% | 0.57% |
| | (6.42) | (7.14) | (2.53) |
| 8 | 1.07% | 1.77% | 0.56% |
| | (5.76) | (6.54) | (2.21) |
| 9 | 1.14% | 1.76% | 0.69% |
| | (5.42) | (6.53) | (2.22) |
| W | 1.19% | 1.87% | 0.70% |
| | (4.94) | (6.74) | (1.89) |
| W-L | 1.53% | 0.73% | 2.14% |
| | (3.23) | (1.40) | (3.02) |

*Notes:*
3 portfolios: winners (W) and losers (L) each comprise 30 per cent of the full sample.
5 portfolios: winners and losers each include 20 per cent of the full sample.
10 portfolios: winners and losers each comprise 10 per cent of the full sample.
T-statistics are shown in parentheses.

**Table 2**
Employing Different Datasets

| | | Entire Period | Floor Period | Automated Period |
|---|---|---|---|---|
| Panel A: Accounting sub-sample | | | | |
| L | | -0.19% | 1.24% | -1.22% |
| | | (-0.48) | (2.41) | (-2.29) |
| W | | 1.28% | 2.20% | 0.62% |
| | | (5.42) | (7.30) | (1.85) |
| W-L | | 1.47% | 0.96% | 1.84% |
| | | (3.22) | (1.61) | (2.92) |
| 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% |
| | | (1.81) | (4.43) | (-0.67) |
| W | | 1.47% | 2.16% | 0.97% |
| | | (7.67) | (9.40) | (3.40) |
| W-L | | 0.89% | 0.35% | 1.28% |
| | | (2.36) | (0.74) | (2.39) |

**Table 3**

Size and Book-to-Market Adjustment

$$R_{it}^{CH} = R_{it} - R_{t}^{CH}$$

| | Entire Period | Floor Period | Automated Period |
|---|---|---|---|
| L | -0.61% | -0.36% | -0.79% |
| | (-1.92) | (-0.54) | (-2.98) |
| W | 0.38% | 0.38% | 0.39% |
| | (1.19) | (0.65) | (1.10) |
| W-L | 0.99% | 0.74% | 1.18% |
| | (2.19) | (0.84) | (2.66) |

## Table 4

Aggregate Betas

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

| | Entire period | Floor Period | Automated Period |
|---|---|---|---|
| L | 1.51 | 0.91 | 1.81 |
| 2 | 1.17 | 0.85 | 1.37 |
| 3 | 1.14 | 0.92 | 1.29 |
| 4 | 1.10 | 0.93 | 1.22 |
| 5 | 1.08 | 0.91 | 1.19 |
| 6 | 1.08 | 0.98 | 1.14 |
| 7 | 1.12 | 1.04 | 1.17 |
| 8 | 1.09 | 0.93 | 1.21 |
| 9 | 1.18 | 1.03 | 1.29 |
| W | 1.42 | 1.22 | 1.59 |
| W-L | -0.09 | 0.31 | -0.22 |

## Table 5

Aggregate Betas of the Arbitrage Portfolio

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

| | | -1 | | -2 | | -3 |
|---|---|---|---|---|---|---|
| +1 | F | 0.26 | F | 0.44 | F | 0.51 |
| | A | -0.34 | A | -0.24 | A | -0.21 |
| | | | | | | |
| +2 | F | 0.22 | F | 0.40 | F | 0.47 |
| | A | -0.29 | A | -0.19 | A | -0.15 |
| | | | | | | |
| +3 | F | 0.22 | F | 0.40 | F | 0.48 |
| | A | -0.32 | A | -0.21 | A | -0.17 |

*Note:*
F and A represent the floor and automated sub-periods respectively.

## Table 6

Controlling for Risk with the Three-Factor Model

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

| | Entire period | Floor period | Automated period |
|---|---|---|---|
| Panel A: Losers | | | |
| $a_p$ | -1.26% | 1.51% | -1.08% |
| | (-4.50) | (1.78) | (-2.63) |
| $\beta_p$ | 1.28 | 1.20 | 1.37 |
| | (17.92) | (15.21) | (12.68) |
| $s_p$ | 0.87 | 1.07 | 0.69 |
| | (9.01) | (8.98) | (5.25) |
| $h_p$ | -0.18 | 0.09 | -0.23 |
| | (-1.97) | (0.82) | (-1.91) |
| $adj-R^2$ | 0.52 | 0.70 | 0.48 |
| Panel B: Winners | | | |
| $a_p$ | 0.00% | 2.30% | 0.56% |
| | (0.00) | (2.77) | (1.04) |
| $\beta_p$ | 0.98 | 1.04 | 0.91 |
| | (17.09) | (16.92) | (10.31) |
| $s_p$ | 0.59 | 0.69 | 0.52 |
| | (7.63) | (7.52) | (4.76) |
| $h_p$ | -0.35 | -0.06 | -0.45 |
| | (-4.90) | (-0.64) | (-4.57) |
| $adj-R^2$ | 0.51 | 0.76 | 0.41 |
| Panel C: Winners-Losers | | | |
| $a_p$ | 1.26% | 0.80% | 1.64% |
| | (4.99) | (2.49) | (4.45) |
| $\beta_p$ | -0.30 | -0.16 | -0.46 |
| | (-4.71) | (-1.77) | (-4.96) |
| $s_p$ | -0.28 | -0.37 | -0.18 |
| | (-3.23) | (-2.67) | (-1.58) |
| $h_p$ | -0.17 | -0.15 | -0.22 |
| | (-2.15) | (-1.12) | (-2.16) |
| $adj-R^2$ | 0.09 | 0.06 | 0.14 |

**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% |
| | (-0.77) | (0.53) | (-1.64) | (-0.97) | (0.76) | (-0.56) |
| W | 0.41% | 1.13% | -0.22% | -0.11% | 1.85% | 1.02% |
| | (0.70) | (5.42) | (-0.28) | (-0.21) | (0.82) | (4.05) |
| W-L | 1.20% | 0.96% | 1.45% | 1.25% | 0.43% | 1.31% |
| | (1.08) | (2.55) | (1.13) | (0.83) | (0.73) | (3.35) |
| Panel B: 5 Portfolios | | | | | | |
| L | -1.14% | -0.04% | -2.17% | -1.99% | 1.52% | -0.53% |
| | (-0.85) | (-0.10) | (-1.90) | (-1.28) | (0.92) | (-1.15) |
| W | 0.88% | 1.15% | -0.33% | -0.70% | 2.06% | 1.12% |
| | (1.23) | (5.11) | (-0.35) | (-0.96) | (1.06) | (4.43) |
| W-L | 2.01% | 1.19% | 1.85% | 1.29% | 0.54% | 1.65% |
| | (1.33) | (2.85) | (1.26) | (0.75) | (0.77) | (3.33) |
| Panel C: 10 Portfolios | | | | | | |
| L | -2.07% | -0.35% | -2.79% | -2.38% | 1.90% | -0.86% |
| | (-1.09) | (-0.85) | (-2.13) | (-1.18) | (1.56) | (-1.65) |
| W | 0.86% | 1.18% | -0.34% | -1.30% | 3.01% | 1.12% |
| | (1.07) | (4.79) | (-0.32) | (-1.24) | (2.10) | (3.12) |
| W-L | 2.94% | 1.53% | 2.45% | 1.08% | 1.10% | 1.98% |
| | (1.42) | (3.21) | (1.46) | (0.48) | (0.94) | (3.09) |

**Figure 1**

Momentum Profits in Floor and Automated Sub-periods