The Post-Cost Profitability of Momentum Trading Strategies: Further Evidence from the UK

Sam Agyei-Ampomah[†]
Aston Business School
Aston University
Birmingham, B4 7ET
United Kingdom
Tel: +44 (0)121 204 3013
Fax: +44 (0)121 333 5708
Email: s.agyei-ampomah@aston.ac.uk

Abstract

This paper examines the post-cost profitability of momentum trading strategies in the UK over the period 1988 – 2003 and provides direct evidence on stock concentration, turnover and trading cost associated with the strategy. We find that after factoring out transaction costs the profitability of the momentum strategy disappears for shorter horizons but remains for longer horizons. Indeed, for ranking and holding periods up to 6-months, profitable momentum returns would not be available to most average investors as the cost of implementation outweighs the possible returns. However, we find post-cost profitability for ranking and /or holding periods beyond 6 months as portfolio turnover and its associated cost reduces. We find similar results for a sub-sample of relatively large and liquid stocks.

Keywords: Momentum strategy, Transaction costs, Portfolio Turnover, Market Efficiency

JEL Classifications: G10, G11, G14

[†] I am grateful to Patricia Chelley-Steeley, David Hillier, Alan Hodgson, Nathan Joseph, Khelifa Mazouz, James Steeley and seminar participants at Bristol University for helpful comments on earlier drafts of the paper. I am also grateful to David A Lesmond for providing his computer codes for the estimation of the LDV model. All errors are my own.

The Post-Cost Profitability of Momentum Trading Strategies: Further Evidence from the UK

Executive Summary

The literature on momentum strategies suggests that buying previously winning stocks (winners) and selling previously losing stocks (losers) are profitable trading strategies in many financial markets. However, there is no consensus on the sources of the momentum effect and whether or not the return generated is profitable net of transaction costs. Whilst some studies suggest the momentum effect is inconsistent with market efficiency, others argue that the momentum premium could be a compensation for higher risk. The 'higher risk higher return' argument implies that the momentum effect is not inconsistent with market efficiency. Others offer alternative behavioural explanations. Recently, some US studies suggest that momentum returns might be illusory after all, since the cost of trading exceeds the returns generated.

In this paper we examine the post-cost profitability of price momentum strategies in the UK over the period 1988 – 2003. We provide evidence on stock concentration, portfolio turnover and trading cost associated with various momentum strategies that have not been previously reported. We find that the loser portfolios, consisting of stocks that have performed poorly in the recent 3 – 12 months, are disproportionately weighted on small and illiquid stocks relative to the distribution of stocks in the total sample. However, we do not find any evidence of industrial concentration in either the loser portfolio or the winner portfolio to suggest that price momentum is driven by industry momentum. If industry momentum drives price momentum, then we would expect either or both the winner and loser portfolios to be disproportionately weighted towards certain industries, compared to the weight of those

industries in the total sample. Although we find instances of industrial concentration, particularly in the loser portfolio, this does not occur consistently over time.

On post-cost profitability, we find that for ranking and holding periods up to 6-months, momentum return would not be available to most average investors as the cost of implementation dominates the returns. However, we find profitable momentum returns (both raw and risk-adjusted) net of transaction costs for relatively longer ranking and /or holding horizons as portfolio turnover and its associated cost reduces. We find similar results for a sub-sample of large and liquid stocks. Our findings suggest that trading costs does not completely explain the momentum premium; though rebalancing the portfolios more frequently is not profitable. Furthermore, investors could achieve even better results net of transaction costs by focusing on relatively large stocks. Nonetheless, the short position in the loser portfolio generates majority of the momentum returns in our sample. As a result, it may be difficult to realise the momentum returns if an investor faces short-selling constraints.

1 Introduction

Empirical studies on return predictability have attracted a lot of interest from both investment professionals and research academics.[1] Previous studies on momentum strategies suggest that buying previously winning stocks and selling previously losing stocks are profitable trading strategies in many financial markets. Using US data, Jegadeesh and Titman (1993, 2001), Chan *et al* (1996, 1999), among others, report that over a 3 to 12 month period, investors would have obtained significant abnormal returns had they followed the momentum strategy. Doukas and McKnight (2005) find significant momentum returns in 8 out of 13 European markets, Forner and Marhuenda (2003) find significant momentum returns in the Spanish market, whilst Liu *et al* (1999) and Hon and Tonks (2003) find momentum returns in UK stocks. Significant momentum returns in international stocks have also been reported by Rouwenhorst (1998, 1999), Griffin, Ji and Martin (2003) and Chui *et al* (2000).

Indeed, the body of research on momentum strategies has grown extensively over the past 20 years. However, there is no common explanation for the momentum premium. In an efficient market trading strategies based on past prices or publicly available information are unlikely to succeed as the information that investors seek to exploit is already reflected in prices. Ceteris paribus, a profitable momentum strategy is an anomaly because it is inconsistent with market efficiency. On the one hand, the momentum premium has been described variously as a compensation for bearing higher risk (Conrad and Kaul; 1998), a consequence of data mining (Black, 1993; MacKinlay, 1995), or illusory and economically insignificant (Lesmond *et al*, 2004; Hanna and Ready, 2003) in an attempt to rationalise the anomaly. However, other studies show that the risk-based and data mining arguments do not adequately explain the

[1] Trading strategies based on return predictabilities are very popular among investment professionals. For example, Grinblatt and Titman (1995) assessed the investment strategies of 155 mutual funds and found that 77 per cent of the mutual funds analysed used such trend chasing strategies to some extent.

momentum premium. For instance, momentum returns have been reported in different markets and time periods, and a number of studies investigating the risk factors do not completely explain the higher returns generated by these strategies.[2]

Another strand of the literature adopts a behavioural perspective in explaining the momentum premium. Proponents of this view argue that momentum strategies produce higher returns by exploiting irrational market behaviour, such as investor underreaction and/or overreaction to news.[3] For example, Daniel et al (1998) suggest that the momentum effect is a consequence of a delayed market overreaction. The models of Hong and Stein (1999) and Barberis and Shleifer (2003) also predict initial underreaction and a subsequent overreaction which is consistent with short term price continuations. Doukas and McKnight (2005) find evidence in support of this view, as in Hong and Stein (1999, 2000).

Regardless of the sources of momentum profits, one important but unsettled issue concerns the economic significance of the momentum returns. Although it is commonly accepted that transaction costs are essential in evaluating an investment strategy, earlier momentum studies underestimated the trading costs associated with the strategy. For example, Jegadeesh and Titman (1993) and Liu *et al* (1999) both assume a one-way cost of 0.5%. This estimate is based on average trading cost and thus ignores the nature of stocks that go into the momentum portfolio or the frequency of trades from rebalancing the portfolio.

Recently, a number of US studies (Lesmond *et al*, 2004; Korajczyk and Sadka, 2004; Hanna and Ready, 2003; and Keim, 2003) examine the post-cost profitability of the momentum

[2] See studies such as Jegadeesh and Titman (2001, 2002), Grundy and Martin (2001), Liu *et al* (1999).

[3] Cognitive biases such as conservatism, overconfidence, representativeness and self-attribution have been used to explain market behaviour. Conservatism, overconfidence and self-attribution biases could lead to underreaction as these biases tend to limit the individual's ability to learn.

strategies but the evidence is mixed. For example, Lesmond *et al* (2004) re-examine the studies by Jegadeesh and Titman (1993), Hong *et al* (2000) and Jegadesh and Titman (2001) and conclude that transaction costs outweigh the reported momentum returns. Thus, momentum returns cannot be realised due to substantial transaction costs. In contrast, Korajczyk and Sadka (2004) find that for certain momentum strategies it would require a fund size of about $5bn for momentum profits to disappear as a result of transaction costs. Thus, although transaction costs associated with the momentum strategy could be substantial, they (transaction costs) do not completely explain the persistence of the momentum premium. While the literature is replete with evidence of significant momentum returns in different markets, there is as yet no evidence on which to support the relative effect of transaction costs on the momentum strategy in other non-US markets. In this respect, further work on the cost effectiveness of the momentum strategy in other markets is warranted.

In this paper we examine the transaction costs and profitability associated with price momentum strategies in the UK over the period 1988 – 2003. Given that momentum stocks tend to be small stocks and small-cap stocks generally have larger trading costs, the findings above have serious implications for trading strategies on the UK market which has a larger concentration of small-cap and illiquid stocks relative to the US market.[4] Keim and Madhavan (1997) show that transaction costs vary between investment styles, different exchanges and even different stocks on the same exchange. In this regard, our paper contributes to the literature by providing out-of-sample evidence in terms of a different market and time period, which includes the recent general decline in stock markets. In the process, we provide

[4] For instance, Dimson, Nagel and Quigley document that UK small-cap stocks are more thinly traded than their US counterparts and that the daily non-trading probabilities of UK small-cap stocks as at 2001 was only comparable to the 1994 levels for the US small-cap stocks. Our analysis also shows an over-concentration of small-cap stocks in the UK market. We observe that over 80% of the stocks in the sample contribute, altogether, less than 10% of total market capitalisation during the sample period.

evidence on stock concentration, portfolio turnover and the potential trading costs associated with various momentum strategies that have not been previously reported in the literature.

As suggested in Keim and Madhavan (1997) and Barber and Odean (2000) transaction cost, among other things, is dependent on the investment horizon and style. We examine momentum strategies of various ranking and holding periods that include the widely reported 6 x 6 strategy. We are therefore able to examine the sensitivity of momentum profits net of transaction cost to different ranking and holding periods. Finally, we analyse the momentum effects across a sub-sample of large-cap stocks. The momentum effect is usually associated with small stocks and for that reason can easily be explained by short selling constraints and higher transaction costs related to these stocks. Evidence of profitable momentum returns among the sample of large stocks which have relatively lower cost of trading would be interesting. Our findings are summarised below.

We show that the loser portfolios are disproportionately weighted on small and illiquid stocks relative to the distribution of stocks in the total sample. Our evidence on industrial concentration is however mixed. We find instances where the two portfolios, particularly the loser portfolio, show evidence of industrial concentration but this does not occur consistently over the sample period.

On profitability net of transaction costs, we find that for ranking and holding periods up to 6-months, momentum return would not be available to most average investors as the cost of implementation dominates the returns. However, we find profitable momentum returns (both raw and risk-adjusted) net of transaction costs for relatively longer ranking and /or holding horizons as portfolio turnover and its associated cost reduces for longer horizons. We find similar results for a sub-sample of large-cap stocks. We also find that the short position in the loser portfolio generates majority of the momentum returns in our sample, which makes it difficult to achieve under short-selling constraints. In conclusion, if momentum profits are illusory, it cannot be attributed to transaction costs alone.

The remainder of the paper is structured as follows. In Section 2, we present the data and the methodology used in this study. Section 3 presents the results of the basic momentum analysis, results of the analysis of the sub-sample of large stocks and further robustness checks, whilst section 4 concludes.

2 Data and Methodology

2.1 Data

The analysis begins with all stocks traded on the London Stock Exchange with available data on Datastream, excluding investment trusts, unit trusts, warrants, foreign stocks and ADRs. Our analysis covers the sixteen-year period from January 1988 to December 2003, in view of the fact that the bid- and ask-price data needed to estimate the cost of trading are only available from 1987. The sample period is also appropriate as we focus on the post-cost profitability of the momentum strategy. Hon and Tonks (2003) show that, over the period 1955 to 1996, profitable momentum returns in the UK market occur only in the more recent past.

The sample includes both surviving and non-surviving stocks and therefore free from survivorship bias. In total, the sample includes 3,200 stocks but the number of stocks available each month ranges between 1,370 and 1,740 with an average of 1,550 stocks. For each stock in the sample, we collect information on monthly returns, industry group, share price, quoted bid- and ask-prices and market value.

2.2 Momentum Portfolios

To form the momentum portfolios, we follow the methodology of Jegadeesh and Titman (1993). This is a standard technique in the literature on momentum strategies. Each month, stocks are ranked according to their total returns over the previous J months (J = 3, 6, 9 and 12). The stocks are then put into 10 equally weighted portfolios based on these rankings.[5] P10 (winner Portfolio) contains stocks in the top performing decile, whilst portfolio P1 (loser Portfolio) contains stocks in the worst performing decile. Stocks in the intermediate deciles are assigned to portfolios P2 – P9 accordingly. The performance of each of the 10 portfolios and the "winner minus loser" portfolio is calculated over a holding period of K months following the ranking period (K = 1, 2, 3, 6 and 12). Stocks that are delisted during the portfolio formation period are excluded from the sample at that point but if a stock becomes delisted in the holding period the missing monthly returns are assigned to zero. The holding period begins one month after the ranking period in order to mitigate any market microstructure effects. The "winner minus loser" portfolio is the zero-cost investment strategy of selling the loser portfolio to buy the winner portfolio and consistent with Jegadeesh and Titman (1993), the portfolio returns were calculated on an overlapping holding period basis.[6]

---

[5] In the analysis of the sub-sample of large stocks, stocks were assigned to one of five quintile portfolios.

[6] We use overlapping portfolio returns in order to increase the power of the statistical tests. Although, we do not analyse non-overlapping returns Hon and Tonks (2003) obtain similar conclusions using non-overlapping and overlapping returns.

Previous momentum studies have shown that the various winner and loser portfolios generate significantly non-zero returns. In this paper we focus on testing whether the average returns from the individual momentum portfolios are significantly different from the average return of a randomly selected portfolio of similar size using bootstrapping techniques. This approach enables us to access the information content of past returns by assessing whether the returns generated by the portfolios conditioned on past returns can be obtained by chance. First, a pseudo-portfolio consisting of N_t stocks randomly drawn from the total sample of all available stocks is constructed, where N_t is the number of stocks in the portfolio of interest, *P*, at time t. The average return of the pseudo-portfolio over the relevant holding period is then calculated. This procedure is repeated 2000 times to generate an empirical distribution of 2000 pseudo-portfolio returns.[7] We then estimate the probability that the average return of a randomly selected portfolio is less than the average return of portfolio P. If the probability is less (greater) than 0.025 (0.975), we conclude that the average return of portfolio *P* is significantly less (greater) than the return generated by a randomly selected portfolio of similar size at the 5% level or lower. Otherwise, the return of portfolio *P* is not significantly different from the return generated by a randomly selected portfolio of similar size. However, when evaluating the significance of the winner minus loser portfolio we use the traditional t-test.

2.3 Stock Concentration of the Winner and Loser Portfolios

A number of studies on momentum have documented that, sorting within size groups, momentum profits is larger among the smallest stocks (see for example Jegadeesh and Titman (1993,2001) and Liu et al (1999)). While these findings suggest a positive relationship between momentum returns and firm size, they provide little information on the cross-

[7] Note that on average there are 1550 stocks available each month t. A decile portfolio will consist of 155 stocks. Hence, there are ${}^{1550}C_{155} = 2.2913 \times 10^{217}$ possible portfolios of 155 stocks that can be formed. Consequently, the empirical distribution from the 2,000 cases may not reflect the exact distribution

sectional distribution of stocks in the winner and loser portfolios. In this paper, we are particularly interested in identifying the type of stocks that fall into the winner and loser portfolios. Identifying the type of stocks in these portfolios, for all stocks taken together, would highlight the possible factors and costs that may impede the implementation of the momentum strategy. For example, if most of the stocks in the momentum portfolio were small-cap stocks we would expect the implementation cost to be higher than average. The inverse relationship between transaction costs and firm size is well documented in the literature.

Towards this end, we use a methodology that examines whether the momentum portfolios are disproportionately weighted towards certain type of stocks compared to the weight of those stocks in the total sample of all the stocks taken together. First, stocks in the total sample are categorised into groups based on the variable of interest (industry, size, share price and liquidity). On industry classification, stocks are assigned to one of eleven industry groups on the basis of their FTA Level 3 industrial classification. We then calculate the weight of each group *i* in the total sample, denoted as m_i and the proportion of stocks in the portfolio of interest that belong to group *i*, denoted as p_i. The m_is for the industry classification vary from group to group, depending on the number of stocks in each industry group. On size, share price and percentage bid-ask spread, the stocks are grouped on the basis of quintiles with m_i = 0.2, for all *i* = 1, 2, 3…5.[8]

As an illustration, consider how we measure the extent of size concentration. First, we divide the total sample of stocks available at month *t* into quintiles based on market capitalisation. Hence, the proportion of each size quintile in the total sample is 0.2 (i.e. $m_i = 0.2$ for all i = 1,

[8] Although the chi-square test might be dependent on how the stocks are grouped, this does not appear critical to our analysis since a decile instead of a quintile grouping yielded similar conclusions.

2 … 5). We then calculate the proportion of stocks in the portfolio of interest, say *P*, which come from each of the size quintiles above. Suppose there are 150 stocks in portfolio *P* at time t and suppose that 70 out of the 150 stocks in the portfolio come from the first size quintile, then p_i for portfolio *P* is 0.467 (i.e. 70/150). In this case the weight of stocks from Size Quintile 1 in portfolio *P* is 46.7% compared to 20% in the total sample.

The chi-squared statistic, χ^2, is then calculated as:

$$\chi^2 = \sum_{i=1}^{I} \frac{(\mathrm{Np_i} - \mathrm{Nm_i})^2}{\mathrm{Nm_i}} \tag{1}$$

where *N* is the portfolio size and *I* is the number of groups. The number of degrees of freedom associated with the chi-square test is *I-1*. In the special case where the distribution of stocks in the portfolio is identical to the distribution of stocks in the total sample, χ^2 equals zero. Otherwise, the higher χ^2 is the higher the concentration of stocks in the portfolio. The χ^2 is calculated each month and averaged over the sample period.

2.4 Portfolio Turnover and Transaction Costs Estimation

Notice that, the composition of the momentum portfolios would change from time to time as the relative performance of the stocks changes. To maintain the strategy, investors will have to rebalance the portfolios at the end of the holding period, selling stocks that no longer meet the eligibility criteria (dropouts) and buying in newly eligible ones. Frequent trading activity will lead to higher trading costs, thus reducing portfolio returns (see for example Barber and Odean, 2000). Hence, the cost of implementing the momentum strategy can be considered as a function of portfolio turnover and cost per trade. In this paper, portfolio turnover is estimated as %Turnover = ½(%Dropouts + %New), where %Dropout is proportion of stocks in the portfolio at month *t-K* that did not meet the eligibility criteria at month *t* and %New is the proportion of stocks in the portfolio at month *t* that were not in the portfolio at month *t-K* (newly eligible stocks). The %Turnover is calculated each month and averaged over the sample period.

Generally, trading costs include explicit costs such as commissions, taxes and bid-ask spreads as well as implicit costs such as the market impact of trades. Whilst commissions and taxes can be easily quantified, the effects of bid-ask spread and the market impact of trades cannot be known with certainty but can only be estimated. There are also models that extract implied trading costs indirectly from stock returns data. For example, Roll (1984) argue that the effective spread can be extracted from the first order serial correlation of firm returns, provided markets are informationally efficient. Lesmond et al (1999) also extract roundtrip costs from daily returns using their LDV model.[9] In this paper, we estimate trading cost using the spread (quoted or effective) plus commissions and taxes as well as the LDV model following Lesmond et al (1999) as another alternative.[10]

When using the spread plus commissions approach, estimates of commission charges are taken from the Survey of London Stock Exchange Transactions 2000. It shows that, for trades where commissions were paid, average commission rates for private clients, institutions and intermediaries are 0.67%, 0.15% and 0.13% respectively but these rates could change depending on order size. For example, average commission rate for order sizes under £600 is 4.28% whilst that for larger trades of £1million and over is 0.15%. For simplicity, we apply

[9] The Roll measure is not used in this study because studies such as Lesmond et al (1999), Lesmond et al (2004) and Lesmond (2005) show that the Roll estimates of transaction cost tend to be lower than the quoted spread and the LDV estimates. For our purposes, a lower cost estimate would only make our findings stronger.

[10] When calculating the effective spread we have used the closing price as the execution price.

the commission rates for private clients. We also take account of the 0.5% stamp duty on UK stock purchases. Thus, the roundtrip cost based on this approach is given by:

Roundtrip cost = spread + (2 x commissions) + stamp duty.

The LDV model is given as:

$$R_{i,t} = \begin{cases} R^{*}_{i,t} - \alpha_{1,i} & \text{if} \quad R^{*}_{i,t} < \alpha_{1,i} \\ 0 & \text{if} \quad \alpha_{1,i} \le R^{*}_{i,t} \le \alpha_{2,i} \\ R^{*}_{i,t} - \alpha_{2,i} & \text{if} \quad R^{*}_{i,t} > \alpha_{2,i} \end{cases} \tag{2}$$

where $R_{i,t}$ is the observed return of firm *i*, $R^{*}_{i,t} = \beta R_{i,t} + \varepsilon_{i,t}$ is the expected return of firm *i* based on the market model, $\alpha_{1,i} <0$ is the trading cost on selling the stock, $\alpha_{2,i} >0$ is the trading cost on buying the stock. The intuition behind this model is that, transaction costs discourage arbitrageurs from trading on any new information unless the expected returns are sufficient to cover the trading cost. As a result, daily returns of 0% occur if the expected return is not large enough to induce a sale or buy transaction. Thus, non-zero returns are observed only if they exceed the required trading cost. It is assumed that the required trading cost contains both implicit and explicit costs of trading. With the estimates of $\alpha_{1,i}$ and $\alpha_{2,i}$, the all-in (explicit and implicit) roundtrip cost for firm *i* is given by $\alpha_{2,i} - \alpha_{1,i}$.[11] This is estimated each month using daily returns of the past 12 months.

The trading costs are estimated for different firm-size quintiles based on the fact that transaction cost is a function of firm size, among others. We then calculate the cost associated with each portfolio as a weighted average of the costs for the 5 size quintiles, where the relevant weights are the proportion of stocks in the portfolio from each size quintile as explained in section 2.3. Given the weighted average roundtrip cost for the portfolio, we

[11] We are grateful to David A. Lesmond for advice on estimating the LDV model and for providing us with his computer codes.

calculate its annualised trading cost for the month as the % Turnover multiplied by the Roundtrip cost.

3 Empirical Results

3.1 Unrestricted Sample

Our first study is to analyse the full (unrestricted) sample of all available stocks as described in section 2.1. The results of this analysis are discussed below, whilst section 3.2 present the results of the analysis on a restricted sample of large stocks. This sample therefore excludes most of the stocks with very high trading costs. We also examine risk-adjusted portfolio returns in section 3.3.

3.1.1 Momentum returns

Table 1 presents the average annualised returns to the momentum strategy for the total sample. As indicated earlier, the portfolios are formed based on the returns of the previous J-months (J = 3, 6, 9 and 12) and held for a period of K-months (K = 1, 2, 3, 6 and 12). For each of these J x K strategies, we report the average monthly returns to Portfolio P1 (losers), Portfolio P10 (winners), an intermediate portfolio P5 and the winner minus loser portfolio. In all cases, holding the loser portfolio for periods up to twelve-months generates returns that are significantly lower than the returns generated by a randomly selected portfolio of similar size. Given that small-cap stocks generally have larger trading costs, the findings above have serious implications for trading strategies on the UK market. On the other hand, holding the winner portfolio generates returns that are significantly greater than those generated by the randomly selected portfolio. This is indicative of the predictive ability of historical price information and therefore inconsistent with weak form market efficiency. These results complement those reported by Griffin, Ji and Martin (2003). They find that the loser portfolio underperforms the market as a whole in many European markets.

For the case of J=6 and K=6, the returns from holding the winner portfolio averaged 8.76% per annum whereas the loser portfolio earned returns averaging –24.96%, a difference of 33.72% per annum. Returns from the entire winner minus loser portfolios, and across the various holding periods in the short term, are statistically significant. However, the return on the winner minus loser portfolio is largely driven by the negative returns on the loser portfolio. This finding supports similar findings by Hong, Lim and Stein (2000), Grinblatt and Moskowitz (2003) and Doukas and McKnight (2005). Consequently, any restrictions on short selling would affect the viability of the strategy.

Table 1 also reports the average stock price, average market value and the average percentage bid-ask spread at the portfolio formation date. Compared to the market average, stocks in the extreme portfolios are generally smaller in size but the average size of the winner portfolio is larger than that of the corresponding loser portfolio. The average values for the total sample in terms of price, size and liquidity are 314.8p, £759.5m and 5.9%, respectively. The average percentage bid-ask spread of the loser (winner) portfolio ranges between 11.7% (5.6%) and 13.0% (4.1%) indicating that stocks in the loser portfolio might be less liquid than stocks in the winner portfolio. The differences between the winner and loser portfolios in terms of price, size and the liquidity measures are highly significant for all ranking periods.

3.1.2 Stock Concentration of the Winner and Loser Portfolios

In Table 1 we find that on average the loser portfolio is smaller and less liquid than the winner portfolio. Table 2 (see also Figure 1) presents the extent of stock concentration within the winner and loser portfolios in respect of size, liquidity, share price and industry group. If momentum returns are driven by small firms, stocks with lower prices, stocks with larger percentage bid-ask spread (lower liquidity) or industry momentum, then we would expect either or both the winner and loser portfolios to be disproportionately weighted towards these stocks, relative to the weight of such stocks in the total sample. Results are reported for all the four formation periods in Table 2, whilst Figure 1 illustrates the results for the 6-month formation period. In Figure 1, the 45 degree line shows what we would expect if the diversity of stocks in the portfolio is the same as the diversity of stocks in the total sample (or the market) from which the portfolio is drawn. Where the two distributions differ, a curved line results and the greater the curvature the greater the concentration of stocks in the portfolio.

Panel A of Table 2 shows the concentration of stocks based on size (market capitalisation). We observe that the proportion of stocks with lower market capitalisation is much greater in the loser portfolio than in the winner portfolio, for all formation periods (see also Panel A of Figure 1). The proportion of stocks in the loser portfolio that come from the lowest size quintile ranges between 38%, for the 3-month formation period, and 46% for the 12-month formation period. At the same time, the proportion of stocks in the loser portfolio from the largest size quintile ranges between 8%, for the 3-month formation period, and 4% for the 12-month formation period. Thus only a small number of stocks in the top size quintile are in the loser portfolio. This is an interesting observation as stocks in the largest-size quintile of the sample contribute over 90% of the total market capitalisation of the sample. The concentration of small-cap stocks in the loser portfolio is also supported by the large average chi-squared (CHI) values. In addition, the proportion of significant cases for the chi-square test is 100% indicating that significant deviations from the sample distribution were observed each month. In comparison, the proportion of stocks in the winner portfolio that come from the lowest (largest) size quintile ranges between 20% (16%) and 12% (20%). These results show that the distribution of stocks in the winner portfolio is no significantly different from that of the market. Notice that as the chi-squared test is non-directional, a large chi-square value is not necessarily undesirable. Although the winner portfolio also showed some deviations from the sample distribution in some periods, the deviation was a migration from small stocks towards larger stocks. These findings have implications for the cost of trading associated with the strategy. As trading cost is inversely related to firm size, applying an average market cost to the loser portfolio would grossly understate the effective trading cost for that portfolio.

Panel B and Panel C describe the results for the concentration of stocks based on liquidity, as measured by percentage bid-ask spread, and share price respectively. Once again, the results show that the loser portfolio is disproportionately weighted towards illiquid stocks with even greater average chi-square values than the size concentration. Less than 3% of stocks in this portfolio are in the high liquidity quintile. This result is not surprising as small firms generally tend to have small share prices and larger bid-ask spreads. On the whole, the results suggest that if momentum premium is a small firm, low share-price and illiquid stocks effect, then it is driven by the loser portfolio. Nevertheless, as majority of stocks in the loser portfolio have very high bid-ask spreads the profitability of the momentum strategy net of transaction costs can be critically affected.

Panel D describes the results for the industrial concentration of the portfolios. We observe that the industrial diversity of the stocks in both the winner and loser portfolios is, on average, not significantly different from that of the total sample. We do not find any significant evidence that the winners and losers are consistently weighted towards particular industry groups, although instances of significant industrial concentration occur from time to time and the frequency of such occurrence is higher for the loser portfolio than that of the winner portfolio. Looking at the 6-month formation period, the loser (winner) portfolio shows significant industrial concentration 89.9% (45%) of the time. Thus, whilst industry effects may drive momentum returns at certain points in time, it does not totally drive the momentum returns. Our findings therefore partially support the results of Moskowitz and Grinblatt (1999) as well as providing direct evidence in support of the view that industry momentum does not totally explain returns of price momentum strategies (see for example Grundy and Martin, 2001; Nijman, Swinkels and Verbeek, 2004).

3.1.3 Portfolio Turnover and Implementation Cost

The returns reported in section 3.1.1 ignore transaction costs but the costs associated with implementing these strategies, can significantly reduce the portfolio returns. First, we estimate the turnover of stocks required to maintain the strategy. Figure 2 shows the turnover of stocks associated with the 6 x 6 strategy for each month within the sample period. The percentage turnover of the winner portfolio ranges between 75% and 87% every six months, whilst that of the loser portfolio ranges between 55% and 87%.[12] Average portfolio turnover for the various strategies are presented in Table 3. For each cell the top number is the percentage turnover per holding period, whilst the number in squared brackets [ ] represent the corresponding annualised percentage turnover. For the 6 x 6 strategy the average turnover

[12] We can expect that a value weighted % turnover will be lower than the equally weighted % turnover but since the portfolio returns are equally weighted we believe that the equally weighted % turnover is an appropriate measure of the turnover associated with the strategy. For consistency, a value weighted % turnover would be unsuitable in this case. See also Lesmond et al (2004).

rates are 76.3% and 84.3% for the loser and winner portfolios, respectively. Interestingly, these rates are very close to the findings of Lesmond et al (2004) which suggests turnover rates of 77.3% and 85%, respectively in their US study.

The results show that implementation of the momentum strategy would involve a substantial amount of trading as the portfolio is rebalanced. They also reveal substantial differences in portfolio turnover for the various strategies. The turnover rate of the winner portfolio is marginally higher than that of the loser portfolio, over all ranking periods. For the 3 x 1 strategy, the average turnover rate for the loser portfolio is 44.8% per month (annualised 537.6% = 44.8% x 12). The corresponding turnover rate for the winner portfolio is 51.2% per month (614.4% annualised). This implies that, assuming monthly rebalancing, the entire loser (winner) portfolio would be changed five (six) times in one year. The comparable turnover rates for the 3 x 6 and 3 x 12 holding periods are 157.2% (172.6%) and 81% (86.8%) respectively for the loser (winner) portfolio. Although the average turnover rates for the two portfolios are close to each other for all ranking periods, the average turnover of the winner portfolio tends to be slightly higher than that of the corresponding loser portfolio. As expected, holding the ranking period constant the turnover rates is lower for longer holding periods. Similarly, for a given holding period the turnover rate is inversely related to the ranking period. Given that the cost of trade is a function of trading frequency, we would expect trading cost for the longer ranking and/or holding periods to be lower than that for the shorter periods.

Figure 3 illustrates the behaviour of the various transaction cost measures for different firm-size quintiles over the sample period. Panels A, B and C describe the quoted spread, the effective spread and the LDV cost estimates, respectively. On average, the quoted (effective) spread for firms in the smallest size quintile (SQ1) is 14.5% (4.5%) whilst that for firms in the largest size quintile (SQ5) is 1.2% (0.3%). The corresponding LDV estimates are 16.9% for SQ1 firms, and 2.1%. As expected, all the trading cost measures are inversely related to firm size and for all size quintiles the LDV estimates exceed the quoted spread (see also Lesmond et al (1999) and Lesmond et al (2004)).

The annualised transaction costs and the net returns associated with the various strategies are presented in Tables 4 and 5. Table 4 Panel A reports the average trading cost for the various portfolios based on the quoted spread plus commissions and taxes. The W-L row describes the total cost of the momentum strategy of buying the winners and selling the losers. In Panel B we report the post-cost returns of the winner minus loser portfolios for the various strategies. The corresponding values based on the LDV estimates are presented in Table 5.

We find that the implementation cost associated with the momentum strategy is quite substantial which reduces and in some cases outweighs the return generated. In all cases, the cost associated with trading the loser portfolio exceeds that associated with the winner portfolio, largely as a result of the high concentration of small cap stocks in the loser portfolio. The potential trading cost for the momentum strategy also varies considerably depending on the ranking and holding periods, ranging between 14.2% (10.4%) for the 12x12 strategy and 106.6% (97.5%) for the 3x1 strategy based on the quoted spread (LDV) estimates. The corresponding cost associated with the 6x6 strategy is 29.1% (23.8%).

Consistent with the findings of Lesmond *et al* (2004), the costs associated with some of the strategies dominate the average returns presented in Table 1. For example, for the three month ranking period, only the returns for the nine- and twelve-month holding periods remain profitable after accounting for trading cost using the quoted spread estimates. Even so, the profitability reduces from 24.7% (23.4%) to about 4.5% (8.3%) per annum for the nine-month (twelve-month) holding periods, and the corresponding t-statistics fall to 1.391 (3.111). However, for the twelve-month ranking period we find statistically significant net returns for all the holding periods except for the one-month holding period.

With the LDV estimates 11 out of the 20 strategies reported remain profitable and significant. Apart from the 12 x 3 strategy, none of the strategies with a holding period less than or equal to 3-months is profitable after accounting for the trading costs but all the strategies involving a 12-month holding period are profitable except the 12 x 12 strategy which is positive but insignificant at the 5% level. Indeed, this shows that the economic significance of very short-term momentum strategies is questionable. More interesting however, is what happens as the holding and/or ranking period increases.[13] For example, the most profitable strategy before transaction cost is the 12 x 1 strategy yielding a gross annualised return of 44.64% (see Table1). However, the 12 x 1 strategy is no longer profitable net of transaction cost with the 9 x 9 strategy becoming the most profitable strategy (see Tables 4 and 5).

Our results suggest that in some cases the momentum strategy is profitable net of transaction costs, consistent with the findings of Korajczyk and Sadka (2004). They concluded that the momentum anomaly remains a puzzle as transaction costs do not fully explain the persistence of momentum returns. Nevertheless, if there are additional costs associated with short selling the loser portfolio, then these profits would even reduce further. Our results also reflect the conclusions of Barber and Odean (2000) on trading activity and investment performance. The absence of post-cost profitability associated with some of the strategies follows directly from

[13] Although not reported, the average momentum returns net of trading cost based on the effective spread is significantly positive for all the various strategies except for the 3 x1 and 6 x 1 strategies.

the frequency of trading. Indeed, given the portfolio turnover of the 3 x 1 strategy, the average roundtrip cost necessary to completely eliminate the momentum profit is only 4.2% on the loser portfolio and 1% on the winner portfolio. On the other hand, the corresponding breakeven roundtrip costs for the 12 x 12 strategy are 22% and 26%, respectively.

As indicated earlier, a large proportion of the stocks in this sample are small and illiquid. Trading in such stocks is more difficult and costly, particularly when short selling, which might limit investor's ability to take arbitrage positions. Incidentally, large-cap stocks are easier to trade and have lower trading costs hence we would expect momentum returns to disappear much quicker. In the next section, we examine the investment performance of the momentum strategy among a sub-sample of relatively large and liquid stocks.

3.2 Restricted Sample Analysis

In this section we replicate the analysis above for a sub-sample of large and liquid stocks. Stocks enter the sample at the point where their market capitalisation exceeds the top 30th percentile mark. Once in the sample, stocks are not removed during the holding period if their market capitalisation falls below the cut off mark as a result of poor performance. This sub-sample consists of 978 stocks in total over the entire period. The number of stocks available each month however varies, ranging between 496 and 608 with an average of 541 but accounts for over 95% of the market capitalisation of the unrestricted sample. First, we examine whether the momentum returns observed among the unrestricted sample also occurs among the large stocks. We then examine whether the returns can be realised after taking account of transaction costs. The results are discussed below.

3.2.1 Momentum returns – Large Stocks

Each month, five quintile portfolios are formed based on the returns of the previous J-months (J = 3, 6, 9 and 12) and held for a period of K-months (K = 1, 3, 6, 9 and 12).[14] The average returns to portfolio P1 (losers), portfolio P5 (winners) and portfolio P3, an intermediate portfolio, are presented in Table 6 for each of the J x K strategies. The table also shows the return of the winner minus loser portfolio. We find significant winner minus loser portfolios returns for holding periods up to 12 months, although their magnitudes are lower than those reported for the unrestricted sample. However, in contrast to the earlier results, the contribution of the winner portfolio to the momentum profits is much greater as the negative returns on the loser portfolio are much lower. Once again, the most profitable strategy before costs is the 12 x 12 strategy.

As expected, the average market value and bid-ask spread for both the winner and loser portfolios are far more favourable compared to those reported for the unrestricted sample. For example, the average market value of the loser (winner) portfolio for the six-month formation period is £990.6 million (£1,314.0 million) with an average bid-ask spread of 4.0% (2.0%) compared to the £121.2 million (£440.2 million) and 12.6% (4.8) reported in Table 1. Thus the average size of the loser (winner) portfolio for the sub-sample is about 8 times (3 times) the respective portfolios in the unrestricted sample. The results thus suggest that UK momentum profits are not confined to smaller and illiquid stocks, consistent with earlier findings by Liu et al (1999).

[14] In the analysis of this sub-sample, we form quintile instead of decile portfolios.

3.2.2 Portfolio turnover and transaction costs

Table 6 suggests that there are significant positive momentum returns among the largest stocks with lower bid-ask spread. We now consider whether the returns are enough to cover the trading costs. Table 7 illustrates the portfolio turnover for the sub-sample of large stocks. Potential trading cost associated with the various strategies and the net returns of the winner minus loser portfolio after accounting for transaction costs are presented in Tables 8 and 9. In Tables 8 and 9, Panel A describes the trading cost whilst Panel B describes the net returns.

Similar to the evidence for the unrestricted sample, average portfolio turnover and trading cost is negatively related to the investment horizon. However, the potential trading costs are much lower in magnitude than those reported earlier. This is expected as trading cost is inversely related to firm size. The total trading cost ranges between 37.8% (35.5%) for the 3x1 strategy and 5.4% (4.4%) for the 12x12 strategy using the quoted spread (LDV) estimates. Table 8 shows that using the quoted spread estimates, most of the strategies (17 out of 20) generate enough returns to cover trading costs with 11 of them showing significantly positive returns net of transaction costs. Similarly, Table 9 shows that based on the LDV estimates, the returns from 18 out of the 20 strategies generate positive post cost returns with 12 of these showing significant positive post-cost returns. Once more, for ranking and/or holding periods up to 6 months evidence of significant positive momentum returns weakens if we factor out transactions costs. Overall, our results suggest that some momentum strategies appear profitable net of transaction costs but the profitability depends on the ranking and investment horizons. In addition, although the exclusion of the small stocks reduces the returns before transaction costs, the reduction in potential trading costs far exceeds the return forgone. If after factoring out trading costs, one still finds some momentum strategies profitable then transaction costs alone do not fully explain the momentum anomaly.

3.3 Momentum Returns after Controlling for Risk

One explanation for the significant momentum returns reported earlier is that the momentum portfolios may be riskier. It is generally argued that differences in portfolio returns that are not adjusted for risk could reflect the differential expected returns between high-risk versus low-risk portfolios. In this section, we use the intercept test to examine whether the portfolio returns can be explained by the market risk and the size and book-to-market characteristics of the stocks in the sample. In the first instance, we estimate the risk-adjusted abnormal return as the intercept from the CAPM regression model:

$$R_{Pt} - R_{Ft} = \alpha_P + \beta_P \left(R_{Mt} - R_{Ft}\right) + \varepsilon_{Pt}\,.$$

where R_{Pt} is the portfolio return, R_{Ft} is the one-month Treasury Bill rate and R_{Mt} is the return on the FTSE All Share Index. For the unrestricted sample portfolios reported in Section 3.1, we also consider risk-adjusted abnormal returns based on the Fama and French (1996) three-factor model:[15]

$$R_{Pt} - R_{Ft} = \alpha_P + \beta_{1P} \left(R_{Mt} - R_{Ft}\right) + \beta_{2P} SMB + \beta_{3P} HML + \varepsilon_{Pt}$$

SMB and HML are the Fama and French factors for size and book-to-market respectively. If the return of the portfolio is a compensation for higher risk we would expect the abnormal returns to disappear when adjusted for the common risk factors. The gross abnormal returns are reported in Table 10.

Panel A and Panel B report annualised abnormal returns for the unrestricted sample portfolios based on the CAPM and the Fama and French model respectively. Panel C shows abnormal

[15] For the subsample of large stocks, we report risk-adjusted returns based on the CAPM only. As do Fama and French (1998), we consider adjustment for size effect for a group of large stocks unsuitable.

returns for the large stocks portfolios based on the CAPM. For all ranking and holding periods, we find significant abnormal returns for the winner minus loser portfolio. We observe that based on the CAPM, none of the winner portfolios in Panels A and C generate significant abnormal returns, but the corresponding loser portfolios generate significant negative abnormal returns. Yet again, the significant abnormal returns from the momentum (winner minus loser) portfolios are driven by the short position in the loser portfolio. However, based on the Fama and French three-factor model, we find significant negative abnormal returns for the loser portfolios but significant positive abnormal returns for the winner portfolios. The combined effect is a more pronounced abnormal return. Even in this case, the magnitude of the abnormal returns of the loser portfolio exceeds that of the winner portfolio. Lesmond, Schill and Zhou (2004) report similar findings for the US market.

Comparing the abnormal returns to the potential cost of trading reported earlier (see Tables 4, 5, 8 and 9), we notice that similar to the raw returns, the abnormal returns generated by the momentum strategies exceed the potential cost associated with the strategy for longer ranking and/or holding periods. For example, the 6 x 12 strategy yields an annualised abnormal return of 27.3% (23.3%) but the cost associated with the strategy is 14.9% (5.4%) for the unrestricted (restricted) sample using the quoted spread estimates. Using the LDV estimates the corresponding trading costs are10.9% and 5.0% for the unrestricted and the restricted samples, respectively.

4. Conclusion

This paper examines the post-cost profitability of momentum returns in the UK market over the period 1988 and 2003. We document that momentum returns continue to persist, and explore issues relating to the concentration of stocks in the momentum portfolios, the turnover of stocks in the portfolios and trading costs associated with the implementation of the strategy. Examining the composition of stocks in the various portfolios, we document that the loser portfolio in particular is disproportionately weighted towards small-cap stocks but the distribution of stocks in the winner portfolio is not significantly different from that of the market. Evidence on industrial concentration suggests that industry momentum does not fully explain price momentum profits. On average, the industrial compositions of stocks in the winner and loser portfolios are not significantly different from that of the market as a whole.

Further, we show that the momentum strategy entails significant portfolio turnover which, given the type of stocks that enter the portfolios, leads to substantial trading costs than have been previously assumed for the UK market. For ranking and holding periods up to six-months, the costs are large enough to prevent investors from profitably trading on these strategies. However, for ranking and holding periods beyond six-months the turnover and associated costs reduces and momentum profits net of transaction costs could be achieved. We find similar results for a sub-sample of relatively large and liquid stocks. The loss of potential higher return on the small stocks excluded from this sample is far less than the potential costs that could be saved. The reduction in trading cost can be at least 9% and as much as 70% per annum.

In conclusion, our results suggest that accounting for transaction costs momentum profits are substantially reduced but some cases of post-cost profitability may exist. We find significant momentum returns (both raw returns and risk-adjusted) net of transaction costs for longer ranking and /or holding periods. It appears that if momentum returns are illusory, then it cannot be attributed to transaction costs alone.

It thus remains a puzzle why investors have not arbitraged away the momentum anomaly, if momentum returns are profitable net of transaction costs even among larger stocks. It appears the answer lies in short selling constraints. Since a greater proportion of the momentum profits comes from short selling the loser portfolio, short selling constraints could prevent the exploitation of this anomaly. Apart from the financial cost of short selling, there might be difficulties maintaining long-term short positions in the majority of stocks in the loser portfolios. In all cases, a long-only strategy of buying the winners is not profitable net of transaction costs. The net return on this is either negative or insignificantly positive.

References

Barber, B. M. and Odean, T., 'Trading is hazardous to your wealth: the common stock investment performance of individual investors', *Journal of Finance*, Vol. 55, 2000, pp. 773-805.

Barberis, N. and Shleifer, A., 'Style investing', *Journal of Financial Economics*, Vol. 68, 2003, pp. 161-99.

Black, F., 'Beta and return' *Journal of Portfolio Management*, Vol. 20, 1993, pp. 8-18.

Chan, L., Jegadeesh, N. and Lakonishok, J., 'Momentum strategies', *Journal of Finance*, 1996, Vol. 51, pp. 1681-1713.

Chan, L., Jegadeesh, N. and Lakonishok, J., 'The profitability of momentum strategies', *Financial Analysts Journal*, Vol. 55, 1999, pp. 80-90.

Chui, A., Titman, S. and Wei, J., 'Momentum, ownership structure and financial crises: an analysis of Asian stock markets' (Working Paper, University of Texas at Austin 2000).

Conrad, J. and Kaul, G., 'An anatomy of trading strategies', *Review of Financial Studies*, Vol. 11, 1998, pp. 489-519.

Cooper, M. J., Guthierrez Jr., R. C. and Hameed, A., 'Market states and momentum', *Journal of Finance*, 2004, Vol. 59, pp. 1345-65.

Daniel, K., Hirshleifer, D. and Subrahmanyam, A., 'Investor psychology and security market under - and overreactions', *Journal of Finance*, Vol. 53, 1998, pp. 1839-85.

Dijk, R. van and Huibers, F., 'European price momentum and analyst behaviour', *Financial Analyst Journal*, Vol. 58, 2002, pp. 96-105.

Dimson, E., Nagel, S. and Quigley, G., 'Capturing the value premium in the United Kingdom', *Financial Analysts Journal*, Vol. 59, 2003, pp. 35-45.

Doukas, J. and McKnight, P. J., 'European momentum strategies, information diffusion, and investor conservatism', *European Financial Management,* Vol. 11, 2005, pp. 313-38

Fama, E. and French, K., ‘Common risk factors in the returns on stocks and bonds’, *Journal of Financial Economics*, Vol. 33, 1993, pp. 3-56.

Forner, C. and Marhuenda, J., ‘Contrarian and momentum strategies in the Spanish stock market’, *European Financial Management,* Vol. 9, 2003, pp. 67-88

Griffin, J. M., Ji, X. and Spencer, M. J., ‘Momentum investing and business cycle risk: evidence from pole to pole’ *Journal of Finance*, Vol. 58, 2003, pp. 2513-48.

Grinblatt, M. and Moskowitz, T. J., ‘Predicting stock price movements from past returns: The role of consistency and tax-loss selling’, *Journal of Financial Economics,* Vol. 71, 2004, pp. 541-79.

Grinblatt, M. and Titman, S., ‘Momentum investment strategies, portfolio performance, and herding: a study of mutual fund behaviour’, *American Economic Review*, Vol. 85, 1995, pp. 1088-1105.

Grundy, B. D. and Martin, S. J., ‘Understanding the nature and risks and the sources of rewards to momentum investing’ *Review of Financial Studies*, Vol. 14, 2001, pp. 29-78.

Hanna, J. D. and Ready, M., ‘Profitable predictability in the cross-section of stock returns’, Unpublished working paper, 2003. Available at http://ssrn.com/abstract=193228.

Hogan, S., Jarrow, R., Teo, M. and Warachka, M., ‘Testing market efficiency using statistical arbitrage with applications to momentum and value strategies’, *Journal of Financial Economics*, Vol. 73, 2004, pp. 525–65.

Hon, M. T. and Tonks, I., ‘Momentum in the UK stock market’, *Journal of Multinational Financial Management*, Vol. 13, 2003, pp. 43-70.

Hong, H., Lim, T. and Stein, J. C., ‘Bad news travel slowly: size, analyst coverage, and the profitability of momentum strategies’, *Journal of Finance*, Vol. 55, 2000, pp. 265-96.

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

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

Jensen, M. C., 'Some anomalous evidence regarding market efficiency', *Journal of Financial Economics*, Vol. 6, 1978, pp. 95-101.

Keim, D. B. and Madhavan, A., 'Transaction costs and investment style: an inter-exchange analysis of institutional equity trades', *Journal of Financial Economics*, Vol. 46, 1997, pp. 265-92.

Keim, D. B. and Madhavan, A., 'The costs of institutional equity trades', *Financial Analysts Journal*, Vol. 54, 1998, pp. 50-69.

Keim, D. B., 'The cost of trend chasing and the illusion of momentum profits', Working paper 11-03, 2003, The Wharton School, University of Pennsylvania.

Korajczyk, R. A. and Sadka, V. 'Are momentum profits robust to trading costs?', *Journal of Finance*, Vol. 59, 2004, pp. 1039-82.

Lesmond, D. A., Ogden, J. P. and Trzcinka, C. A., 'A new estimate of transaction cost', *The Review of Financial Studies*, Vol. 12, 1999, pp. 1113-1141.

Lesmond, D. A., Schill, M. J. and Zhou, C., 'The illusory nature of momentum profits', *Journal of Financial Economics*, Vol. 71, 2004, pp. 349-80.

Lesmond, D. A. 'Liquidity of emerging markets', *Journal of Financial Economics*, Vol. 77, 2005, pp. 411-52.

Liu, W., Strong, N. and Xu, X., 'The profitability of momentum investing', *Journal of Business Finance & Accounting*, Vol. 26, 1999, pp. 1043-91.

MacKinlay, A. C., 1995. Multifactor models do not explain deviations from the CAPM. Journal of Financial Economics 38, 3-28.

Moskowitz, T. J. and Grinblatt, M., 'Do industries explain momentum?', *Journal of Finance*, Vol. 54, 1999, pp. 1249-90.

Nijman, T., Swinkels, L. and Verbeek, M., 'Do countries or industries explain momentum in Europe?', *Journal of Empirical Finance*, Vol. 11, 2004, pp. 461-81.

Roll, R., 'A simple implicit measure of the effective bid–ask spread in an efficient market', *Journal of Finance*, Vol. 39, 1984, 1127–39.

Rouwenhorst, K., 'International momentum strategies', *Journal of Finance*, Vol. 53, 1998, pp. 267-84.

Rouwenhorst, K., 'Local return factors and turnover in emerging markets', *Journal of Finance*, Vol. 54, 1999, pp. 1439-64.

Schiereck, D., DeBondt, W., Weber, M., 1999. Contrarian and momentum strategies in Germany. Financial Analysts Journal 55, 104-116.

Table 1
Average Annualised Portfolio Returns for Various Holding Periods
Unrestricted Sample, 1988 - 2003

Each month stocks are classified into one of ten portfolios based on their past performance in the ranking period. P1 is the loser portfolio (worst performing decile) and P10 is the winner portfolio. Equally weighted overlapping portfolio returns are calculated for various holding periods. The [p-values] are the bootstrapping probabilities for testing whether the portfolio return is significantly different from that of a randomly selected portfolio of similar size. The (t-values) tests whether the winner minus loser portfolio is different from zero. Price describes the average share price (in pence), size describes the average market capitalisation (in £'millions) and liquidity describes the average percentage bid-ask spread of the portfolio. [a] or [b] denotes significant at 1% or 5%, respectively.

Ranking	Portfolio	Holding Period					Price	Size	Liquidity
		1M	3M	6M	9M	12M			
J = 3	P1	-0.2256[a]	-0.2448[a]	-0.2388[a]	-0.2160[a]	-0.2148[a]	211.3	160.1	11.7
	[p-value]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]			
	P5	0.0348	0.0276[a]	0.0240[a]	0.0240[a]	0.0132[a]	278.0	712.0	5.0
	[p-value]	[0.9000]	[0.9995]	[0.9995]	[0.9980]	[0.9985]			
	P10	0.0612[a]	0.0360[b]	0.0360[a]	0.0300[a]	0.0192[a]	294.0	387.8	5.6
	[p-value]	[0.9965]	[0.9875]	[0.9975]	[0.9985]	[0.9990]			
	P10-P1	0.2868[a]	0.2808[a]	0.2748[a]	0.2472[a]	0.2340[a]	82.7[a]	227.7[a]	-6.1[a]
	(t-value)	(6.100)	(6.381)	(7.273)	(8.009)	(8.949)	(4.048)	(7.786)	(-15.601)
J = 6	P1	-0.2700[a]	-0.2748[a]	-0.2496[a]	-0.2448[a]	-0.2184[a]	175.5	121.2	12.6
	[p-value]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]			
	P5	0.0204	0.0228	0.0252	0.0108	0.012[b]	319.7	723.4	4.8
	[p-value]	[0.8555]	[0.9165]	[0.9510]	[0.9700]	[0.9760]			
	P10	0.1068[a]	0.1032[a]	0.0876[a]	0.0696[a]	0.0516[a]	268.2	440.2	4.8
	[p-value]	[1.0000]	[1.0000]	[1.0000]	[1.0000]	[1.0000]			
	P10-P1	0.3768[a]	0.3780[a]	0.3372[a]	0.3132[a]	0.2700[a]	92.7[a]	319.0[a]	-7.8[a]
	(t-value)	(6.863)	(7.495)	(7.892)	(8.717)	(8.524)	(4.124)	(10.276)	(-19.738)
J = 9	P1	-0.2820[a]	-0.2652[a]	-0.2652[a]	-0.2340[a]	-0.2040[a]	150.1	92.2	13.3
	[p-value]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]			
	P5	0.0193	0.0204	0.0096	0.0060	0.0072[b]	256.0	711.7	5.0
	[p-value]	[0.8410]	[0.8580]	[0.9190]	[0.9735]	[0.9845]			
	P10	0.1344[a]	0.1236[a]	0.1008[a]	0.0768[a]	0.0504[a]	274.2	497.5	4.3
	[p-value]	[1.0000]	[1.0000]	[1.0000]	[1.0000]	[1.0000]			
	P10-P1	0.4164[a]	0.3888[a]	0.3660[a]	0.3108[a]	0.2544[a]	124.1[a]	405.3[a]	-9.0[a]
	(t-value)	(7.569)	(7.726)	(8.524)	(8.138)	(7.513)	(6.085)	(13.434)	(-22.290)
J = 12	P1	-0.2916[a]	-0.2784[a]	-0.2436[a]	-0.2136[a]	-0.1716[a]	136.4	83.0	13.0
	[p-value]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]			
	P5	0.0216	0.0121	0.0144	0.0120[a]	0.0216[b]	238.7	705.6	4.7
	[p-value]	[0.7260]	[0.8030]	[0.8655]	[0.9580]	[0.9780]			
	P10	0.1548[a]	0.1368[a]	0.1020[a]	0.0684[a]	0.0468[a]	287.8	554.9	4.1
	[p-value]	[1.0000]	[1.0000]	[1.0000]	[1.0000]	[0.9985]			
	P10-P1	0.4464[a]	0.4152[a]	0.3456[a]	0.2808[a]	0.2184[a]	151.4[a]	471.9[a]	-8.9[a]
	(t-value)	(8.263)	(8.369)	(7.854)	(7.141)	(6.028)	(7.220)	(16.956)	(-21.563)

Table 2
Concentration of Stocks in the Winner and Loser Portfolios

Each month stocks are classified into one of ten portfolios based on their past performance in the ranking period. Stocks in the worst (best) performing decile are assigned to the loser (winner) portfolio. Stocks in the total sample are then categorised into groups based on the variable of interest (industry, size, share price and liquidity). On industry classification, stocks are assigned to one of eleven industry groups based on their FTA Level 3 industrial classification. We then calculate the proportion of stocks in the total sample observed in the i^{th} group, denoted as m_i and the proportion of stocks in the portfolio that come from the i^{th} group of the total sample, denoted as p_i. The chi-squared statistic, χ^2, is then calculated as:

$$\chi^2 = \sum_i \frac{(Np_i - Nm_i)^2}{Nm_i}$$

where N is the portfolio size.

The χ^2 is calculated each month and averaged over the sample period. CHI is the average χ^2 value and % significant is the percentage of times the χ^2 test was rejected. Panels A, B, C and D describes tests based on market capitalisation, bid-ask spread, share price and industry groups respectively.

Panel A: SIZE

	3-Months			6-Months			9-Months			12-Months		
Quintile	**Loser**	**Winner**	**Sample**	**Loser**	**Winner**	**Sample**	**Loser**	**Winner**	**Sample**	**Loser**	**Winner**	**Sample**
Small – 1	0.378	0.198	0.20	0.410	0.162	0.20	0.437	0.135	0.20	0.457	0.116	0.20
2	0.245	0.222	0.20	0.246	0.206	0.20	0.249	0.193	0.20	0.249	0.187	0.20
3	0.178	0.220	0.20	0.175	0.233	0.20	0.168	0.240	0.20	0.162	0.238	0.20
4	0.123	0.199	0.20	0.113	0.221	0.20	0.101	0.239	0.20	0.091	0.254	0.20
Big – 5	0.076	0.162	0.20	0.057	0.179	0.20	0.045	0.193	0.20	0.040	0.204	0.20
CHI	56.07	2.40		81.68	3.82		109.13	8.58		110.87	11.68	
% Significant	100.0	32.5		100.0	55.6		100.0	89.0		100.0	94.6	

Panel B: LIQUIDITY

	3-Months			6-Months			9-Months			12-Months		
Quintile	**Loser**	**Winner**	**Sample**	**Loser**	**Winner**	**Sample**	**Loser**	**Winner**	**Sample**	**Loser**	**Winner**	**Sample**
High – 1	0.052	0.177	0.20	0.039	0.208	0.20	0.030	0.232	0.20	0.026	0.252	0.20
2	0.081	0.205	0.20	0.068	0.235	0.20	0.057	0.255	0.20	0.051	0.268	0.20
3	0.136	0.216	0.20	0.126	0.217	0.20	0.119	0.222	0.20	0.110	0.221	0.20
4	0.244	0.213	0.20	0.236	0.195	0.20	0.230	0.175	0.20	0.225	0.162	0.20
Low – 5	0.487	0.189	0.20	0.531	0.145	0.20	0.565	0.115	0.20	0.588	0.097	0.20
CHI	150.91	1.47		174.72	5.32		228.97	14.45		217.87	19.77	
% Significant	100.0	16.3		100.0	71.5		100.0	94.5		100.0	96.0	

Panel C: SHARE PRICE

	3-Months			6-Months			9-Months			12-Months		
Quintile	**Loser**	**Winner**	**Sample**	**Loser**	**Winner**	**Sample**	**Loser**	**Winner**	**Sample**	**Loser**	**Winner**	**Sample**
Low – 1	0.423	0.214	0.20	0.459	0.177	0.20	0.492	0.148	0.20	0.518	0.130	0.20
2	0.234	0.218	0.20	0.235	0.209	0.20	0.234	0.194	0.20	0.230	0.183	0.20
3	0.147	0.197	0.20	0.136	0.198	0.20	0.125	0.202	0.20	0.115	0.204	0.20
4	0.104	0.187	0.20	0.092	0.208	0.20	0.080	0.223	0.20	0.074	0.230	0.20
High – 5	0.091	0.183	0.20	0.078	0.209	0.20	0.069	0.233	0.20	0.064	0.253	0.20
CHI	78.76	1.21		109.53	0.82		152.12	5.53		155.90	9.95	
% Significant	100.0	12.4		100.0	5.9		100.0	75.3		100.0	92.0	

Table 2 (cont'd.)

Panel D: INDUSTRY

	3-Months			6-Months			9-Months			12-Months		
Industry Group	**Loser**	**Winner**	**Sample**	**Loser**	**Winner**	**Sample**	**Loser**	**Winner**	**Sample**	**Loser**	**Winner**	**Sample**
0–RESOURCES	0.053	0.054	0.040	0.053	0.051	0.040	0.052	0.053	0.040	0.053	0.051	0.040
10–BASIC INDUSTRIES	0.082	0.087	0.107	0.080	0.083	0.108	0.080	0.084	0.109	0.079	0.082	0.109
20–GENERAL INDUSTRIALS	0.117	0.121	0.127	0.115	0.114	0.127	0.114	0.110	0.127	0.113	0.105	0.127
30–CYCLICAL CONSUMER	0.083	0.080	0.088	0.083	0.081	0.089	0.083	0.081	0.089	0.082	0.080	0.089
40–NON-CYCLIC CONSUMER	0.086	0.090	0.088	0.085	0.092	0.088	0.087	0.095	0.088	0.089	0.097	0.089
50–CYCLICAL SERVICES	0.325	0.324	0.312	0.330	0.330	0.312	0.330	0.331	0.312	0.328	0.340	0.312
60–NON-CYCLICAL SERVICES	0.025	0.023	0.022	0.026	0.027	0.022	0.027	0.028	0.022	0.028	0.029	0.022
70–UTILITIES	0.006	0.018	0.019	0.005	0.021	0.019	0.004	0.020	0.019	0.004	0.018	0.019
80–FINANCIALS	0.074	0.082	0.112	0.071	0.080	0.112	0.069	0.077	0.113	0.069	0.077	0.113
90–INFORMATION TECH.	0.117	0.106	0.069	0.119	0.108	0.069	0.120	0.110	0.069	0.121	0.111	0.068
100–UNQUOTED/UNCLASSIFIED	0.032	0.015	0.014	0.033	0.012	0.014	0.033	0.011	0.013	0.034	0.010	0.012
CHI	17.16	8.58		17.06	8.94		20.78	12.76		18.29	14.24	
% Significant	89.0	41.0		89.9	45.0		96.9	72.2		90.1	83.0	

Table 3
Portfolio Turnover – Unrestricted Sample

This table shows the average percentage turnover of the winner and loser portfolios for different ranking and holding periods. Panel A describes the portfolio turnover. For each cell the top number is the percentage turnover per holding period, whilst the number in squared brackets [ ] is the corresponding annualised turnover values.

Formation Period	Portfolio	Holding Period 1-MONTH	3-MONTH	6-MONTH	9-MONTH	12-MONTH
3	LOSER	44.8	73.7	78.6	80.1	81.0
		[537.6]	[294.8]	[157.2]	[106.8]	[81.0]
	WINNER	51.2	81.8	86.3	86.5	86.8
		[614.4]	[327.2]	[172.6]	[115.3]	[86.8]
6	LOSER	30.1	53.3	76.3	78.9	80.2
		[361.2]	[213.2]	[152.6]	[105.2]	[80.2]
	WINNER	36.2	61.4	84.3	85.1	86.7
		[434.4]	[245.6]	[168.6]	[113.5]	[86.7]
9	LOSER	24.4	43.6	61.9	71.2	79.2
		[292.8]	[174.4]	[123.8]	[94.9]	[79.2]
	WINNER	29.2	50.6	69.1	76.8	85.4
		[350.4]	[202.4]	[138.2]	[102.4]	[85.4]
12	LOSER	19.9	36.4	53.2	65.7	77.9
		[238.8]	[145.6]	[106.4]	[87.6]	[77.9]
	WINNER	24.8	42.8	60.4	71.8	84.2
		[297.6]	[171.2]	[120.8]	[95.7]	[84.2]

Table 4
Portfolio Implementation Cost and Net Returns Based on the Quoted Spread Plus Commissions (Restricted Sample)

This table shows the average trading costs based on the quoted spread plus commissions and taxes and the post-cost returns associated with the winner and loser portfolios for different ranking and holding periods. Panel A describes the trading costs. The W-L row describes the total cost of the momentum strategy of buying the winners and selling the losers. Panel B describes the returns of the winner minus loser portfolio after trading cost. [a] or [b] denotes significant at 1% or 5%, respectively.

Panel A: Trading Costs (%) Based on Quoted Spread Plus Commissions and Taxes

Formation Period	Portfolio	Holding Period 1-MONTH	3-MONTH	6-MONTH	9-MONTH	12-MONTH
3	LOSER	56.7	30.7	16.3	11	8.3
	WINNER	49.9	26.5	13.9	9.2	6.8
	W – L	106.6	57.2	30.2	20.2	15.1
6	LOSER	39.3	23.2	16.5	11.2	8.5
	WINNER	32.9	18.6	12.6	8.4	6.4
	W – L	72.2	41.8	29.1	19.6	14.9
9	LOSER	32.7	19.5	13.7	10.4	8.6
	WINNER	25	14.4	9.8	7.2	5.9
	W – L	57.7	33.9	23.5	17.6	14.5
12	LOSER	26.9	16.3	11.9	9.7	8.6
	WINNER	20.2	11.5	8.1	6.4	5.6
	W – L	47.1	27.8	20.0	16.1	14.2

Panel B: Returns of the winner minus loser portfolio after trading cost.

Formation Period	Portfolio	Holding Period 1-MONTH	3-MONTH	6-MONTH	9-MONTH	12-MONTH
3	W – L	-0.7792[a]	-0.2912[a]	-0.0272	0.0452	0.0830[a]
	(t-value)	(-15.910)	(-6.551)	(-0.684)	(1.391)	(3.111)
6	W – L	-0.3452[a]	-0.0400	0.0462	0.1172[a]	0.1210[a]
	(t-value)	(-6.036)	(-0.753)	(1.049)	(3.197)	(3.629)
9	W – L	-0.1606[a]	0.0498	0.1310[a]	0.1348[a]	0.1094[a]
	(t-value)	(-2.890)	(0.980)	(2.898)	(3.494)	(3.069)
12	W – L	-0.0246	0.1372[b]	0.1456[a]	0.1198[a]	0.0764[b]
	(t-value)	(-0.433)	(2.655)	(3.210)	(3.016)	(2.024)

Table 5
Portfolio Implementation Cost and Net Returns Based on the LDV Estimates (Unrestricted Sample)

This table shows the average trading costs based on the LDV estimates and the post-cost returns associated with the winner and loser portfolios for different ranking and holding periods. Panel A describes the trading costs. The W-L row describes the total cost of the momentum strategy of buying the winners and selling the losers. Panel B describes the returns of the winner minus loser portfolio after trading cost. [a] or [b] denotes significant at 1% or 5%, respectively.

Panel A: Trading Costs (%) Based on LDV Cost Estimates

Formation Period	Portfolio	Holding Period 1-MONTH	3-MONTH	6-MONTH	9-MONTH	12-MONTH
3	LOSER	53.9	27.9	14.0	8.9	6.3
	WINNER	43.6	21.9	10.9	6.8	4.8
	W – L	97.5	49.8	24.9	15.7	11.1
6	LOSER	38.0	21.2	14.3	9.2	6.6
	WINNER	27.8	14.8	9.6	6.0	4.3
	W – L	65.7	36.0	23.8	15.3	10.9
9	LOSER	32.0	18.0	12.0	8.7	6.7
	WINNER	20.5	11.2	7.2	5.0	3.9
	W – L	52.5	29.2	19.2	13.6	10.6
12	LOSER	26.8	15.5	10.6	8.2	6.8
	WINNER	16.4	8.9	5.9	4.4	3.6
	W – L	43.2	24.3	16.5	12.6	10.4

Panel B: Returns of the winner minus loser portfolio after trading cost.

Formation Period	Portfolio	Holding Period 1-MONTH	3-MONTH	6-MONTH	9-MONTH	12-MONTH
3	W – L	-0.6882[a]	-0.2172	0.0258	0.0902[b]	0.1230[a]
	(t-value)	(-3.778)	(-1.017)	(1.492)	(2.099)	(2.882)
6	W – L	-0.2802	0.0180	0.0992[b]	0.1602[a]	0.1610[a]
	(t-value)	(-0.182)	(1.685)	(2.206)	(2.901)	(2.743)
9	W – L	-0.1086	0.0968	0.1740[b]	0.1748[b]	0.1484[b]
	(t-value)	(0.639)	(1.853)	(2.586)	(2.442)	(2.119)
12	W – L	0.0144	0.1722[b]	0.1806[b]	0.1548[b]	0.1144
	(t-value)	(1.297)	(2.455)	(2.505)	(2.001)	(1.417)

Table 6
Average annualised portfolio returns for various holding periods
(Restricted Sample)

Each month stocks are classified into one of five portfolios based on their past performance in the ranking period for the restricted sample of large stocks. P1 is the loser portfolio (worst performing quintile) and P5 is the winner portfolio. Equally weighted overlapping portfolio returns are calculated for various holding periods. The [p-values] are the bootstrapping probabilities for testing whether the portfolio return is significantly different from that of a randomly selected portfolio of similar size. The (t-values) tests whether the winner minus loser portfolio is different from zero. Price describes the average share price (in pence), size describes the average market capitalisation (in £'millions) and liquidity describes the average percentage bid-ask spread of the portfolio. [a] or [b] denotes significant at 1% or 5% respectively.

Ranking	Portfolio	Holding Period					Price	Size	Liquidity
		1M	3M	6M	9M	12M			
J = 3	P1	-0.0588[a]	-0.0564[a]	-0.0564[a]	-0.0396[a]	-0.0492[a]	311.9	1096.8	3.7
	[p-value]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]			
	P3	0.0768	0.0744	0.0804	0.0804	0.0684	444.1	1681.5	2.0
	[p-value]	[0.7145]	[0.8360]	[0.9290]	[0.9085]	[0.9115]			
	P5	0.1296[b]	0.1128	0.1140[b]	0.1068[b]	0.0972[a]	455.4	1313.2	2.3
	[p-value]	[0.9890]	[0.9705]	[0.9900]	[0.9895]	[0.9980]			
	P5-P1	0.1884[a]	0.1692[a]	0.1704[a]	0.1464[a]	0.1464[a]	143.5[a]	216.4[a]	-1.4[a]
	(t-value)	(3.792)	(3.598)	(4.074)	(4.036)	(4.525)	(5.960)	(6.153)	(-2.891)
J = 6	P1	-0.0840[a]	-0.0852[a]	-0.0720[a]	-0.0732[a]	-0.0552[a]	276.8	990.6	4.0
	[p-value]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]			
	P3	0.0732	0.0785	0.0864	0.0696	0.0684	513.3	1922.9	1.9
	[p-value]	[0.7725]	[0.7960]	[0.9440]	[0.8970]	[0.8440]			
	P5	0.1656[a]	0.1596[a]	0.1404[a]	0.1248[a]	0.1128[a]	431.2	1314.0	2.0
	[p-value]	[1.0000]	[1.0000]	[0.9995]	[1.0000]	[0.9990]			
	P5-P1	0.2496[a]	0.2448[a]	0.2124[a]	0.1980[a]	0.1680[a]	154.4[a]	323.4[a]	-2.0[a]
	(t-value)	(4.359)	(4.497)	(4.359)	(4.568)	(4.199)	(6.413)	(8.914)	(-4.131)
J = 9	P1	-0.0888[a]	-0.0768[a]	-0.0828[a]	-0.0600[a]	-0.0444[a]	252.9	876.5	4.2
	[p-value]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0010]			
	P3	0.0708	0.0816	0.0648	0.0624	0.0650	534.5	1963.3	1.9
	[p-value]	[0.5735]	[0.8210]	[0.7015]	[0.5710]	[0.5900]			
	P5	0.1596[a]	0.1560[a]	0.1380[a]	0.1224[a]	0.1020[b]	424.3	1420.9	2.0
	[p-value]	[0.9995]	[0.9995]	[0.9990]	[0.9985]	[0.9910]			
	P5-P1	0.2484[a]	0.2328[a]	0.2208[a]	0.1824[a]	0.1464[a]	171.4[a]	544[a]	-2.2[a]
	(t-value)	(4.158)	(4.157)	(4.322)	(3.860)	(3.360)	(7.288)	(14.532)	(-4.440)
J = 12	P1	-0.0936[a]	-0.0936[a]	-0.0672[a]	-0.0468[a]	-0.0204[b]	236.7	758.1	4.4
	[p-value]	[0.0000]	[0.0000]	[0.0005]	[0.0015]	[0.0060]			
	P3	0.0648	0.0650	0.0636	0.0600	0.0648	532.2	2110.1	1.9
	[p-value]	[0.2325]	[0.4725]	[0.5700]	[0.5600]	[0.4695]			
	P5	0.1728[a]	0.1560[a]	0.1368[a]	0.1116[b]	0.0996	359.2	1506.2	1.9
	[p-value]	[1.0000]	[1.0000]	[0.9990]	[0.9915]	[0.9485]			
	P5-P1	0.2664[a]	0.2496[a]	0.2040[a]	0.1584[a]	0.1200[a]	122.5[a]	748.1[a]	-2.5[a]
	(t-value)	(4.330)	(4.268)	(3.804)	(3.191)	(2.603)	(5.046)	(19.535)	(-4.867)

Table 7
Portfolio Turnover – Restricted Sample

This table shows the average percentage turnover of the winner and loser portfolios for different ranking and holding periods for the restricted sample of large stocks. Panel A describes the portfolio turnover. For each cell the top number is the percentage turnover per holding period, whilst the number in squared brackets [ ] is the corresponding annualised turnover values.

Formation Period	Portfolio	Holding Period				
		1-MONTH	3-MONTH	6-MONTH	9-MONTH	12-MONTH
3	LOSER	41.5	68.2	71.7	72.3	72.7
		[498.0]	[272.8]	[143.4]	[96.4]	[72.7]
	WINNER	45.0	71.7	75.9	76.1	76.3
		[540.0]	[286.8]	[151.8]	[101.5]	[76.3]
6	LOSER	28.0	48.5	68.8	70.2	71.2
		[336.0]	[194.0]	[137.6]	[93.6]	[71.2]
	WINNER	30.6	52.7	74.7	75.4	76.1
		[367.2]	[210.8]	[149.4]	[100.5]	[76.1]
9	LOSER	22.1	38.5	54.2	63.0	70.1
		[265.2]	[154.0]	[108.4]	[84.0]	[70.1]
	WINNER	25.3	43.6	59.9	68.1	75.3
		[303.6]	[174.4]	[119.8]	[90.8]	[75.3]
12	LOSER	18.4	31.8	46.4	58.7	69.0
		[220.8]	[127.2]	[92.8]	[78.3]	[69.0]
	WINNER	21.3	36.4	51.7	64.4	74.4
		[255.6]	[145.6]	[103.4]	[85.9]	[74.4]

Table 8
Portfolio Implementation Cost and Net Returns Based on the Quoted Spread Plus Commissions (Restricted Sample)

This table shows the average trading costs based on the quoted spread plus commissions and taxes and the post-cost returns associated with the winner and loser portfolios for different ranking and holding periods for the restricted sample of large stocks. Panel A describes the trading costs. The W-L row describes the total cost of the momentum strategy of buying the winners and selling the losers. Panel B describes the returns of the winner minus loser portfolio after trading cost. [a] or [b] denotes significant at 1% or 5%, respectively.

Panel A: Trading Costs (%) Based on Quoted Spread Plus Commissions and Taxes

Formation Period	Portfolio	Holding Period 1-MONTH	3-MONTH	6-MONTH	9-MONTH	12-MONTH
3	LOSER	23.0	14.1	6.7	4.5	3.5
	WINNER	14.8	7.7	4.1	2.6	2.0
	W – L	37.8	21.8	10.8	7.1	5.5
6	LOSER	17.2	10.5	7.2	4.9	3.8
	WINNER	8.8	4.9	3.5	2.3	1.8
	W – L	26.0	15.4	10.7	7.1	5.6
9	LOSER	14.3	8.5	6.0	4.5	3.7
	WINNER	6.8	4.3	2.6	2.1	1.7
	W – L	21.1	12.8	8.6	6.7	5.5
12	LOSER	12.5	7.1	4.9	4.3	3.8
	WINNER	6.0	3.4	2.3	1.9	1.6
	W – L	18.5	10.6	7.1	6.1	5.4

Panel B: Returns of the winner minus loser portfolio after trading cost.

Formation Period	Portfolio	Holding Period 1-MONTH	3-MONTH	6-MONTH	9-MONTH	12-MONTH
3	W – L	-0.1896[a]	-0.0488	0.0624	0.0754[b]	0.0914[a]
	(t-value)	(-3.778)	(-1.017)	(1.492)	(2.099)	(2.882)
6	W – L	-0.0104	0.0908	0.1054[b]	0.1270[a]	0.1120[a]
	(t-value)	(-0.182)	(1.685)	(2.206)	(2.901)	(2.743)
9	W – L	0.0374	0.1048	0.1348[b]	0.1154[b]	0.0914[b]
	(t-value)	(0.639)	(1.853)	(2.586)	(2.442)	(2.119)
12	W – L	0.0814	0.1436[b]	0.1330[b]	0.0974[b]	0.0660
	(t-value)	(1.297)	(2.455)	(2.505)	(2.001)	(1.417)

Table 9
Portfolio Implementation Cost and Net Returns Based on the LDV Estimates (Restricted Sample)

This table shows the average trading costs based on the LDV estimates and the post-cost returns associated with the winner and loser portfolios for different ranking and holding periods for the restricted sample of large stocks. Panel A describes the trading costs. The W-L row describes the total cost of the momentum strategy of buying the winners and selling the losers. Panel B describes the returns of the winner minus loser portfolio after trading cost. [a] or [b] denotes significant at 1% or 5%, respectively.

Panel A: Trading Costs (%) Based on LDV Cost Estimates

Formation Period	Portfolio	Holding Period 1-MONTH	3-MONTH	6-MONTH	9-MONTH	12-MONTH
3	LOSER	18.6	10.2	5.3	3.6	2.7
	WINNER	16.9	9.0	4.8	3.2	2.4
	W – L	35.5	19.2	10.1	6.8	5.1
6	LOSER	12.7	7.4	5.2	3.5	2.7
	WINNER	11.3	6.5	4.6	3.1	2.4
	W – L	24.0	13.9	9.8	6.6	5.0
9	LOSER	10.1	5.9	4.1	3.2	2.7
	WINNER	13.6	5.0	3.2	2.3	1.8
	W – L	23.7	10.9	7.4	5.5	4.5
12	LOSER	8.7	5.4	3.6	3.0	2.7
	WINNER	8.1	4.6	2.8	2.2	1.8
	W – L	16.8	10.0	6.4	5.2	4.4

Panel B: Returns of the winner minus loser portfolio after trading cost.

Formation Period	Portfolio	Holding Period 1-MONTH	3-MONTH	6-MONTH	9-MONTH	12-MONTH
3	W – L	-0.1666[a]	-0.0228	0.0694	0.0784[b]	0.0954[a]
	(t-value)	(-3.353)	(-0.485)	(1.659)	(2.161)	(2.949)
6	W – L	0.0096	0.1058	0.1144[b]	0.1320[a]	0.1180[a]
	(t-value)	(0.168)	(1.944)	(2.348)	(3.045)	(2.983)
9	W – L	0.0114	0.1238[a]	0.1468[a]	0.1274[a]	0.1014[b]
	(t-value)	(0.191)	(2.211)	(2.874)	(2.696)	(2.327)
12	W – L	0.0964	0.1496[a]	0.1400[a]	0.1064[b]	0.0760
	(t-value)	(1.697)	(2.729)	(2.611)	(2.143)	(1.649)

Table 10
Risk-Adjusted Portfolio Returns

This table reports the risk-adjusted abnormal returns for the winner portfolio, loser portfolio and the winner minus loser (W-L) portfolio. Panel A reports abnormal returns for the unrestricted sample based on the CAPM. Panel B reports abnormal returns for the unrestricted sample based on the Fama and French three-factor model whilst Panel C reports abnormal returns for the restricted sample of large stocks based on the CAPM. The (t-values) tests whether the abnormal return is significantly different from zero. [a] or [b] denotes significant at 1% or 5% respectively.

Ranking Period	Portfolio	PANEL A: UNRESTRICTED SAMPLE – CAPM					PANEL B: UNRESTRICTED SAMPLE - F&F					PANEL C: LARGE STOCKS - CAPM				
		Holding Period					Holding Period					Holding Period				
		1M	3M	6M	9M	12M	1M	3M	6M	9M	12M	1M	3M	6M	9M	12M
	Loser	-0.3293[a]	-0.3384[a]	-0.3299[a]	-0.3105[a]	-0.2958[a]	-0.2466[a]	-0.2565[a]	-0.2380[a]	-0.2189[a]	-0.2012[a]	-0.2851[a]	-0.2812[a]	-0.2732[a]	-0.2588[a]	-0.2480[a]
		(-5.2782)	(-5.6856)	(-5.5167)	(5.4254)	(-5.3411)	(-5.5668)	(-6.0021)	(-6.1710)	(6.0276)	(-5.9102)	(-5.3378)	(-5.4039)	(-5.2263)	(5.1212)	(-5.0118)
3-Month	Winner	-0.0258	-0.0465	-0.0473	-0.0535	-0.0592	0.1593[b]	0.1318[b]	0.1082[b]	0.0933[a]	0.0811[b]	-0.0246	-0.0405	-0.0405	-0.0455	-0.0512
		(-0.4786)	(-0.9124)	(-1.0228)	(1.2077)	(-1.3854)	(2.4416)	(2.4200)	(2.5085)	(2.5172)	(2.5291)	(-0.5540)	(-0.9285)	(-1.0233)	(1.2300)	(-1.3859)
	W-L	0.3035[a]	0.2918[a]	0.2827[a]	0.2578[a]	0.2366[a]	0.4059[a]	0.3883[a]	0.3462[a]	0.3181[a]	0.2823[a]	0.2606[a]	0.2407[a]	0.2326[a]	0.2158[a]	0.1968[a]
		(5.8252)	(5.8101)	(6.1271)	(6.7051)	(7.5721)	(4.8226)	(5.4261)	(6.7472)	(8.5585)	(10.8637)	(6.1361)	(5.8380)	(6.1778)	(6.6405)	(7.3063)
	Loser	-0.3626[a]	-0.3672[a]	-0.3453[a]	-0.3242[a]	-0.3003[a]	-0.2899[a]	-0.2884[a]	-0.2575[a]	-0.2297[a]	-0.2088[a]	-0.3172[a]	-0.3092[a]	-0.2919[a]	-0.2733[a]	-0.2580[a]
		(-5.3665)	(-5.5562)	(-5.4160)	(5.2892)	(-5.1896)	(-6.2061)	(-6.6432)	(-6.5266)	(6.1712)	(-5.7705)	(-5.3529)	(-5.2977)	(-5.1976)	(5.0096)	(-4.8735)
6-Month	Winner	0.0295	0.0212	0.0011	-0.0157	-0.0273	0.2140[a]	0.1937[a]	0.1620[a]	0.1459[a]	0.1253[a]	0.0254	0.0128	-0.0012	-0.0140	-0.0249
		(0.5388)	(0.4268)	(0.0230)	(0.2396)	(-0.6176)	(3.4331)	(3.6798)	(3.9817)	(3.9650)	(3.9476)	(0.5623)	(0.3069)	(-0.0313)	(0.3202)	(-0.6734)
	W-L	0.3921[a]	0.3884[a]	0.3463[a]	0.3133[a]	0.2730[a]	0.5039[a]	0.4821[a]	0.4196[a]	0.3717[a]	0.3341[a]	0.3425[a]	0.3220[a]	0.2907[a]	0.2613[a]	0.2331[a]
		(5.8816)	(6.2404)	(6.3420)	(6.5115)	(6.7553)	(6.1170)	(7.1186)	(9.3461)	(10.6421)	(12.1635)	(6.2968)	(6.2498)	(6.4544)	(6.5038)	(6.5427)
	Loser	-0.3740[a]	-0.3616[a]	-0.3473[a]	-0.3186[a]	-0.2805[a]	-0.3004[a]	-0.2838[a]	-0.2624[a]	-0.2336[a]	-0.1938[a]	-0.3190[a]	-0.3073[a]	-0.2906[a]	-0.2657[a]	-0.2398[a]
		(-5.2720)	(-5.3445)	(-5.4579)	(5.1518)	(-4.8332)	(-6.5549)	(-6.9019)	(-6.6156)	(5.9318)	(-5.2479)	(-5.2623)	(-5.2392)	(-5.1195)	(4.8310)	(-4.4784)
9-Month	Winner	0.0530	0.0365	0.0224	0.0001	-0.0251	0.2427[a]	0.2179[a]	0.1946[a]	0.1670[a]	0.1382[a]	0.0358	0.0236	0.0113	-0.0041	-0.0236
		(1.0338)	(0.7538)	(0.4868)	(0.0032)	(-0.5422)	(4.2172)	(4.6215)	(5.1012)	(4.8388)	(4.4611)	(0.8395)	(0.5891)	(0.2952)	(0.0710)	(-0.6204)
	W-L	0.4270[a]	0.3981[a]	0.3697[a]	0.3011[a]	0.2554[a]	0.5431[a]	0.5017[a]	0.4570[a]	0.3920[a]	0.3320[a]	0.3549[a]	0.3309[a]	0.3019[a]	0.2633[a]	0.2162[a]
		(6.2793)	(6.3148)	(6.9077)	(6.3894)	(5.6435)	(7.3555)	(9.1283)	(11.7504)	(11.8090)	(11.8609)	(6.4315)	(6.4155)	(6.6086)	(6.0428)	(5.4047)
	Loser	-0.3841[a]	-0.3610[a]	-0.3267[a]	-0.2840[a]	-0.2491[a]	-0.3160[a]	-0.2906[a]	-0.2474[a]	-0.2101[a]	-0.1742[a]	-0.3107[a]	-0.2991[a]	-0.2769[a]	-0.2458[a]	-0.2146[a]
		(-5.8636)	(-5.6804)	(-5.1862)	(4.7802)	(-4.3223)	(-7.7726)	(-7.2842)	(-6.2918)	(5.2870)	(-4.5594)	(-5.2214)	(-5.0711)	(-4.7528)	(4.2666)	(-3.9288)
12-Month	Winner	0.0694	0.0574	0.0222	-0.0032	-0.0296	0.2705[a]	0.2544[a]	0.2117[a]	0.1767[a]	0.1444[a]	0.0529	0.0328	0.0091	-0.0097	-0.0270
		(1.3279)	(1.1291)	(0.4404)	(0.0215)	(-0.5860)	(4.9384)	(5.5039)	(5.5832)	(5.0305)	(4.6464)	(1.2305)	(0.7960)	(0.2258)	(0.1970)	(-0.6737)
	W-L	0.4535[a]	0.4184[a]	0.3488[a]	0.2867[a]	0.2195[a]	0.5865[a]	0.5450[a]	0.4590[a]	0.3958[a]	0.3186[a]	0.3636[a]	0.3319[a]	0.2861[a]	0.2319[a]	0.1876[a]
		(7.1294)	(7.0767)	(6.1752)	(5.3826)	(4.2420)	(9.1336)	(10.6659)	(12.2324)	(11.1759)	(10.3789)	(6.7264)	(6.3923)	(5.7404)	(4.8861)	(4.1285)

Figure 1
Lorenz Curves Illustrating Stock Concentration in the Portfolios Relative to Stock Distributions in the Sample

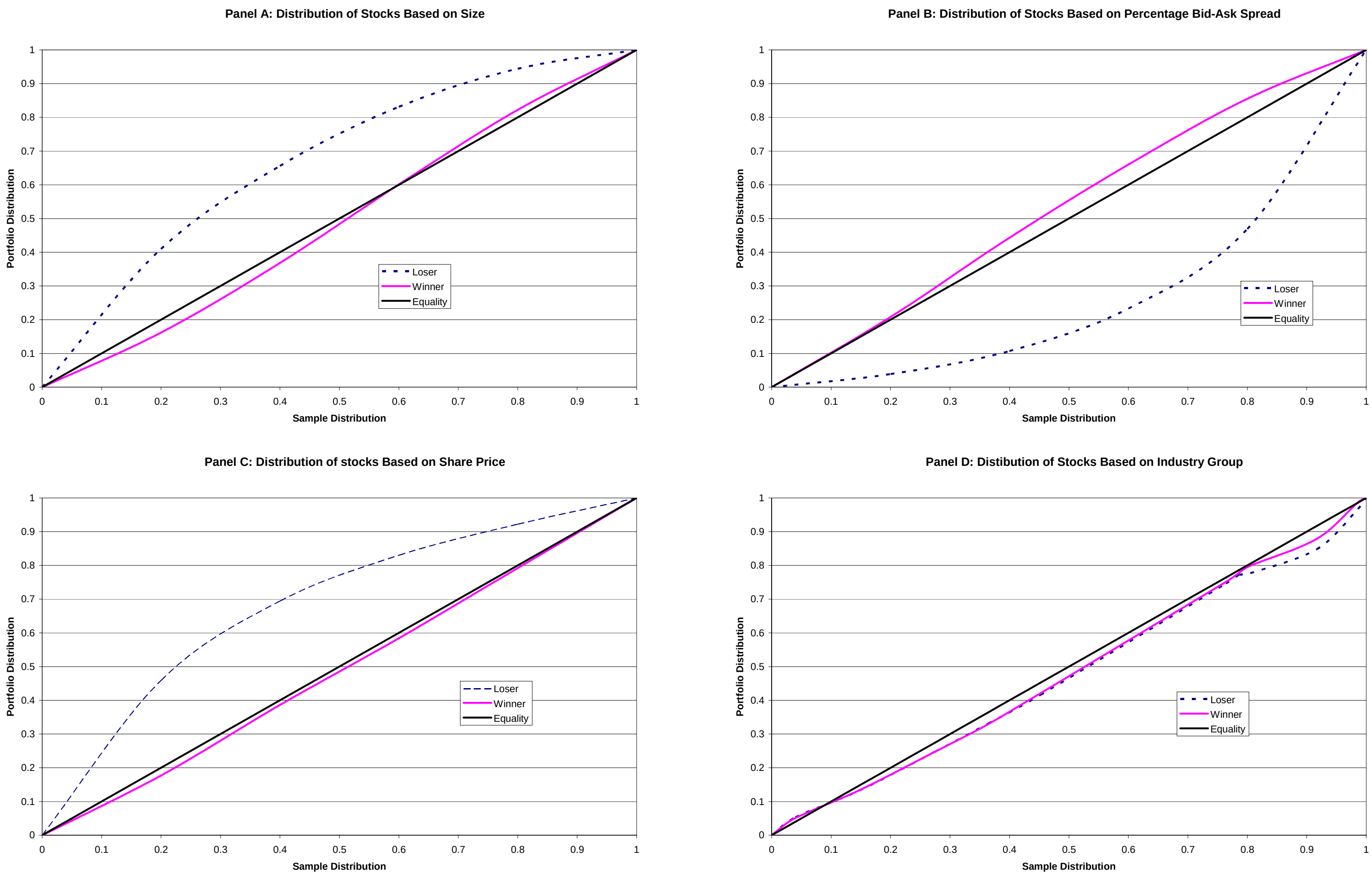


Figure 2
Portfolio turnover for the 6 x 6 strategy

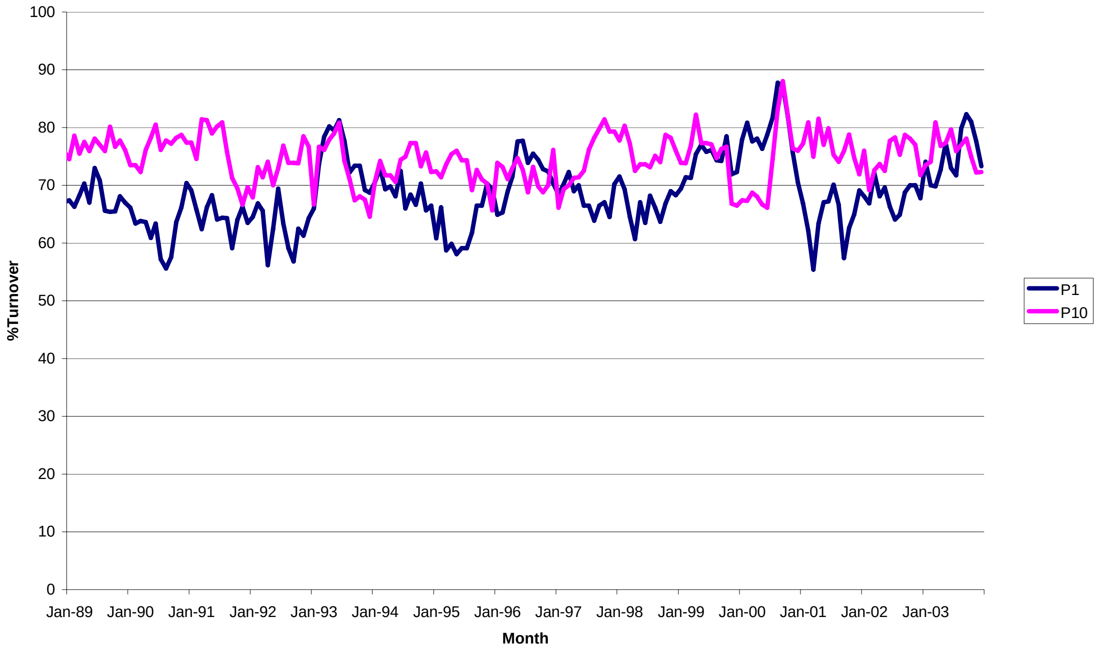
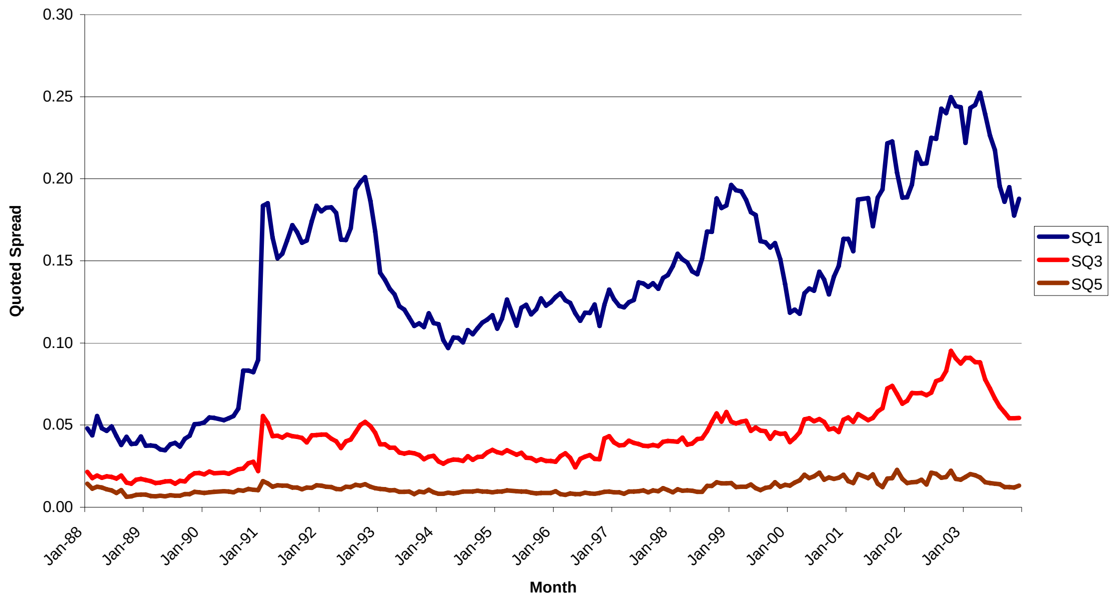


Figure 3
Estimated trading cost for different size quintiles over the sample period

Panel A: Mean quoted spread for different size quintiles



Panel B: Mean effective spread for different size quintiles

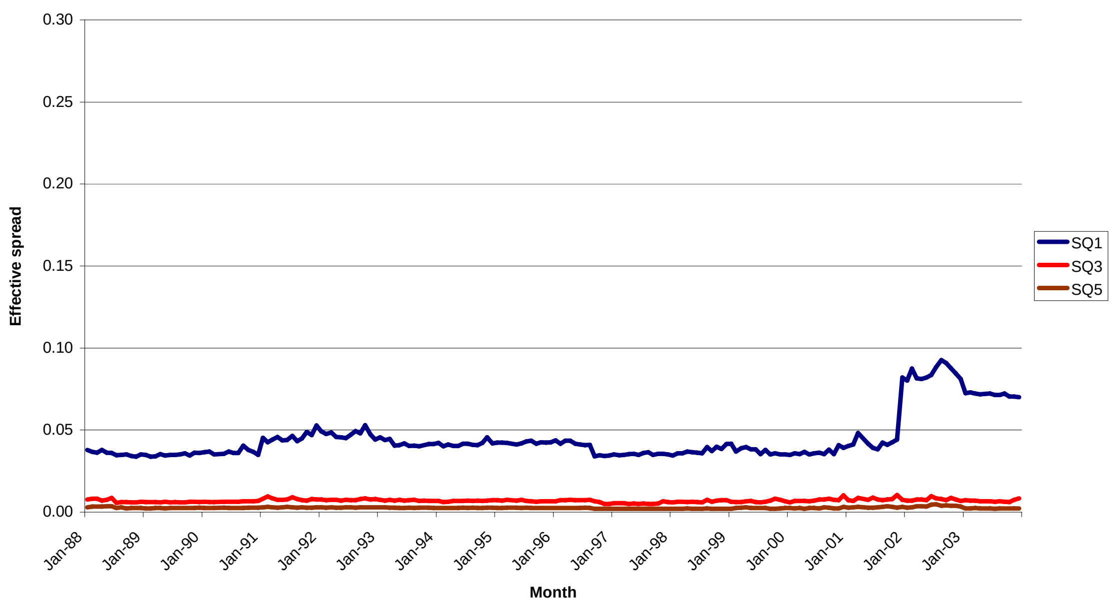


Figure 3 cont'd.