Divergence in Opinion, Limits to Arbitrage and Momentum Trading

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Abstract

We examine whether limits to arbitrage, divergence in investors' opinion, and risk factors can explain the persistence in momentum profits. The results reveal that momentum profits: (i) are driven almost entirely by loser stocks that are difficult to short; (ii) originate from initial overvaluation brought about by excessively optimistic investors in the presence of limits to arbitrage and; (iii) cannot be explained by known risk factors. Overall, momentum profits are caused by limits to arbitrage and divergence in opinion and hence, are not easily exploitable.

JEL Classification: G12, G14

Keywords: Divergence in opinion, Limits to arbitrage, Momentum, Overvaluation, Short-sale constraints.

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I. Introduction

Momentum trading strategies that take advantage of persistence in stock price movements short stocks that have recently performed poorly (out-of-favour stocks) to buy stocks that have recently performed well (favoured stocks). These strategies have attracted considerable attention from both practitioners and academics alike. In the UK, about 23 percent of institutional traders are characterised as momentum traders (Keim, 2004). The importance of this trading strategy for practitioners is also evident from the introduction of momentum indexes to measure the intermediate-term momentum effects[1]. In the academic literature, profits from momentum trading strategies represent one of the main challenges faced by modern neo-classical based finance theory. Success of this strategy suggests that excess returns can be earned by observing prior changes in stock prices and thus rejects the prediction of the efficient market hypothesis. Momentum in stock returns has been observed internationally (see, for instance, Jegadeesh and Titman, 1993; Griffin et al., 2003) and attempts have been made in explaining its causes. However, the issues, such as what causes continuation in stock returns and whether momentum profits are genuine and exploitable or are only reflecting some kind of market imperfection/friction, have remained unresolved. This study addresses these issues.

Fama and French (1996) concede that their three-factor model fails to explain continuation in returns. Similarly, after controlling separately for systematic risk, size, price, book-to-market ratio, and the Fama-French three factors, Liu et al. (1999) confirm that significant momentum profits exist in the UK. Thus, the observed momentum in stock prices is not due to risk differences or firm specific factors. Alternative explanations of momentum in stock returns include market under-reaction to firm specific information (Jegadeesh and Titman, 1993; Chan et al., 1996); gradual diffusion of information (Hong and Stein, 1999; Hong et al., 2000); investors' behaviour (Barberis et al., 1998; Daniel et al., 1998); cross-sectional dispersion in

[1] See, www.momentumindex.com.

unconditional and conditional expected returns (Conrad and Kaul, 1998; Chordia and Shivakumar, 2002); market frictions such as trading costs, price impact and liquidity (Korajczyk and Sadka, 2004; Lesmond et al., 2004). Similarly, Hong et al. (2000) show that momentum profits are driven almost entirely by short-side portfolios and Ali and Trombley (2003) report that momentum profits are positively related to short-sale constraints.

Miller (1977) theorised that stocks that are subject to both short-sale constraints and high dispersion in opinion are overvalued and generate low subsequent returns. This view rests on the argument that due to short-sale constraints, pessimistic traders cannot enter into the market and, hence, only optimistic investors continue to trade (buy) driving prices up, leading to overvaluation. Such overvaluation is maintained until the divergence in opinion is narrowed, at the point at which more investors realise that the stock is overvalued and start off-loading their holdings. If this prediction holds, stocks that were initially overvalued should earn low (negative) subsequent returns. Thus, Miller's views on the effects of short-sale constraints (a case of limits to arbitrage) and the divergence in opinion on the value of stocks can be extended to examine the possible reason(s) and exploitability of momentum profits[2]. In spite of its plausibility, no prior study has examined the implications of both conditions of Miller's theory (limits to arbitrage and divergence in opinion) on momentum returns. This study fills this gap. More specifically, this paper aims to address three main questions that are still unresolved: (i) what are the sources of momentum profits? (ii) to what extent are momentum profits linked to limits to arbitrage and divergence in opinion? and (iii) are the apparent momentum profits exploitable?

Given the nature of equity ownership distribution, trading strategies adopted by major investors, opportunities available to professional investors to engage in short-selling and the availability of measures of variations in investors' opinion, the UK stock market is an excellent platform to test for the above issues on momentum in the context of Miller's proposition. Unlike in many other developed markets, the UK financial institutions (active traders) hold a large proportion of equity traded on the

[2] Although some recent studies (for instance, Diether et al., 2002; Chen et. al., 2002) attempt to examine the overpricing hypothesis they do not consider the consequences of interaction between short-sale constraints and divergence in opinion simultaneously.

London Stock Exchange (LSE). Recent statistics (HMSO, 2004) suggest that at the end of December 2003, domestic institutions were holding 52.8 percent (£722 billion) of equity traded on the LSE, only 14.9 percent (£204 billion) were owned by individual shareholders and the rest were owned by foreign investors. Among the domestic institutions, insurance companies and pension funds are the major players in the market. Given that only one in four UK institutional investors are momentum traders[3] and short-selling is a professional activity used by institutional investors[4], opportunities to short-sell (arbitrage opportunities) should have implications on stock returns. D'Avolio (2002) shows that institutional investors are the main providers of stock loan supply. Therefore, using the details of institutional ownership we could test for the implications of arbitrage opportunities on momentum profits. Similarly, proxy measures of divergence in opinion (for example, analysts' forecasts) are also available for the UK. All of these offer an excellent opportunity to examine the implications of limits to arbitrage and divergence in opinion on momentum profits on the LSE.

We arrive at several conclusions. First, using alternative proxies of limits to arbitrage and divergence in investors' opinion we find that momentum profits are driven almost entirely by loser stocks that are costly or impossible to short. The absence of their exploitability could potentially explain the persistence in price momentum. Second, the limits in short-selling loser stocks defeat the idea of constructing a self-financing (hedge) portfolio to profit from momentum trading. High costs and/or the impossibility of short-selling out-of-favour stocks prohibit arbitrageurs from taking an appropriate position to exploit the profit opportunities and correct overpricing. Third, momentum profits originate from initial overvaluation brought about by excessively optimistic investors in the presence of limits to arbitrage (short-sale constraints). Finally, the known risk factors fail to explain the momentum profits. Therefore, momentum profits are caused by limits to arbitrage and, hence, are not easily exploitable.

The remainder of the paper is organised as follows. Section II discusses limits to arbitrage and divergence in opinion and develops testable hypotheses. Section III describes the data and methodology. Section IV empirically examines the relation

[3] Keim (2004) categorises 23 percent of institutional investors as momentum traders.
[4] See Financial Services Authority (2002) for further details.

between momentum profits and short-sale constraints and overvaluation. Section V provides further evidence on the relation between market's optimism and momentum profits. Section VI concludes the study.

II. Theories and hypotheses development

Miller (1977) shows that when there is a high level of uncertainty among investors about the value of a security, short-sale constraints could prevent pessimistic investors' opinion being incorporated into stock prices. In this scenario, optimistic investors can buy or continue to hold the stocks driving the prices up. However, due to short-sale constraints, pessimistic investors face limits on the sale side trade resulting in supply constraints and failure to bring the prices down. On balance, this leads to overpricing. Therefore, Miller's hypothesis requires two conditions to be satisfied: (a) short-sale constraints and; (b) divergence in investors' opinion. In a system where short-selling is permitted (both by regulations and transaction costs) pessimists can sell additional shares to optimists. This improves the supply causing the stock price to fall. However, Jarrow (1980) argues that the price of an individual stock can increase or decrease when short sales are allowed. For a strategy of buying favourable stocks with the proceeds from the short-sale of out-of-favour stocks to be profitable, the long position must outperform the short-position after accounting for transactions costs and the risks associated with short-selling. In reality, the costs and the risks of short-selling a stock could be prohibitive and, hence, we cannot be sure whether prices of stocks will change to reflect the balance of opinion. Moreover, Diamond and Verrecchia (1987) suggest that, under rational market conditions, other investors will identify the existence of short-sale constraints and will alter their own beliefs in a way to prevent the existence of overvaluation on average. Since the theoretical arguments on short-sale constraints and the overvaluation or undervaluation of stocks are inconclusive, the overpricing hypothesis is an empirical issue.

Miller's view is important to stock market anomalies that consist of short-side portfolios like value vs. growth, contrarian, and momentum trading strategies. If both growth stocks (in value vs. growth strategy) and loser stocks (in momentum trading) are impeded by short-sale constraints, the stocks will be overpriced resulting in lower subsequent returns. These low returns may be sufficient to produce the existence of an ‘illusory premium’.

2.1 Limits to arbitrage and overvaluation

Direct costs of short-selling (a measure of arbitrage opportunities) are difficult to measure; therefore, studies use proxy measures. The costs of short-selling reflected in the stock loan market can be considered as a measure of constraints in selling short. Several studies (see, for example, D’Avolio, 2002; Mitchell et al., 2002) have analysed the market for borrowing stocks, however, their sample periods are rather short. On the other hand, Jones and Lamont (2002) analysed the NYSE ‘loan crowd’ rebate rate[5] as the proxy for the cost of short-selling with a longer sample period. Their findings suggest that stocks that are expensive to short or that enter the lending market with high valuations tend to have low subsequent returns.

Some studies (see, for example, Figlewski, 1981; Dechow et al., 2001) measure the demand for short-sales with short-interest. However, this measure also suffers from some limitations. Since the quantity of shorting represents the costs and benefit of shorting the stocks, stocks that are difficult to short will have low short-interest. Stocks that are impossible to short have an infinite shorting cost; however, the level of short-interest is zero. To illustrate, Lamont and Thaler (2003) examine a sample of technology carve-outs that appear to be overpriced. They show that the apparent overpricing and the implied cost of shorting fall over time, while the level of short-interest rises. As such, short-interest can be negatively correlated with the demand for shorting, overpricing, and the cost of shorting. These limitations weaken the reliability of empirical findings based on short-interest.

Another proxy measure of short-sale constraints is lack of institutional ownership. D’Avolio (2002) shows that stocks with low institutional ownership are likely to be ‘special’ and expensive to borrow. This view rests on the principle of demand and supply of stocks in the stock-loan market. Short-sellers must borrow the stocks and return them on demand. The cost of shorting is likely to be lower for stocks with substantial institutional ownership, since it is easier to find alternative lenders of such

[5] The rebate is the interest earned on the proceeds from the sale of borrowed shares.

stocks. Nagel (2005) employs institutional ownership as a proxy for short-sale constraints, and finds that the book-to-market effect, in particular the underperformance of growth stocks, is primarily concentrated in stocks that are difficult to short. He suggests that the overpricing hypothesis is behind the book-to-market anomaly. Similarly, Phalippou (2003) confirms that the value premium is created by a few overvalued stocks that are difficult to sell short, and suggests that limited arbitrage, rather than risk, plays a major role in the existence of the value premium. Ali and Trombley (2003) report that momentum profits are higher from stocks that experience high short-sale constraints and the results are mainly driven by loser stocks. Although they suggest that momentum returns are positively related to the cost of short-selling, they do not test the hypothesis that divergence in opinion drives the price/profit of stocks that are difficult to short. Therefore, we hypothesise that 'there is a positive association between momentum profits and short-sale constraints'.

2.2 Interaction between short-sale constraints and dispersion in opinion

Another factor that Miller (1977) attributes to overvaluation is high divergence in opinion. Scherbina (2001) uses dispersion in analysts' earnings forecasts (IBES) as a proxy for divergence in opinion and shows that the highest dispersion in opinion portfolio earns lower average return than the lowest dispersion in opinion portfolio. Chen et al. (2002) use breadth of ownership as a proxy for divergence in opinion and find that when few mutual fund managers have long positions in a given stock (low breadth of ownership), prices are high relative to fundamentals and that when the breadth decreases, subsequent returns decline. Danielsen and Sorescu (2001) contend that exchange-traded options mitigate short-sale constraints and examine the effects of option listings on the prices of underlying securities. They consider four measures of dispersion in investors' belief[6]. Their results generally support the conjecture that stock options mitigate the short-sale constraints that would otherwise lead to overvaluation. Diether et al. (2002) show that stocks with higher dispersion in analysts' earnings forecasts earn significantly lower future returns than otherwise similar stocks. Such results suggest that disagreement in investors' opinion is priced at

[6] The four proxies of dispersion in investors' opinion they used are: (a) the standard deviation of weekly (five-day) raw returns from day *t*-250 to date *t*-6; (b) the standard deviation of the error terms of the market model estimated from day *t*-100 to date *t*-6 relative to the event date; (c) the *ex ante* mean daily trading volume and; (d) the dispersion of analysts' forecast.

a discount as we would expect under Miller's hypothesis. Previous studies on the overpricing hypothesis do not consider the interaction of short-sale constraints and differences in opinion simultaneously – i.e. they do not examine the central theme of Miller's hypothesis. In this paper, we test for the implications of such an interaction on momentum returns. We hypothesise that 'momentum profits are high when both short-sale constraints and divergence in investors' opinion are high'.

2.3 Investors' confidence and momentum profit

If Miller's (1977) proposition that in the absence of short-sales, stocks continue to be overpriced until the divergence in opinion is narrowed holds, then out-of-favour stocks, which were initially overvalued, will earn low subsequent returns. These stocks should initially be bought by optimistic investors and, hence, the negative opinion of pessimistic investors is not incorporated in market price. Thus, we hypothesise that 'momentum returns are driven by the underperformance of overpriced loser stocks with high short-sale constraints.'

Stocks with good past performance tend to attract investors' attention. Behavioural models predict that traders are either slow to react or overreact to good news. The optimistic investors, usually less sophisticated[7], tend to rely on their own private information/belief in determining the firm's future cash flows. As noted by Daniel et al. (1998), when public information confirms investors' private information their confidence increases. Disconfirming public news draws less attention and the investor's confidence in their private signals remains unchanged. It is also consistent with a particular type of representativeness bias, the law of small numbers in which people expect even a small sample to reflect the properties of the entire population[8]. In this case, if investors perceive some good news about a firm, they will continue to believe that the stock will do well in the future. This belief will escalate his/her confidence level and lead to excessive optimism about the firm. In addition, short-sale constraints prevent a timely incorporation of bad news into prices. This suggests a testable proposition that 'momentum stocks should be initially bought by optimistic

[7] Indeed, Barber and Odean (2002) show that small investors are more likely to trade in stocks that have had recent extreme performance, possibly due to attention effects.

[8] To illustrate, suppose that an investor sees many periods of good earnings, the law of small numbers leads her to believe that earnings growth has gone up, and thus earnings will continue to remain high in the future.

investors and pessimists' opinion is not incorporated in market price'.

Tests of the above propositions are important as they shed light on how the mispricing arises that eventually generates the predictability of stock returns, and indeed, the momentum profits. Figure 1 summarises the potential sources of momentum profits. A low institutional ownership for a particular stock implies that the stock is more likely to be owned by individual/unsophisticated investors, and such stocks should be difficult and expensive to short as stock loan supply tends to be sparse. Opinions of pessimistic investors cannot be incorporated in the price due to the fact that such investors are unable to trade (sell) based on their views. Optimistic investors, however, continue to trade – the demand for stocks increases. The excess optimism, together with short-sale constraints, widens the divergence in opinions and drives the stock prices up. The overpricing sustains until the divergence in opinions becomes narrower and subsequent returns are reduced. Thus, this paper examines whether the overpricing hypothesis of Miller based on limits to arbitrage can explain the underperformance of loser stocks and the momentum anomaly.

Insert Figure 1 about here

III. Data and methods

3.1 Data

For the reasons stated earlier, the LSE is an excellent platform for testing the implications of limits to arbitrage and divergence in investors' opinion on momentum profits. On the LSE, the regulations on short-selling are fairly relaxed for institutional investor[9]. They also hold a large fraction of stocks traded on the LSE and are active in short-selling. Although direct observations on short-sale contracts are not available, as evident from the studies of D'Avolio (2002) and Nagel (2005), the distribution of institutional ownership (hereafter IO) offers an excellent proxy of the possibilities of stock loan supply[10]. Therefore, we use the ownership distribution as a measure of constraints to sell short; stocks with lower institutional holdings experience higher short-sale constraints.

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[9] See Financial Services Authorities (2002) for further details.
[10] For an excellent discussion on the relation between short-sale constraint and institutional ownership see Nagel (2005).

Our data on ownership distribution comes from the PricewaterhouseCoopers Corporate Register published by Hemmington-Scott. For each company, this unique database records the name of each shareholder and his/her proportion (percent) of share holdings (ordinary share capital). To improve the comparability of our results with US studies that use the CDA/Spectrum Institutional Holdings (13F) database, we extract quarterly institutional holdings from the Hemmington-Scott databases[11]. We then match (manually) the ownership database with Datastream[12]. First, for each company, institutions that are holding 3 percent or more of its equity shares are identified. Then, the total institutional holding of the company is estimated by adding the holdings of all institutions identified in the first step. If no record of institutional holding is available, it is considered zero. The sample excludes financial companies. The final sample consists of 86,151 observations for 2,556 unique firms from January 1993 to December 2002. This choice of sample period has been guided by the availability of ownership data at the time of data collection.

3.2 Residual institutional ownership

Earlier evidence (see, for example, Nagel, 2005) shows a high degree of association between firm size and institutional ownership (INST). Therefore, as in Nagel (2005), we measure short-sale constraints by residual institutional ownership that is adjusted for firm size[13]. Given that the degree of institutional ownership is a proportion ranging from 0 to 1, the residuals will not be normally distributed. Therefore, before controlling for the firm size a logit transformation is applied on INST (equation (1)).

$$(1) \qquad \text{Logit (INST)}_{i,t} = \log\left(\frac{\text{INST}_{i,t}}{1-\text{INST}_{i,t}}\right)$$

If INST is below 0.0001 or above 0.9999 it is replaced with 0.0001 and 0.9999 respectively. In equation (1) i,t represents firm i at time t (quarter). To control for any size effect, we estimate equation (2):

$$(2) \qquad \text{Logit (INST)}_{i,t} = \alpha + \beta \ln S_{i,t} + \varepsilon_t$$

[11] For the definition of institutional investors, we follow the CDA/Spectrum Institutional Holding database in order to provide comparable results.
[12] While merging these data bases we use Lexis-Nexis and FAME to identify company name changes.
[13] The method used in this sub-section is based on Nagel (2005).

Where, $S_{i,t}$ is the market capitalisation of firm i at time t. This cross-sectional equation is estimated for the period between January 1993 and December 2002. The residual (ε_t) of equation (2) is the residual institutional ownership (RIO). This allows us to measure the variation in institutional ownership, holding the firm size fixed.

3.3 Momentum trading strategies

For the computation of momentum profits, we follow n x m (where n, m = 3, 9, 6, 12) strategies[14]. From the sample stocks we compose P (P = 3 or 5) portfolios. In a 6 x 6 strategy, for instance, for each month *t*, all stocks are allocated into three (or five) portfolios (P=1 to 3) based on their six-month formation-period (*t*-7 to *t*-2) returns. Portfolio P1 (i.e. P=1) is an equally weighted portfolio of stocks in the worst-performing 30 percent stocks, portfolio P2 (i.e. P=2) contains the middle 40 percent stocks, and portfolio P3 (i.e. P=3) comprises of the best-performing 30 percent stocks. The position is held for the following six-month period (t_0 to *t*+5). We employ a one month gap between the formation and the holding period to avoid the momentum effect with short-term price reversals and the bid-ask bounce effects established by previous studies (see, for example, Jegadeesh, 1990; Jegadeesh and Titman, 1995). Throughout this study, unless otherwise stated, we analyse equally weighted portfolio returns.

3.4 Divergence in investors' opinion

We measure the divergence in investors' opinion by the dispersion in analysts' earnings per share (EPS) forecasts and trading volume[15]. The dispersion in analysts' EPS forecasts is defined as the standard deviation of EPS forecasts scaled by the stock price per share at the beginning of the month of forecast. Both the standard deviation of EPS forecasts and corresponding share prices are obtained from the I/B/E/S Summary History file. To allow for the calculation of standard deviation, only the stocks followed by at least two analysts are included in the sample. Trading volume is measured by the ratio of the number of shares traded to the number of shares outstanding, both obtained from Datastream.

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[14] In most cases, we report the results of the most commonly used 6 x 6 strategy.

[15] Diether et al. (2002), among others, use analysts' EPS forecasts as a measure of divergence in opinion while Lee and Swaminathan (2000) use trading volume to measure the same.

3.5 Analysts' optimism

We measure the markets' optimism about a firms' future ($Opt_{i,t}$) by the consensus EPS forecast (the median value of the one fiscal year-ahead forecast) minus the actual EPS scaled by the stock price per share at the beginning of the month of forecast[16], as in equation (3). This is compiled from the I/B/E/S Summary History file.

$$(3) \qquad Opt_{i,t} = (F_{i,t} - A_{i,t}) / P_{i,t-k}$$

Where, $F_{i,t}$ is the average EPS forecasted for stock i at time t, $A_{i,t}$ is the actual EPS and $P_{i,t-k}$ is the price for stock i at the beginning of the month of forecast (t-k).

3.6 Good/bad news environment

George and Hwang (2004) document that the 52-week high price explains a large portion of momentum profit. Following a similar idea, we use a 52-week high price to proxy for the good/bad news environment. A stock whose price is at or near its 52-week high is considered to have recent good news. On the other hand, a stock price far from its 52-week high implies recent bad news. The 52-week high is calculated as $P_{i,t-1}$/ $High_{i,t-1}$; where $P_{i,t-1}$ is the price of stock *i* at the end of month *t*-1 and $High_{i,t-1}$ is the highest price of stock *i* during the 12-month period that ends on the last day of month *t*-1. Data on 52-week high stock price are compiled from Datastream.

IV. Momentum profits, short-sale constraints and overvaluation

4.1 Short-sale constraints and gross returns from momentum trading

To examine the hypothesis that 'there is a positive association between momentum profits and short-sale constraints', we sort all stocks into quintiles at the end of each month *t* based on their returns during the six month formation period (*t*-7 to *t*-2). We then group the stocks of each price momentum category into five portfolios (equal stocks) on previous quarter's RIO obtained from equation (2)[17]. We form portfolios at different points during the year. Such overlapping portfolios increases the power of

[16] Analysts optimism are constructed as in Jackson (2005, p. 683).

[17] In a further test, we replace residual institutional ownership with institutional ownership (i.e. without adjusting for size). The results are qualitatively similar.

tests (see Jegadeesh and Titman, 1993). To avoid the momentum effect with very short-term price reversals and the bid-ask bounce effects, we allow for a one month gap between the formation period and the holding period. The portfolios are held for the subsequent six months (t_0 to t+5). Newey-West (1987) standard errors (adjusted for serial dependence caused by the use of overlapping lagged data) are used.

The results in Table 1 (panel A) support the predictions that momentum profits are most pronounced in loser stocks with high short-sale constraints. The average difference between the monthly returns of winner (P5) and loser (P1) portfolios in the lowest RIO quintile is 1.81 percent (T-statistic = 4.98). In contrast, the differences between returns of P5 and P1 in RIO4 and RIO5 portfolios are statistically insignificant. The results (panel A) also show that almost all of the contribution to momentum profits comes from loser stocks. Besides, momentum returns (P5-P1) decrease monotonically with the increase in RIO quintiles suggesting that momentum of loser stocks can be exploited by selling the stocks short. This confirms the importance of opportunities to short-sell in exploiting momentum profit. Figure 2 depicts the momentum profits against the RIO quintiles and confirms that momentum profits from the lowest two quintiles are caused by the tendency of loser stocks to lag behind. This evidence supports our hypothesis that ‘there is a positive association between momentum profits and short-sale constraints’.

Insert Table 1 and Figure 2 about here

We examine the robustness of the above findings using alternative measures of short-sale constraints. Some earlier studies (for example, Chen et al. (2002) and Diether et al. (2002)) suggest that firm size can be a proxy measure of stocks available for short-selling. Therefore, to examine whether momentum profit is firm size dependent we group the sample stocks on their market capitalisation and estimate momentum profits. The results show that momentum profit is inversely related to firm size and most of the profits come from loser stocks (Table 1, panel B). This reconfirms that loser stocks that have short-sale constraints make a substantive contribution to momentum profits. Next, it is also possible that the presence of exchange-traded options and/or futures can serve as a route to short-sales, and therefore, reduce the consequences of constraints in short-selling. Only 108 sample firms have individual traded options and/or futures. To maintain a reasonable number of stocks in each portfolio we sort them into three groups (as opposed to quintiles). P1 includes the worst performing 30 percent stocks, P2 includes the middle 40 percent stocks, and P3 includes the best performing 30 percent stocks. The results in Table 1 (panel C) show that stocks that have individual options and futures experience significantly lower momentum profits than other stocks. These results reconfirm earlier findings that stocks, especially the loser stocks, with short-sale constraints generate higher momentum profits.

Overall, short-sale constraints play a significant role in generating momentum profits. Considering Nagel's (2005) view that size can proxy for many other things, rather than just the short-sale constraints, and only limited observations are available on individual options and futures we believe that our RIO can serve as the best proxy (among the available alternatives) of short-sale constraints. Moreover, RIO accounts for size effects. Therefore, we measure short-sale constraints by RIO in further analysis.

4.2 Short-sale constraints and excess returns from momentum trading

It is possible that the observed momentum profit discussed in the previous section is simply a manifestation of differences in risk premium rather than excess returns. To account for this possibility, we estimate excess returns that are adjusted for three benchmark returns, viz. (a) market-adjusted, (b) Fama-French three-factor adjusted, and (c) industry adjusted. The market-adjusted return (raw return less the market return) of each stock is estimated for the end of each month *t*. Portfolios are formed on such market adjusted returns. Although the excess returns (Table 2, panel A) are smaller than gross returns, the overall findings support our earlier findings that the momentum profits come from loser stocks that face higher short-sale constraints. This evidence suggests that risk differences cannot explain momentum profits.

Contemporary finance literature advocates the superiority of the Fama-French three factor model against other single factor models (see, for instance, Davies et al., 1999). Therefore we estimated the returns that are adjusted for three risk factors as in equation (4):

(4) $R_{P,t} = \alpha + \beta_{Mkt}(R_{Mkt} - R_F)_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \varepsilon_t$

Where, $R_{P,,t}$ is raw return from portfolio p (for p = 1 to 25, as in Table 1), R_{Mkt} is market return measured by the FTSE All share index, R_F is the risk-free rate measured by the return on three-month Treasury bills, SMB and HML are small minus big, and high minus low as defined in Fama and French (1996)[18]. A significant α (alpha) in equation (4) represents excess return that is not explained by the three risk factors. Table 2 (panel B) documents the excess returns (alpha of equation 4) for each of the 25 portfolios. The estimates confirm that the adjustment for risk using the three-factor model does not alter our earlier conclusion that momentum profits originate largely from loser stocks with high short-sale constraints (i.e. low RIO). In fact, the three risk factors adjusted returns are slightly higher than the raw returns. In summary, this suggests that the Fama-French three factor model cannot explain momentum profits.

Finally, some earlier studies show that stock returns could be industry specific reflecting business cycle conditions. To allow for this possibility, we estimate the industry adjusted excess return of each stock (stock return *minus* return on industry portfolio)[19]. This method implies that stocks are as risky as their industry peers. The results in Table 2 (panel C) show that part of the industry adjusted momentum profits comes from winner stocks but a substantial part of momentum profits comes from loser stocks. More importantly, momentum profits are concentrated mainly in high short-sale constraint (low RIO) stocks. Therefore, the results reported in earlier paragraphs are not driven by industry effects. Overall, the results that loser stocks characterised by short-sale constraints contribute most in momentum profits continue to hold even after controlling for known risk and industry factors.

4.3 Divergence in opinion and excess returns from momentum trading

Miller (1977) suggests that stocks that are subject to both short-sale constraints and high divergence in investors' opinion are overpriced. To test this conjecture along with momentum profits, we first sort stocks in quintiles (for each *t* month) on the

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[18] We thank Stefan Nagel for providing the factor returns data. Since his data is only available until 2001, we follow his methodology to construct the factors for the year of 2002. His methodology is important as the construction of the factors captures the unique characteristics of UK data (see also Dimson et al. 2003 for details).

[19] The industry classifications are obtained from Datastream (INDC3).

previous quarter's residual institutional ownership (RIO) – a proxy for short-sale constraints. Next, stocks in each RIO portfolios are sorted into three groups on trading volume of the three months prior to the first day of the formation period (VO = 1 to 3), a measure of dispersion in opinion[20]. Portfolio VO1 contains stocks with the lowest 30 percent trading volume, portfolio VO2 contains the middle 40 percent trading volume stocks, and portfolio VO3 includes the highest 30 percent trading volume stocks. All stocks belonging to each element of the (RIO x VO) matrix are then grouped into three further portfolios on their formation period price performance. The momentum portfolios are P1 (the worst performing 30 percent), P2 (the middle 40 percent), and P3 (the best performing 30 percent) for each category of RIO classification. This three dimensional analysis allows us to test the hypothesis that momentum profits are high when both short-sale constraints and divergence in investors' opinion are high.

Table 3 documents average monthly raw returns of the momentum strategy during the holding period (t_0 to t+5). The results show that momentum profits (P3-P1) in each cell (VO x RIO) are driven substantially by loser stocks. In addition, they are mainly concentrated in the lowest two RIO quintiles, and decrease monotonically with increases in the possibility of selling short. This result is consistent with our earlier findings that short-sale constraints are important in determining the magnitude of momentum profits. Moreover, returns across divergence in opinion (VO) portfolios decline monotonically with reductions in trading volume for each RIO category. This is consistent with the hypothesis that momentum profits are high when both short-sale constraints and divergence in investors' opinion are high. Momentum profits decline as we move further away from these two conditions. These findings lend strong support to the overpricing hypothesis of Miller (1977) and explain the sources and reasons of persistence in momentum profits. More precisely, the stocks that are expensive or impossible to short have low subsequent returns. Among these difficult-to-short stocks, the stocks that have highest divergence in investors' opinion have the lowest subsequent returns.

[20] Jones et al. (1994) argue that the number of trades is a better proxy for dispersion of opinion compared to trading volume. We therefore repeat the analysis using the number of trades. The results are qualitatively similar.

An alternative, perhaps more representative, measure of divergence in investors' belief is the dispersion in analysts' earnings per share (EPS) forecasts. In implementing this test, all stocks are first sorted on the previous quarter's RIO and then on dispersion in analysts' EPS forecasts during the three months prior to the first day of the portfolio formation period (Disp). RIO, a measure of short-sale constraints, is obtained from equation (2). Next, three equally weighted portfolios are formed on their prior price performance. Portfolio P1 consists of the 30 percent worst-performing stocks, portfolio P2 contains the middle 40 percent, and portfolio P3 includes the 30 percent best-performing stocks. The estimates in Table 4 show that momentum profit is concentrated in low RIO stocks (high short-sale constraints), and is driven by loser stocks. Within each RIO portfolio, momentum profit is most pronounced on the portfolio of stocks with high dispersion in analysts' EPS forecasts. Thus, our results are robust to the choice of proxies of dispersion in investors' opinion.

In summary, the findings of this section have major implications for trading. First, momentum returns are more likely to be 'paper' returns as these profits primarily come from loser stocks that are very costly or impossible to short. Second, investors' inability to short-sale loser stocks defeats the original idea of generating momentum profits from a self-financing (hedge) portfolio. The persistence in momentum in stock prices is therefore caused by limits to arbitrage rather than investors' under-reaction to firm-specific information reported in some earlier studies. Some behavioural finance theorists argue that the persistence in momentum profits may be attributed to the disposition effect, implying that investors are reluctant in selling losers and eager in disposing of winners (see Shefrin and Statman, 1985). Ranguelova (2001) points out that the disposition effect operates entirely through the selling behaviour of individual investors. However, in our case, we do not assume that individual (unsophisticated) investors are subject to any irrational behaviour/bias in their selling decisions[21]. We only assume that short-sale constraints prohibit arbitrageurs from correcting mispricing immediately.

Institutional investors generally do not hold momentum (loser) stocks and less

[21] The problem of using the disposition effect to explain the persistence of momentum profits is that it requires investors to consistently reject selling their stock. While it may be true that individual investors are sometimes reluctant to sell assets that are trading at a loss, it is hard to believe that they always do so.

sophisticated individual investors are unlikely try to get involved in short-selling. These trading behaviours of investors help maintain persistence in momentum profits that come from loser stocks. The finding of Keim (2004) that only 23 percent of institutional traders in the UK are characterised as momentum traders (50 percent are index/diversified traders and 27 percent are value/fundamental traders) suggests that momentum strategies are less popular among British institutional investors. Finally, our findings are consistent with Miller's overpricing hypothesis that loser stocks earn low subsequent returns because they were initially overpriced.

V. Over-optimism and momentum profits

Discussions in the previous section confirm that momentum profit originates mainly from underperformance of loser stocks, and the continued underperformance is concentrated in stocks with high short-sale constraints and high divergence in investors' beliefs. One of the possible reasons for such a pattern is that investors remain optimistic about the stocks that have had good performance in the recent past and are reluctant to sell them. This optimism, generally excessive, together with short-sale constraints widens the differences in opinion which leads to overvaluation resulting in subsequent low returns. To test this proposition we examine several conjunctures in which investors display (over)optimism for loser stocks.

5.1 Initial overpricing and momentum profit from loser stocks

To examine whether the observed gradual decline in the price of loser stocks is due to prior overvaluation, we analyse their pre-formation (*t*-17 to *t*-7) period and post-formation (*t*-1 to *t*+23) period returns. Five portfolios are composed on loser stocks' RIO and their average monthly returns are depicted in Figures 3 and 4. The figures show that the lowest RIO portfolio (RIO1, the most difficult to short-sell) had considerable positive returns during the 12 months prior to the formation period. This is followed by slightly higher than zero returns for RIO2 portfolio. These results, combined with the results in the previous section that momentum profits can only be earned from the lowest two RIO quintiles, confirm that loser stocks characterised with short-sale constraints are initially overpriced. The 24 month holding period return reveals that the market eventually corrects for the mispricing. This evidence is consistent with the predictions of behavioural models of Daniel et al. (1998), and

Hong and Stein (1999) that momentum profit is caused by initial overreaction and a long-run price reversal.

5.2 Analysts' optimism and momentum profit

Extant literature on the quality of analysts' earnings forecasts shows that their forecasts are generally optimistic. In this section, we examine whether analysts' optimism is more pronounced for stocks with short-sale constraints and whether this contributes to momentum profits. Analysts' optimism (Opt) is obtained from equation (3). We perform a two dimensional analysis. First, the stocks are grouped into three portfolios based on their previous quarter's RIO. Second, stocks in each RIO portfolio are then grouped again into three portfolios on their analysts' optimism (Opt) for three months (t-10 to t-8) prior to the formation period (t-7 to t-2). Finally, stocks within each element of the matrix (RIO x Opt) are then allocated into three further portfolios on the basis of their return performance during the formation period (t-7 to t-2). Portfolio P1 contains the worst performing 30 percent stocks, P2 includes the middle 40 percent stocks, and P3 includes the best performing 30 percent stocks. The holding period (t to t+5) returns (raw) of these portfolios are reported in Table 5. The results reconfirm that momentum profits are mostly concentrated within the lowest RIO portfolios of loser stocks. The table further reveals that for each RIO portfolio, momentum returns decline monotonically with the decline in analysts' optimism. These results confirm that momentum profit comes from the stocks that had initial over optimism.

5.3 Good news, investors' over confidence and momentum profit

It is also possible that increased investor attention or visibility can promote optimism in share prices when agents differ in opinion and there are limits to arbitrage. This is feasible when optimistic investors can buy but only a few pessimists are able to sell due to short-sale constraints. For this reason, stocks with low institutional share ownership (due to short-sale constraints) are more likely to under react to bad news and over react to good news. As described in section 3.6 we measure good news according to a 52-week high price.

Stocks are first grouped into quintiles on previous quarter's residual institutional ownership (RIO). Next, stocks belonging to each RIO portfolio are divided into five groups in a three month period (*t*-10 to *t*-8) of their 52-week high (H) prior to the first day of the formation period (*t*-7 to *t*-2). The 52-week high is calculated as $P_{i,t\text{-}8}/High_{i,t\text{-}8}$, where $P_{i,t\text{-}8}$ is the price of stock *i* at the end of month *t*-8 and $High_{i,t\text{-}8}$ is the highest price of stock *i* during the 12 month period ending the last day of month *t*-8. Finally, stocks belonging to each element of the (RIO x H) matrix are grouped into three portfolios on their formation period price performance. They are P1 (the worst performing 30 percent stocks), P2 (the middle 40 percent stocks), and P3 (the best performing 30 percent stocks). Momentum profits from these portfolios (Table 6) reconfirm that they are most pronounced at the lowest two RIO quintiles, and are driven by loser stocks. Additionally, the momentum profits decline across 52-week high quintiles for each RIO quintiles. This suggests that the stocks that contribute to momentum profits (losers) initially stand at their 52-week high performance.

Overall, the findings of this section are consistent with the prediction that return continuation on loser stocks are most pronounced with low institutional ownership (high short-sale constraints) and prior good performance. The results show that stocks with high past returns, high optimism in analysts' EPS forecasts, and at their 52-week high performance provide an environment in which unsophisticated investors accelerate their confidence level, and leads to excessive optimism about the firm and subsequent momentum profits.

5.4 Cross-sectional regressions

Results discussed in previous sections establish the facts that momentum profits come from loser stocks, difficult-to-short stocks, initially overpriced stocks and stocks with higher divergence in investors' opinion. To allow for interaction between the factors that are potentially responsible for the momentum anomaly, we model momentum profits as a function of various factors as in equation (5). It also serves as a robustness check on the methodology of two/three dimensional analysis applied in previous sections.

$$RET_{i,p,t} = \alpha + \beta_1 PR_{i,m,t} + \beta_2 RIO_{i,t} + \beta_3 VO_{i,t} + \beta_4 Disp_{i,t} + \beta_5 Opt_{i,t} + \beta_6 52\text{-}high_{i,t} + \varepsilon_t \quad (5)$$

Where, *RET* is the average monthly return over the n months (n = 3, 6, 9, 12) holding periods subsequent to the current month t. *PR* is the average monthly returns over the m months formation period (m = 3, 6, 9, 12) prior to the current month t. *RIO* is the previous quarter's residual institutional ownership at month t. *VO* is the three months' trading volume prior to the first day of the formation period. *Disp* is the three months' dispersion in analysts' EPS forecasts prior to the first day of the formation period. *Opt* is the analysts' optimism three months prior to the first day of the formation period. *52-high* (a measure of goods news) is calculated as the price of stock *i* at the end of month *t*-1 over the highest price of stock *i* during the 12 month period that ends on the last day of month *t*-1. Cross-sectional regressions are estimated for each month *t* from January 1993 to December 2002. The coefficient estimates reported in Table 7 are the time-series averages of the monthly estimates. Table 7 also records the distribution of the coefficients. T-statistics are based on Newey-West autocorrelation consistent standard errors.

Results show that the coefficients of the prior returns (*PR*) for the (3 x 3) and (6 x 6) strategies are statistically significant suggesting strong evidence of momentum on the cross-section of individual stocks returns. In addition, the coefficient of *PR* for the (9 x 9) strategy is also marginally significant (at 10 percent). However, the coefficient of *PR* for the (12 x 12) strategy is insignificant indicating that long-term momentum trading strategies do not generate significant profits. This supports the evidence documented in the extant literature that momentum profit is strong over the medium term horizon and becomes weaker over the long horizon.

Consistent with the discussions in previous sections, evidence from cross-sectional regressions also shows that momentum profits are high when the divergence in investors' opinion (measured by trading volume) is high[22]. Furthermore, the coefficients of *RIO* are negative and significant for (3 x 3) and (9 x 9) strategies. However, its coefficients for the (6 x 6) and (12 x 12) strategies are insignificant. Hence, our cross-sectional regression analysis confirms our previous results that momentum profits are most pronounced when divergence in investors' opinion are high and short-sale constraints are binding. Moreover, momentum profit becomes weaker as the investment horizon increases. The coefficients of good news measure

[22] An alternative measure of dispersion in investors' opinion, the dispersion in analysts' EPS forecast, however, does not have a significant effect on momentum profits. This might be because the relationship between dispersion in investors' opinion and momentum profits is contaminated by trading volume.

(52-week high) decrease monotonically with the horizons of momentum strategies. They are significant for (3 x 3) and marginally significant for (6 x 6) strategies. This indicates that the under-reaction to short term and medium term news helps to explain part of momentum profits.

It is also possible that momentum profits identified earlier are simply a manifestation of a risk premium. Therefore, we repeat the cross-sectional regression of risk-adjusted momentum profits as in equation (6)

$$(6) \qquad R^*_{i,p,t} = \alpha + \beta_1 PR_{i,m,t} + \beta_2 RIO_{i,t} + \beta_3 VO_{i,t} + \beta_4 Disp_{i,t} + \beta_5 Opt_{i,t} + \beta_6 52\text{-}high_{i,t} + \varepsilon_t$$

Where, R* is the unpredicted component ($\alpha + \varepsilon_t$) of time series equation (7) in the framework of Fama-French three factor model for n months (n = 3, 6, 9, 12) holding period subsequent to the current month t. *PR*, *RIO*, *VO*, *Disp*, *Opt*, and *52-high* are as defined in equation (5).

$$(7) \qquad R_{i,t} = \alpha + \beta_{Mkt}(R_{Mkt} - R_F)_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \varepsilon_t$$

$R_{i,t}$ is the return of stock i at time t, R_{Mkt} is market return (FTSE All share index), R_F is risk-free rate measured by return on three month Treasury bills, SMB and HML are small minus big, and high minus low as defined in Fama and French (1996). Results presented in Table 8 confirm that the adjustment for risk using the three-factor model does not alter our earlier conclusion that momentum profits are high when divergence of opinion is high and short-selling is difficult. Moreover, our results suggest that under-reaction to short-term and medium term news is most pronounced when momentum profits are high.

VI. Conclusions

Extensive evidence on the persistence of momentum profits has challenged the rational expectation-based predictions of modern finance theory, yet its causes and exploitability are unknown. To fill this gap, we examine three issues. They are: (a) what are the possible sources of momentum profits?; (b) to what extent are momentum profits linked to limits to arbitrage and divergence in opinion? and; (c) are momentum profits exploitable? More specifically, following the predictions of Miller (1977) we examine whether stocks characterised with limits to arbitrage and high divergence in investors' beliefs contribute to momentum profits. Several conclusions emerge. We find that momentum profits come from loser stocks. There is strong evidence of a positive relationship between short-sale constraints and the magnitude of momentum profits. The known risk factors cannot explain the momentum profits. Therefore, our results support Miller's (1977) view that stocks that are subject to both short-sale constraints and high divergence in opinion are initially overvalued and generate low subsequent returns. Loser stocks that were initially overpriced earn low subsequent returns. We also find that investors' persistent optimism in loser stocks is due to perceived good signals about the stock in the recent past. This excessive optimism together with short-sale constraints widens the differences in opinion, leading to overvaluation and therefore low subsequent returns.

The findings of this paper have several implications. First, momentum profits are not exploitable as these are generated primarily by loser stocks that are costly or impossible to sell short. Second, the investors' inability to short-sell loser stocks defeats the original theme of momentum trading that argues for a self-financing hedge portfolio. Third, the persistence in momentum profits is caused by limits to arbitrage rather than investors under-reacting to firm-specific information. Finally, our results support the view that momentum profit results primarily from mispricing due to limits to arbitrage and divergence in opinion as theorised in Miller (1977) and, hence, it is not a compensation for bearing risks.

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Table 1: Raw Returns by Price Momentum and Short-sale Constraints

Average monthly raw returns (percent) of portfolios composed on price momentum and three measures of short-sale constraints are reported. At the end of each month *t*, all stocks are allocated into five price portfolios (P1, P2,…, P5) based on their returns during the six month formation-period (*t*-7 to *t*-2). Stocks in each price portfolios are grouped into five further portfolios for each measure of short-sale constraints. The measures of short-sale constraints are: (a) previous quarter's residual institutional ownership (RIO), Panel A; firm size (S), Panel B; and the presence of exchange-traded options and/or futures, Panel C. RIO is the residual of equation (2). Firm size (S) is measured my market capitalisation. All portfolios are equally weighted. The position is held for six-months (*t* to *t*+5). *T*-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *(**) Denotes significance at the 5(10) percent level. The sample period is January 1993 to December 2002.

Panel A: Residual Institutional Ownership (RIO)

	RIO1 (Low)	RIO2	RIO3	RIO4	RIO5 (High)	RIO1– RIO5
P1 (Loser)	-1.81	-1.64	-1.27	-1.45	-1.16	-0.65 (-1.80**)
P2	-0.99	-0.98	-0.91	-1.17	-0.96	-0.02 (-0.07)
P3	-0.87	-1.20	-0.71	-1.29	-0.93	0.07 (0.20)
P4	-0.58	-0.60	-0.65	-0.85	-0.72	0.14 (0.41)
P5(Winner)	0.00	-0.38	-0.45	-0.70	-0.64	0.64 (1.53)
P5 – P1	1.81 (4.98*)	1.26 (3.24*)	0.83 (2.01*)	0.76 (1.85)	0.52 (1.23)	1.30 (3.79*)

Panel B: Size (S)

	S1 (Low)	S2	S3	S4	S5 (High)	S1 – S5
P1 (Loser)	-2.53	-2.24	-1.92	-1.79	-1.33	-1.20 (-2.40*)
P2	-0.73	-1.24	-1.82	-1.44	-0.91	0.18 (0.51)
P3	-0.52	-0.75	-1.00	-0.89	-0.60	0.08 (0.28)
P4	-0.15	-0.31	-0.39	-0.40	-0.23	0.08 (0.29)
P5(Winner)	-0.16	-0.23	-0.27	-0.43	-0.07	-0.09 (-0.24)
P5 – P1	2.37 (5.13*)	2.01 (5.27*)	1.64 (3.79*)	1.37 (2.94*)	1.26 (3.00*)	1.11 (2.88*)

Panel C: Individual options and futures

	Without options and futures = 1	With options and/or futures = 0	1 - 0
P1 (Loser)	-2.14	-0.47	-0.35 (-1.09)
P2	-0.78	0.13	-0.91 (-3.25*)
P3(Winner)	-0.17	0.18	-2.01 (-3.61*)
P3 – P1	1.97 (4.86*)	0.65 (1.63)	

Table 2: Excess Returns by Price Momentum and Short-sale Constraint

Average monthly excess returns (percent) of portfolios composed on price momentum and short-sale constraint are reported. Short-sale constraint is measured by the RIO, the residual of equation (2). At the end of each month *t*, all stocks are allocated into five price portfolios (P1, P2,…, P5) based on their returns during the six month formation-period (*t*-7 to *t*-2). Stocks in each price portfolios are grouped into five further portfolios on each bench-mark adjusted returns. Bench-marks adjusted excess returns are estimated as: *first*, individual stock returns are adjusted for the market (FTSE All share index) returns, Panel A; *second*, individual stock returns are adjusted for Fama-French three factors, Panel B; and *third*, individual stock returns are adjusted for industry returns, Panel C. Industry portfolios are formed using the Datastream's industry-classification (data type: INDC3). All portfolios are equally weighted. The position is held for six-months (*t* to *t*+5). *T*-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *(**) Denotes significance at the 5(10) percent level. The sample period is January 1993 to December 2002.

Momentum	Residual Institutional Ownership					
	RIO1 (Low)	RIO2	RIO3	RIO4	RIO5 (High)	RIO1 – RIO5
Panel A: Market Adjusted Returns						
P1 (Loser)	-2.18	-1.92	-1.68	-1.43	-1.23	-0.96 (-2.35*)
P2	-1.24	-1.01	-0.98	-0.65	-0.59	-0.66 (-2.72*)
P3	-0.74	-1.01	-0.42	-0.36	-0.08	-0.66 (-3.12*)
P4	-0.40	-0.42	-0.27	-0.21	-0.07	-0.33 (-1.70**)
P5(Winner)	-0.09	-0.13	-0.03	0.14	0.01	-0.10 (-0.37)
P5 – P1	2.09 (6.20*)	1.79 (5.77*)	1.65 (5.09*)	1.57 (4.17*)	1.24 (3.51*)	0.85 (2.17*)
Panel B: Three-factor Adjusted Returns						
P1 (Loser)	-2.26	-2.26	-1.69	-1.93	-1.66	-0.60 (-1.81**)
P2	-1.40	-1.41	-1.32	-1.61	-1.44	0.04 (0.47)
P3	-1.28	-1.58	-1.11	-1.71	-1.32	0.04 (0.20)
P4	-1.01	-1.01	-1.02	-1.30	-1.14	0.13 (0.42)
P5(Winner)	-0.42	-0.66	-0.81	-1.08	-0.98	0.56 (1.55)
P5 – P1	1.84 (5.01*)	1.61 (3.82*)	0.88 (2.03*)	0.85 (1.86**)	0.68 (1.24)	1.16 (3.79*)
Panel C: Industry Adjusted Returns						
P1 (Loser)	-1.39	-1.35	-1.18	-0.59	-0.31	-1.08 (-4.54*)
P2	-0.08	-0.22	-0.18	-0.38	-0.37	0.28 (2.10*)
P3	0.36	0.14	0.34	0.06	0.08	0.28 (2.04*)
P4	0.59	0.45	0.33	0.27	0.27	0.32 (3.17*)
P5(Winner)	0.59	0.38	0.28	0.21	0.10	0.48 (2.37*)
P5 – P1	1.98 (5.09*)	1.73 (6.47*)	1.45 (3.66*)	0.80 (1.92**)	0.41 (1.42)	1.57 (5.72*)

Table 3: Momentum Returns by Short-sale Constraint and Divergence in Opinion (Trading Volume)

Average monthly raw returns (percent) of portfolios composed on short-sale constraint (RIO) and divergence in investors' opinion measured by trading volume (VO) are reported. Short-sale constraint is measured by the RIO, the residual of equation (2). Trading volume is measured as the ratio of the number of shares traded to the number of shares outstanding. First, at the end of each month *t*, all stocks are allocated into five RIO portfolios. Second, stocks in each RIO portfolios are grouped into 3 further portfolios on their trading volume 3-months prior to the first day of the formation period (*t*-7 to *t*-2). Portfolio VO1 contains lowest 30 percent trading volume stocks, portfolio VO2 contains the middle 40 percent trading volume stocks, and portfolio VO3 includes the highest 30 percent trading volume stocks. All stocks belonging to each element of the (RIO x VO) matrix are then grouped into three portfolios. The portfolios are P1 (the worst performing 30 percent), P2 (the middle 40 percent), and P3 (the best performing 30 percent). The position is held for six-months (*t* to *t*+5). All portfolios are equally weighted. *T*-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *(**) Denotes significance at the 5(10) percent level. The sample period is January 1993 to December 2002.

	Trading Volume Portfolios			
RIO Portfolios	**VO3 (High)**	**VO2**	**VO1 (Low)**	**VO3 – VO1**
RIO1 (Low)	P3 = 0.71 P1 = -2.06 P3 – P1 = 2.77 (5.32*)	P3 = 0.65 P1 = -1.78 P3 – P1 = 2.43 (5.19*)	P3 = 0.09 P1 = -1.91 P3 – P1 = 2.00 (4.11*)	P3 – P1 = 0.77 (1.28)
RIO2	P3 = 0.78 P1 = -1.81 P3 – P1 = 2.58 (4.92*)	P3 = 0.37 P1 = -1.75 P3 – P1 = 2.11 (3.74*)	P3 = -0.41 P1 = -2.03 P3 – P1 = 1.62 (3.08*)	P3 – P1 = 0.97 (1.60)
RIO3	P3 = -0.03 P1 = -1.24 P3 – P1 = 1.21 (2.55*)	P3 = -0.01 P1 = -0.82 P3 – P1 = 0.81 (1.36)	P3 = -0.28 P1 = -0.84 P3 – P1 = 0.57 (1.09)	P3 – P1 = 0.64 (1.09)
RIO4	P3 = 0.20 P1 = -0.37 P3 – P1 = 0.57 (1.07)	P3 = 0.23 P1 = -0.42 P3 – P1 = 0.65 (1.20)	P3 = -0.29 P1 = -0.77 P3 – P1 = 0.48 (0.94)	P3 – P1 = 0.09 (0.14)
RIO5 (High)	P3 = 0.01 P1 = -0.37 P3 – P1 = 0.38 (0.78)	P3 = -0.10 P1 = -0.66 P3 – P1 = 0.56 (1.23)	P3 = -0.30 P1 = -0.79 P3 – P1 = 0.49 (0.86)	P3 – P1 = -0.11 (-0.19)
RIO1 – RIO5	P3 – P1 = 2.40 (3.79*)	P3 – P1 = 1.87 (3.99*)	P3 – P1 = 1.51 (2.76*)	

Table 4: Momentum Returns by Short-sale Constraint and Divergence in Opinion (Dispersion in Analysts' EPS Forecasts)

Average monthly raw returns (percent) of portfolios composed on short-sale constraint and divergence in opinion are reported. Short-sale constraint is measured by the RIO, the residual of equation (2). Divergence in opinion on each stock is measured by the standard deviation in EPS forecasts made in 3-months prior to the formation period scaled by the stock price per share at the beginning of the month of forecast. First, at the end of each month *t*, all stocks are allocated into three RIO portfolios. Second, stocks in each RIO portfolios are grouped into 3 further portfolios on divergence in opinion (Disp). All stocks belonging to each element of the (RIO x Disp) matrix are then grouped into three portfolios. The portfolios are P1 (the worst performing 30 percent), P2 (the middle 40 percent), and P3 (the best performing 30 percent). The position is held for six-months (*t* to *t*+5). All portfolios are equally weighted. *T*-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *(**) Denotes significance at the 5(10) percent level. The sample period is January 1993 to December 2002.

	Dispersion in Analysts' EPS Forecasts portfolios			
RIO Portfolios	**Disp3 (High)**	**Disp2**	**Disp1 (Low)**	**Disp3 – Disp1**
RIO1 (Low)	P3 = -0.20 P1 = -2.49 P3 – P1 = 2.28 (4.12*)	P3 = -0.32 P1 = -2.04 P3 – P1 = 1.72 (2.99*)	P3 = -0.15 P1 = -1.72 P3 – P1 = 1.57 (2.82*)	P3 – P1 = 0.59 (0.81)
RIO2	P3 = -0.08 P1 = -1.54 P3 – P1 = 1.45 (2.89*)	P3 = -0.48 P1 = -1.54 P3 – P1 = 1.06 (1.89**)	P3 = -0.67 P1 = -1.71 P3 – P1 = 1.04 (1.77**)	P3 – P1 =0.38 (0.56)
RIO3 (High)	P3 = -0.69 P1 = -1.00 P3 – P1 = 0.31 (0.43)	P3 = -0.22 P1 = -0.55 P3 – P1 = 0.34 (0.63)	P3 = -0.81 P1 = -0.87 P3 – P1 = 0.06 (0.10)	P3 – P1 =0.25 (0.34)
RIO1 – RIO3	P3 – P1 = 1.97 (2.66*)	P3 – P1 = 1.07 (1.45)	P3 – P1 = 1.50 (2.00*)	

Table 5: Momentum Returns by Short-sale Constraint and Investors' Optimism

Average monthly raw returns (percent) of portfolios composed on short-sale constraints and Investors' optimism are reported. Short-sale constraint is measured by RIO, the residual of equation (2). Investors' optimism on each stock is measured by the analysts' consensus EPS forecast (median) minus actual EPS scaled by stock price. First, at the end of each month *t*, all stocks are allocated into three RIO portfolios. Second, stocks in each RIO portfolios are grouped into three further portfolios on investors' optimism (Opt). All stocks belonging to each element of the (RIO x Opt) matrix are then grouped into three portfolios. The portfolios are P1 (the worst performing 30 percent), P2 (the middle 40 percent), and P3 (the best performing 30 percent). The position is held for six-months (*t* to *t*+5). All portfolios are equally weighted. *T*-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *(**) Denotes significance at the 5(10) percent level. The sample period is January 1993 to December 2002.

RIO Portfolios	Investors' Optimism Portfolios Opt3 (High)	Opt2	Opt1 (Low)	Opt3 – Opt1
RIO1 (Low)	P3 = -0.95 P1 = -2.66 P3 – P1 = 1.71 (2.45*)	P3 = -0.33 P1 = -1.65 P3 – P1 = 1.32 (2.30*)	P3 = -0.41 P1 = -1.56 P3 – P1 = 1.15 (2.28*)	P3 – P1 = 0.56 (0.87)
RIO2	P3 = -0.62 P1 = -1.78 P3 – P1 = 1.16 (1.91**)	P3 = -0.87 P1 = -1.74 P3 – P1 = 0.87 (1.69**)	P3 = -0.21 P2 = -0.89 P3 – P1 = 0.68 (1.53)	P 3 – P1 = 0.48 (0.92)
RIO3 (High)	P3 = -1.04 P1 = -1.50 P3 – P1 = 0.45 (0.89)	P3 = -0.27 P1 = -0.31 P3 – P1 = 0.04 (0.09)	P3 = -0.80 P1 = -0.71 P3 – P1 = -0.09 (-0.20)	P3 – P1 = 0.54 (0.96)
RIO1 – RIO3	P3 – P1 = 1.26 (1.84**)	P3 – P1 = 1.28 (2.27*)	P3 – P1 = 1.24 (2.38*)	

Table 6: Momentum Returns by Short-sale Constraint and Good News

Average monthly raw returns (percent) of portfolios composed on short-sale constraints and availability of good news are reported. Short-sale constraint is measured by the RIO, the residual of equation (2). First, at the end of each month *t*, all stocks are allocated into five RIO portfolios. Second, stocks in each RIO portfolios are grouped into five further portfolios on good news (H). Good news of each stock is measured with $P_{i,t-1}$/ $High_{i,t-1}$, where $P_{i,t-1}$ is the price of stock *i* at the end of month *t*-1 and $High_{i,t-1}$ is the highest price of stock *i* during the 12-month period ending on the last day of month *t*-1. All stocks belonging to each element of the (RIO x H) matrix are then grouped into three portfolios. The portfolios are P1 (the worst performing 30 percent), P2 (the middle 40 percent), and P3 (the best performing 30 percent). The position is held for six-months (*t* to *t*+5). All portfolios are equally weighted. *T*-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *(**) Denotes significance at the 5(10) percent level. The sample period is January 1993 to December 2002. RET12 is the mean raw returns for 12 months after the month *t*. T-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *(**) Denotes significance at the 5(10) percent level. The sample period is January 1993 to December 2002.

	52-week high Portfolios					
RIO Portfolios	**H5 (High)**	**H4**	**H3**	**H2**	**H1 (Low)**	**H5 – H1**
RIO1 (Low)	P3 = -0.79 P1 = -3.39 P3 – P1 = 2.61 (4.49*) RET12 = -2.08	P3 = -0.43 P1 = -2.68 P3 – P1 = 2.25 (4.40*) RET12 = -1.43	P3 = 0.42 P1 = -1.78 P3 – P1 = 2.20 (4.90*) RET12 = -0.74	P3 = 0.26 P1 = -1.39 P3 – P1 = 1.65 (3.64*) RET12 = -0.62	P3 = 0.34 P1 = -1.34 P3 – P1 = 1.69 (3.64*) RET12 = -0.42	P3 – P1 = 0.92 (1.73**)
RIO2	P3 = -0.53 P1 = -2.88 P3 – P1 = 2.34 (4.01*) RET12 = -1.66	P3 = -0.45 P1 = -2.73 P3 – P1 = 1.40 (3.81*) RET12 = -1.34	P3 = -0.53 P1 = -2.27 P3 – P1 = 1.74 (3.05*) RET12 = -1.21	P3 = -0.40 P1 = -1.67 P3 – P1 = 1.27 (2.45*) RET12 = -0.84	P3 = 0.43 P1 = -0.77 P3 – P1 = 1.20 (2.59*) RET12 = -0.28	P3 – P1 = 1.15 (2.12*)
RIO3	P3 = -0.37 P1 = -1.88 P3 – P1 = 1.51 (2.86*) RET12 = -1.22	P3 = 0.01 P1 = -1.49 P3 – P1 = 1.50 (3.08*) RET12 = -0.75	P3 = -0.31 P1 = -1.56 P3 – P1 = 1.25 (2.37*) RET12 = -0.87	P3 = -0.40 P1 = -1.82 P3 – P1 = 1.41 (2.73*) RET12 = -0.89	P3 = -0.02 P1 = -1.27 P3 – P1 = 1.25 (2.65*) RET12 = -0.46	P3 – P1 = 0.26 (0.47)
RIO4	P3 = 0.26 P1 = -0.81 P3 – P1 = 1.07 (2.24*) RET12 = -0.31	P3 = -0.08 P1 = -1.04 P3 – P1 = 0.96 (2.11*) RET12 = -0.47	P3 = -0.15 P1 = -0.64 P3 – P1 = 0.48 (1.05) RET12 = -0.58	P3 = -0.12 P1 = -0.38 P3 – P1 = 0.26 (0.64) RET12 = -0.41	P3 = 0.20 P1 = -0.16 P3 – P1 = 0.36 (0.86) RET12 = -0.13	P3 – P1 = 0.71 (1.63)
RIO5 (High)	P3 = -0.58 P1 = -1.18 P3 – P1 = 0.60 (1.27) RET12 = -0.80	P3 = -0.24 P1 = -0.73 P3 – P1 = 0.49 (1.03) RET12 = -0.50	P3 = -0.33 P1 = -0.39 P3 – P1 = 0.06 (0.13) RET12 = -0.43	P3 = -0.33 P1 = -0.48 P3 – P1 = 0.15 (0.33) RET12 = -0.43	P3 = 0.04 P1 = -0.08 P3 – P1 = 0.13 (0.28) RET12 = -0.06	P3 – P1 = 0.48 (0.88)
RIO5 – RIO1	P3 – P1 = 2.00 (3.66*)	P3 – P1 = 1.76 (4.35*)	P3 – P1 = 2.14 (4.35*)	P3 – P1 = 1.50 (3.36*)	P3 – P1 = 1.56 (2.98*)	

Table 7: Cross-sectional regression analysis

Average coefficients and their distribution of cross-sectional regression coefficients (equation (5)) are presented.

(5) $RET_{i,\,p,\,t} = \alpha + \beta_1 PR_{i,\,m,\,t} + \beta_2 RIO_{i,\,t} + \beta_3 VO_{i,\,t} + \beta_4 Disp_{i,\,t} + \beta_5 Opt_{i,\,t} + \beta_6 52\text{-}high_{i,\,t} + \varepsilon_t$

RET is the average monthly return over n-months (n = 3, 6, 9, 12) holding periods subsequent to the current month t. *PR* is the average monthly returns over the m-months formation period (m = 3, 6, 9, 12) prior to the current month t. *RIO* is the previous quarter's residual institutional ownership at month t. *VO* is the 3-months' trading volume prior to the first day of the formation period. *Disp* is 3-month period of analysts' forecasts dispersion prior to the first day of the formation period. *Opt* is the 3-month period of analysts' optimism prior to the first day of the formation period. *52-high* is calculated as the price of stock *i* at the end of month *t*-1 over the highest price of stock *i* during the 12-month period that ends on the last day of month *t*-1. T-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *(**) Denotes significance at the 5(10) percent level. R^2 is the time-series average of the monthly adjusted R^2. All coefficients are multiplied by 100. The (m x n) strategy refers to m month formation period and p month holding period. The sample covers January 1993 to December 2002.

	Intercept	PR	RIO	VO	Disp	Opt	52-high	Adj R^2(%)
				Panel A: (3 x 3) strategy				
Mean	-0.8150	8.9766	-0.0613	0.0001	2.4152	8.4599	14.904	8.30
(T-stat)	(-1.58)	(2.27*)	(-1.88**)	(3.53*)	(0.46)	(0.88)	(2.09*)	
Median	-0.6327	5.3985	-0.0540	0.0001	-0.9803	0.0000	15.807	
Std. Dev	3.3022	27.552	0.3326	0.0002	39.225	74.640	42.862	
Min	-11.977	-54.685	-0.9880	-0.0004	-73.740	-127.21	-94.560	
Max	5.3449	106.09	1.0839	0.0010	120.28	663.91	132.68	
N	104	104	104	104	104	104	104	
				Panel B: (6 x 6) strategy				
Mean	-1.8336	14.304	-0.0158	0.0002	-1.0044	4.5626	11.356	11.11
(T-stat)	(-4.06*)	(2.78*)	(-0.38)	(4.40*)	(-0.33)	(1.20)	(1.83**)	
Median	-1.4192	10.226	-0.0375	0.0001	-1.8814	0.0000	10.614	
Std. Dev	2.4948	34.843	0.2844	0.0002	22.537	24.645	41.853	
Min	-8.7532	-68.468	-0.5770	-0.0002	-109.71	-85.034	-85.854	
Max	2.8100	130.91	1.1160	0.0010	49.698	129.39	139.48	
N	101	101	101	101	101	101	101	
				Panel C: (9 x 9) strategy				
Mean	-0.9316	12.526	-0.0463	0.0001	2.3297	3.5903	1.2330	9.38
(T-stat)	(-2.78*)	(1.84**)	(-1.83**)	(5.90*)	(0.58)	(0.73)	(0.15)	
Median	-0.9082	8.0955	-0.0011	0.0001	-2.1292	0.0000	4.1388	
Std. Dev	1.8306	44.084	0.1902	0.0001	24.567	27.177	50.512	
Min	-5.2079	-116.26	-0.4898	-0.0002	-51.152	-43.379	-131.09	
Max	2.8170	109.44	0.5527	0.0004	93.745	144.58	159.65	
N	98	98	98	98	98	98	98	
				Panel D: (12 x 12) strategy				
Mean	-1.0190	10.783	-0.0380	0.0001	1.0672	-1.0419	---	6.75
(T-stat)	(-3.39*)	(-1.58)	(-1.33)	(6.05*)	(0.32)	(-0.23)		
Median	-0.8038	8.4636	-0.0349	0.0001	-1.3940	0.0000	---	
StdDev	1.5639	34.620	0.1929	0.0001	18.977	22.540	---	
Min	-4.7704	-66.510	-0.5370	-0.0002	-52.084	-47.407	---	
Max	2.0994	114.85	0.4845	0.0005	54.622	90.345	---	
N	92	92	92	92	92	92	---	

Table 8: Cross-sectional regression analysis of risk adjusted returns

Average coefficients of cross-sectional regression (equation (6)) are presented.

(6) $$R^*_{i,p,t} = \alpha + \beta_1 PR_{i,m,t} + \beta_2 RIO_{i,t} + \beta_3 VO_{i,t} + \beta_4 Disp_{i,t} + \beta_5 Opt_{i,t} + \beta_6 52\text{-}high_{i,t} + \varepsilon_t$$

Where, R^* is the unpredicted component ($\alpha+\varepsilon_t$) of time series equation (7) for p-months (p = 3, 6, 9, 12) holding period subsequent to the current month t. *PR, RIO, VO, Disp, Opt* and *52-high* are as defined in equation (5)/Table 7.

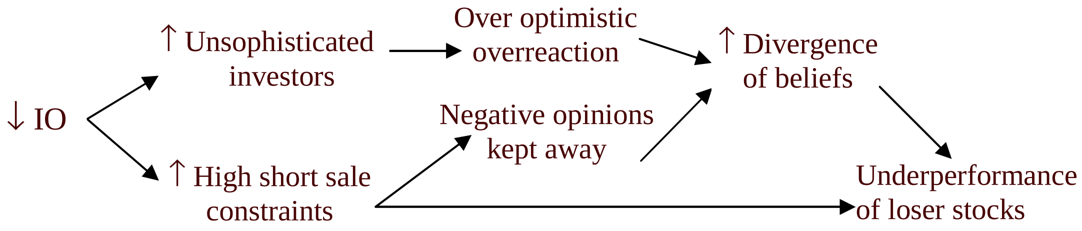
(7) $$R_{i,t} = \alpha + \beta_{Mkt}(R_{Mkt} - R_F)_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \varepsilon_t$$

$R_{i,t}$ is the return of stock i at time t, R_{Mkt} is market return (FTSE All share index), R_F is risk-free rate measured by return on three-month Treasury bills, SMB and HML are small minus big, and high minus low as defined in Fama and French (1996).

T-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *(**) Denotes significance at the 5(10) percent level. R^2 is the time-series average of the monthly adjusted R^2. All coefficients are multiplied by 100. The (n x m) strategy refers to n-month formation period and m-month holding period.

Strategies (n x m)	Intercept (T-stat)	PR (T-stat)	RIO (T-stat)	VO (T-stat)	Disp (T-stat)	Opt (T-stat)	52-high (T-stat)	Adj R^2(%)
(3 x 3)	-1.3315 (-7.35*)	6.6366 (2.14*)	-0.0771 (-2.12*)	0.0001 (4.46*)	-3.1265 (-0.80)	17.4464 (1.32)	11.3841 (2.02*)	5.22
(6 x 6)	-2.2437 (-12.30*)	21.2241 (2.19*)	-0.0132 (-0.44)	0.0001 (5.94*)	-4.3483 (-1.49)	2.7461 (-0.82)	59.4141 (9.94*)	16.92
(9 x 9)	-1.2021 (-8.02*)	16.8905 (2.83*)	-0.0360 (-0.13)	0.0001 (5.72*)	-5.3289 (-1.56)	3.2628 (0.86)	-3.4324 (-0.61)	4.74
(12 x 12)	-0.8979 (-3.95*)	23.4293 (1.62)	-0.063 (-0.22)	0.0001 (4.31*)	-5.1917 (-1.74**)	-0.2979 (-0.07)	-12.6819 (-0.91)	4.20

Figure 1:The potential sources of momentum profits



Note: IO represents Institutional Ownership

Figure 2: Short-sale Constraints and Momentum Profits

This figure represents the estimates reported in Table 1 (Panel A). See Table 1 for further details and method of estimation.

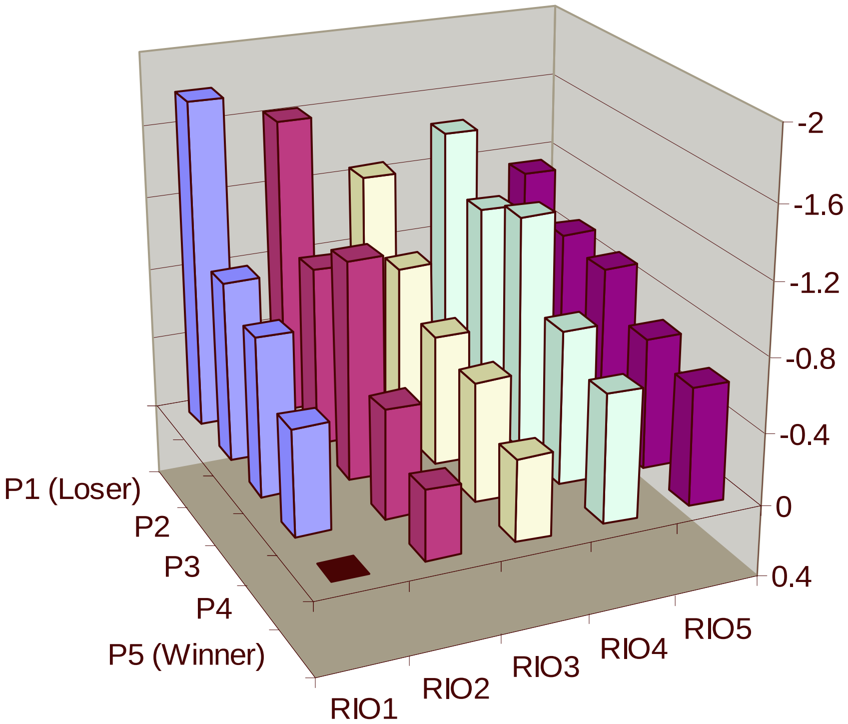


Figure 3: Cumulative momentum returns of portfolios of loser stocks under five quintile groups of short-sale constraints

At the end of each month *t*, stocks are allocated into quintile based on their six-month formation-period (*t*-7 to *t*-2) returns and by the end of the previous quarter residual institutional ownership (RIO). RIO is obtained from a cross-sectional regression equation (2). Quintile portfolios are formed monthly by equally weighting the stocks in the quintile. The time scales are 12-month prior formation period (1-12), formation period (13-18), and 24-month post formation period (19-42).