Are contrarian investment strategies profitable in the London Stock Exchange? Where do these profits come from?

Antonios Antoniou
Centre for Empirical Research in Finance,Department of Economics and Finance,
University of Durham, 23-26 Old Elvet, Durham DH1 3HY, UK.

Emilios C. Galariotis*
Centre for Empirical Research in Finance, Department of Economics and Finance,
University of Durham, 23-26 Old Elvet, Durham DH1 3HY, UK.

Spyros I. Spyrou
Athens University of Economics and Business,
Department of Accounting and Finance, Patission 76, 10434, Athens, Greece,

Abstract

Given the lack of evidence in the literature regarding UK short-term contrarian profits and their decomposition, this paper investigates the existence of contrarian profits for the London Stock Exchange (LSE), and decomposes them to sources due to common factors and to firm-specific news, building on the methodology of Jegadeesh and Titman (1995). Furthermore, in view of recent evidence that longer-term contrarian profits in the US are explained by firm characteristics such as size and book-to-market equity, the paper decomposes shorter-term contrarian profits to sources similar to the ones in the Fama and French (1996) three-factor model. For the empirical testing, size-sorted sub-samples that are rebalanced annually are used, and in addition, adjustments for infrequent trading and the Bid-Ask bias are made to the data. The results indicate that contrarian strategies are profitable for UK stocks and more pronounced for extreme market capitalization stocks (smallest – largest); the profits persist even after the sample is adjusted for market frictions, such as infrequent trading and bid-ask bias, and irrespective of whether raw or risk-adjusted returns are used to calculate them. Further tests indicate that the magnitude of the contribution of the delayed reactions to contrarian profits is small, while the magnitude of the contribution of investor overreaction to firm-specific information to profits is far larger (consistent with the findings of Jegadeesh and Titman 1995 for the US).

JEL Classification: G1
Keywords: Overreaction, Delayed reaction, Contrarian Profits, Multi-factor Models

Corresponding author: E. Galariotis, Department of Economics and Finance, University of Durham, 23-26 Old Elvet, Durham DH1 3HY. Emilios.Galariotis@durham.ac.uk

* We would like to thank Phil Holmes and Krishna Paudyal for comments and suggestions on an earlier version of this paper. Financial support from INQUIRE UK is gratefully acknowledged.

1. Introduction

DeBondt and Thaler (1985) have challenged the notions of market efficiency and of rational investor behaviour. More specifically, they find that portfolios that experience negative returns tend to outperform portfolios that experience positive returns for the same period during the subsequent period by about 25%. In other words, stock returns may be predictable, and this may be due to excessive investor optimism and pessimism. Negative serial correlation in returns is well documented in the literature (Fama, 1965), however, these results indicate that return reversals may also be economically significant.

Whilst there is mounting empirical evidence to suggest that contrarian strategies are profitable, there is considerable disagreement as to the sources of these profits. For example, possible explanations are investor overreaction, size-effects, changes in risk, lead-lag effects, behavioural aspects, and microstructure biases. Furthermore, most of the evidence refers to the US market, and much less to other markets such as the UK market. Nonetheless, it is very important to test phenomena that are well documented in the US, using other data (Kryzanowski and Zhang, 1992, Clare and Thomas, 1995).

Thus, this paper investigates the profitability of contrarian strategies and the sources of contrarian profits for the London Stock Exchange[1] (LSE henceforth), a leading global equity market. There are only a handful of studies that examine this issue for

[1] The LSE has been established as a regulated exchange since 1801, and is one of the world's leading markets (Clara Furse, Chief Executive LSE, Annual Report 2002). The main market alone offers trading in 2,238 securities, including 447 overseas issuers from 60 countries. For example, between April 2001 to March 2002, the LSE attracted 66% of all western European IPO's (LSE, Annual Report 2002).

the UK market, most of which examine a number of stock markets simultaneously without focusing solely in the UK. Their evidence (see next section for a discussion) indicates the existence of contrarian profits that may be due to investor overreaction, size, or low-price. None of the UK studies so far however, considers short-term contrarian strategies, or attempts to decompose contrarian profits into sources due to reactions to common and firm-specific factors. However, the identification of the precise source of contrarian profits is very important for the success of such strategies, and furthermore, practitioners have nowadays investment horizons that are not as long-term as these earlier studies assume. To this end, the paper decomposes contrarian profits to sources due to reaction to common factors, overreaction to firm-specific information, and profits not related to the previous two terms.

More specifically, the paper attempts to address the following questions: Is negative serial correlation present in UK stock returns? Can this correlation lead to contrarian profits? Are contrarian profits due to market microstructure biases, such as infrequent trading or bid-ask biases? Are contrarian profits possible once various risk factors are considered? Are contrarian profits due to investor overreaction to firm-specific information or due to reactions to common news? Do market frictions affect the results of the profits' decomposition? Does the choice of a one- or three-factor model affect the results of the decomposition of contrarian profits to various sources?

For the decomposition, the paper builds on the methodology suggested by Jegadeesh and Titman (1995). Jegadeesh and Titman employ a single-factor model, however, motivated from Fama and French (1996), who present a multi-factor explanation of asset pricing anomalies, this paper employs a three-factor model. In addition, size-sorted sub-samples that are annually rebalanced are employed, and the effect of market frictions such as infrequent trading and bid ask bias are considered. To anticipate the results, contrarian strategies appear profitable in the UK; profits persist even after the sample is adjusted for market frictions and irrespective of whether raw or risk-adjusted returns are used to calculate profits. The profits are more pronounced for extreme market capitalization stock portfolios (smallest - highest). In addition, prices do not fully react contemporaneously to factor realizations, but part of the effect is incorporated with a lag. However, the contribution of the delayed reactions to profits is small, in contrast to the contribution of investor overreaction to firm-specific information, which is much larger. The rest of the paper is organised as follows: section 2 discusses the literature, section 3 discusses the data, and section 4 presents contrarian profits. Section 5 discusses the testing methodology, and results are presented in section 6. Section 7 concludes the paper.

2. Contrarian Profits & Overreaction to Information

As mentioned in the introduction, in the mid 1980s, DeBondt and Thaler (1985, 1987) find that US long-term stock returns may be predictable on the basis of past performance. They also find that loser portfolios experience exceptionally large January returns as late as five years after portfolio formation. They argue that equity prices systematically overshoot due to excessive investor optimism and pessimism. Later studies on US stocks indicate that contrarian strategies are also profitable for short-term horizons (Jegadeesh, 1990, Lehman, 1990, Jegadeesh and Titman, 1995). Zarowin (1990) argues that the tendency of losers to outperform winners in the USA may be due to the tendency of losers to be smaller sized firms than winners, i.e. an explanation based on the size-effect (Banz, 1981). Other authors argue that the explanation lies in market frictions such as bid-ask biases and infrequent trading which are not properly accounted for (Conrad and Kaul, 1993); or risk missmeasurement and changes in the equilibrium required returns between the formation and testing periods (Chan, 1988, Ball and Kothari, 1989). There is also a number of studies that attempt to explain return predictability within an overreaction and/or underreaction context employing behavioural models (Barberis, Shleifer, and Vishny, 1997, Amir and Ganzach, 1998).

Lo and MacKinlay (1990) argue that profits from such strategies may be possible even in the absence of return reversals. That is, profits may also arise when the returns of some stocks react faster to information than the returns of other stocks; i.e. the returns of the former lead the returns of the later stocks. Lo and MacKinlay find that such a lead-lag relationship is an important source of profits from contrarian strategies. However, Jegadeesh and Titman (1995) (JT hereafter) suggest that the measure of the contribution of the lead-lag effect to contrarian profits employed in the Lo and MacKinlay study may be misleading, and present a different decomposition. Their results indicate that stock prices (on average) react with a delay to common factors, however, most of the profits are due to firm-specific overreaction (although there is a size-related lead-lag structure).

As regards to the UK market, Poterba and Summers (1988), in a study of 15 markets, find long-term negative serial correlation consistent with contrarian strategies for the UK. Dissanaike (1997) employs long-term contrarian strategies adjusted for risk and finds that not only past losers outperform past winners, but that they are also less risky. Brouwer, Van DerPut and Veld (1997) test value strategies in connection to the overreaction hypothesis for the UK, France, and Germany and find that past losers (based on several accounting ratios) outperform past winners for longer-run strategies. Richards (1997) unveils long-run overreaction profits that are not due to risk or anomalies, using data on 16 markets. Balvers, Wu, and Gilliland (1999) test for long-term contrarian strategies in 18 markets, with results that are positive for mean reversion and consistent with the overreaction hypothesis. Baytas and Cakiki (1999) test the overreaction hypothesis in 7 markets including the UK, using long-term horizons, and obtain positive and significant profits for contrarian portfolios. However, they suggest that the results may be due to a low-price effect or a size-effect. Clare and Thomas (1995), use 1000 randomly selected stocks and find long-term evidence consistent with the overreaction hypothesis, not explained by risk or the January effect. They argue that the results are related to the size-effect; most of the outperforming firms are smaller firms. International evidence on price reversals indicate that the effect is present, among others, in Brazil (DaCosta and Newton, 1994), New Zealand (Bowman and Iverson, 1998), and Finland (only for domestic investors, Grinblatt and Keloharju, 2000).

In summary, there is international empirical evidence to suggest that contrarian strategies are profitable, a fact that directly contradicts the notion of market efficiency in its weak form. However, there is considerable disagreement as to the causes behind such results. Some authors suggest overreaction or underreaction, others suggest a size-effect, changes in risk, microstructure biases, or a lead-lag structure in stock returns. More importantly, as can be seen from the above discussion, there is a lack of evidence on shorter-term contrarian profits and their decomposition for the UK.

3. Data

The paper uses weekly price observations for all stocks listed on the LSE that had at least 260 consecutive observations[2], for the period between December 1984 and September 2000. The FTSE100[3] Price Index is employed as a proxy for the common factor (market portfolio). Returns are continuously compounded, defined as the first difference of the logarithmic price levels, and all data are collected from Datastream International. Table 1, presents descriptive statistics on the number of firms available for each year and the market value of the sample firms. For example, the maximum number of firms is available during 1990 (1645 firms) while the minimum number of firms is encountered in 1985 (1164 firms). The minimum market value of a firm in the sample is below 0.01 million Sterling for years 1989 through 1996, while the maximum market value is for year 2000 (119,814.1 million sterling). Mean market values range from 255.2 million (year 1985) to 1,234.6 million (year 2000).

For the empirical analysis, all stocks available in the sample are used. Stocks are assigned to five sub-samples based on market capitalization (i.e. smallest, small, medium, large, largest firm sub-samples) as follows: every year all available stocks are ranked on the basis of the previous year-end stock market capitalization and subsequently grouped to five sub-samples that each contain 20% of firms.[4] For example, to create the five sub-samples for the year 1997, all 1520 stocks available for that year are sorted according to the last market value of the previous year (1996)

[2] This avoids downward bias of the autocovariance estimates that is known to occur in small samp les.
[3] The FTSE100 index is used because it appears not to be serially correlated according to the Ljung-Box statistic (Probability value: 1st order 0.836 2nd order 0.188, etc), while the FTSE ALL-SHARE INDEX (Probability value: 1st order 0.033, 2nd order: 0.003 etc).

and assigned to one of the five sub-samples, leaving 304 firms in each sub-sample. The procedure is repeated every year, allowing for five size-sorted sub-samples per year, for a period of sixteen years. Tests are then performed on every stock for the whole sample period.

Descriptive return statistics, based on closing prices, for all sample groupings are presented in Table 2 (Panel A). The average weekly return for all stocks is 0.05% with a standard error of 0.017, while the highest mean weekly return is that of the smallest stock sub-sample (0.001). The largest stock sub-sample has the second highest mean weekly return (0.001) and the highest standard error (0.020). However, Kaul & Nimalendran (1990) find that the bid-ask error component explains over 50% (23%) of the small (large) firm variance. Their findings suggest that how prices are measured (e.g. closing prices, bid or ask prices) may affect the empirical results on asset behaviour. For this reason the paper also considers bid prices to compute descriptive statistics and presents them in Panel B: the mean weekly return is much lower (0.0003) and now the smallest, small, and medium stock sub-samples all have negative returns. At the same time the mean return for the large stock sub-sample is virtually unaffected (although its total risk is now much lower) and the return on the largest sub-sample is somewhat reduced. These results suggest that whether one uses closing or bid prices may affect the risk and return characteristics of the assets.

Next, the existence of serial correlation in UK stock returns (closing prices) is investigated, since negative serial correlation could lead to short-run contrarian profits. For example, a contrarian strategy that each period shorts past winners and

[4] When the number of stocks available for a year is such that cannot be divided into portfolios that contain an equal number of stocks, the remaining stock is added to the largest sub-sample. If there is

longs past losers could benefit from first order negative serial correlation in individual stock returns, because this will transform winners to losers and losers to winners, and a contrarian strategy could then deliver profits. Tables 3a and 3b look into three different types of returns following the suggestion of Chopra *et al*. (1992) that the definition of abnormal returns is very important for examining the profitability of contrarian strategies. More specifically, the paper does not only examine raw returns (Panel A) but also examines risk-adjusted returns (Panels B and C), using two methods to account for risk. Risk is first considered to be related to a common market factor (i.e. a market index) as is usually done in most studies. That is, risk adjusted returns are defined as the residuals ($e_{i,t}$) from a market model:

$$r_{i,t} = a_0 + b_0\ r_{m,t} + e_{i,t} \qquad (1)$$

where $r_{i,t}$ is the raw return of stock i at time t, $r_{m,t}$ is the return of the market portfolio (m) at time t, and $e_{i,t}$ is the market-adjusted return for stock i at time t (Panel B).

However, recent evidence indicate that the expected return on a portfolio in excess of the risk-free rate is explained by the sensitivity of its return to three-factors (Fama and French, 1993, 1996, FF hereafter). The FF factors are: (a) the excess returns on a broad market portfolio; (b) the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (SMB, Small Minus Big); and (c) the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks (HML, High Minus Low). More specifically, FF have shown that the expected excess return on asset i is:

---

more than one stock, they are assigned to the two extreme sub-samples, giving priority to the largest.

$$E(r_i) - r_f = b_i[E(r_m) - r_f] + s_i E(SMB) + h_i E(HML) \qquad (2)$$

where r_f is the risk free rate of return, $E(r_m)$-r_f, E*(SMB)*, and E*(HML)* are expected premiums and the factor sensitivities are the slopes in the time-series regression:

$$r_i - r_f = a_i + b_i(r_m - r_f) + s_i SMB + h_i HML + e_i \qquad (3)$$

In effect, FF have shown that extending the Capital Asset Pricing Model (CAPM) to include additional factors explains the contrarian profits in the US[5]. For this reason we also examine 3-factor-adjusted returns (Panel C) defined as the residuals ($e_{i,t}$) from a model very similar to theirs, the only difference being that instead of the excess returns of stocks and the market, this paper employs raw returns. This is done in order to obtain results that are not only directly comparable with the JT ones, but also allow the exact measurement of the power added to the model by the two additional factors:

$$r_{it} = a_i + b_m r_{m,t} + b_{SMB} SMB_t + b_{HML} HML_t + e_{i,t} \qquad (4)$$

where *SMB* is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks, and HML is the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks[6].

[5] This, according to FF occurs because losers are relatively distressed while winners are stronger firms, and as a result losers have higher expected returns compared to winners. FF argue that their model is able to capture this. However FF focus on long-term horizons, while we focus on short term ones.

[6] The SMB factor is constructed as follows: every year stocks are ranked according to the previous year's market capitalization. The top and bottom 20% of stocks are then selected to form two equally weighted portfolios of high and low capitalization stocks respectively. The factor is constructed as the difference of the returns of the two portfolios. A similar procedure is followed for the construction of the *HML* factor. Every year stocks are ranked according to the previous year's book-to-market ratio. The top and bottom 20% of stocks are then selected to form two equally weighted portfolios of high and low book-to-market stocks respectively. The factor is constructed as the difference of the returns of the two portfolios.

The results (Table 3a) indicate that negative serial correlation is indeed present in the data, even after stock returns are adjusted for risk factors. With raw returns (Panel A) 453 of the sample firms exhibit negative 1st order serial correlation. It is interesting to note that when market risk is considered (Panel B) 643 firms exhibit 1st order negative serial correlation, while when returns are adjusted for factors similar to the FF factors 739 firms exhibit 1st order serial correlation. In other words, in Panel C more than 50% on average of the firms in the sample are negatively serially correlated in the first order, 40% of which is significant at the 10% level.

These results are encouraging for contrarian investment strategies; however, many of the sample firms may trade infrequently, which may affect the reported results. To this end, the paper next adjusts the sample for infrequent trading by removing any firm that does not trade for 4 consecutive weeks (this leaves 660 firms in the sample) and re-estimates serial correlation, reporting the results in Table 3b. Note that many firms still exhibit negative and significant serial correlation. For example, 293 (44%) of the frequently trading firms exhibit negative first order serial correlation when returns are adjusted for the three FF factors, 45% of which is statistically significant at the 10%. Note that for contrarian strategies to work, not all of the firms have to be negatively serially correlated. Even if a particular sub-sample exhibits the particular correlation characteristics, the strategy could be employed for this specific sub-sample, while other strategies could be performed on other samples depending on their characteristics. In addition, part of the profits could for example be related to other factors such as the lead lag effect. To summarize thus far, it appears that negative correlation is present in the UK even after adjusting for various risk factors, in line with Poterba and Summers (1988) and Balvers, Wu, and Gilliland (1999).

4. Are contrarian strategies profitable in the LSE?

The negative serial correlation observed in the previous Section, could potentially lead to profitable contrarian strategies. In order to examine whether contrarian profits are present and exploitable, the paper employs a standard contrarian strategy[7] that involves shorting every week the previous week's winners, to go long on losers. The zero-investment portfolios are re-balanced every week, and the profits for the sub-sample, p_t, are estimated as:

$$p_t = -\frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1} - \overline{r}_{t-1})r_{i,t} \tag{5}$$

where, $\overline{r}_{t-1}$ is the lagged return on an equally-weighted portfolio that contains all stocks in the relevant sample, $r_{i,t-1}$ is the return on stock i at time $t\text{-}1$, and N is the number of stocks in the sample. In order to examine the profits' economic significance, the contrarian profit per Sterling long (?) are estimated as follows (see for details, Bacmann and Dubois 1998):

$$y_{t,k} = \frac{\sum_{1=1}^{N_{t-1}} w_{i,t}^{+} r_{i,t}}{\sum_{1=1}^{N_{t-1}} w_{i,t}^{+}} \tag{6}$$

where $w_{i,t}^{+} = -\frac{1}{N_{t-1}}(r_{i,t-1} - r_{m,t-1})$ if $r_{i,t-1} < r_{m,t-1}$ or *0* otherwise. The way ? is defined, it provides profits only when weights are positive, i.e. when each asset's lagged returns are lower than the lagged average returns of all stocks in the sample, in which case the position on that asset next period would be long. Obtaining a weighted average of returns (?) results to returns per Sterling long.

[7] See for example, Jegadeesh and Titman (1995), Lo and Mackinley (1990).

Table 4 reports the average contrarian profit (equation 5) and the contrarian profit per Sterling long (equation 6) as well as the respective *t*-statistics (in parenthesis), for all size sub-samples and the full sample. More specifically, Panel A reports the profits for all sub-samples when closing prices are used to compute returns. As can be seen, contrarian profits are statistically significant for the smallest, large, and largest sub-sample. However, there are loses for the large sub-sample. For example, the average weekly contrarian profit (πx10^3) is 0.156, -0.016, 0.036, -0.068, and 0.338 for the smallest, small, medium, large and largest sub-sample respectively. Note that, for the same strategy with US data, JT report average weekly contrarian profits (px10^3) of 0.615, 0.325, 0.226, 0.147, 0.084, and 0.262 for similar size groups, respectively. Thus, contrarian profits appear somewhat reduced in the UK. Furthermore, while in the US contrarian profits decline as one moves from small stocks to large stocks the opposite seems to happen in the LSE.

In order to examine whether the contrarian profits reported above are due to market frictions, such as a bid-ask bias or infrequent trading, the paper next re-estimates the profits of the contrarian strategies using bid-to-bid prices[8] rather than closing prices (Panel B). In addition, we exclude from the sample firms that trade infrequently[9], i.e. stocks that do not trade for a consecutive number of weeks (Panel C). The profits with

[8] Bid-to-bid data are available to the authors from the second half of 1986 onwards, thus sorting the sub-samples starts from 1987. In this case the annual sub-samples are: 384 firms for year 1987, 452 firms for year 1988, 446, 1085, 1111, 1135, 1230, 1315, 1270, 1235, 1135, 1015, and 935 firms for each of the remaining years thereafter. All firms trade frequently and do not suffer from thin trading, and have data for at least 48 out of 52 weeks per annum.

[9] That is, if any of the stocks does not trade for more than 4 consecutive weeks it is removed from the sample for that year. This leaves for 1985 to 2000: 945, 1085, 1230, 1230, 1280, 1150, 1055, 980, 1025, 1100, 1025, 1130, 1155, 1125, 1000, and 945 firms respectively. Distributing these in each size sub-sample between 1985 and 2000, provides 189, 217, 246, 246, 256, 230, 211, 196, 205, 220, 205, 226, 231, 225, 200 and 189 firms respectively. For the all-sample group, stocks that have zero returns for a period longer than six weeks, and stocks that trade once between months are removed. As a result, there are 660 firms for that group.

the bid-to-bid prices appear reduced: the average weekly profit for the all stocks sample from 0.076 becomes 0.029 and statistically insignificant. Note though that the average weekly profit for the largest stock sub-sample is still statistically and economically significant but also significantly reduced (0.096 with bid prices from 0.338 with closing prices). Thus, it appears once again that bid-ask biases may affect results, and explain a portion of them, but we shall return to this important point later.

A similar pattern (i.e. lower contrarian profits) emerges when infrequently trading firms are excluded from the sample. For example, the average weekly contrarian profit for the largest stock sub-sample is now 0.101 from 0.338 that it was for closing prices (in Panel A) while for the smallest stock sub-sample it is 0.081 from 0.156 for closing prices (both statistically and economically significant). These results indicate that part of the contrarian profits could be due to the effect of infrequent trading, but we shall return to this point as well later. It is also interesting to note that, so far, unlike the JT study, profits for medium and large stocks are negative irrespective of how stock returns are estimated, suggesting that contrarian strategies are profitable only for the two extreme size sub-samples.

However, all the above return specifications fail to take into account for one important factor: risk. Given that it might be more appropriate to use risk-adjusted returns to estimate profits, in Section 3, two procedures are employed to adjust for risk. Firstly, market risk is considered (equation (1)) and the results are reported in Panel D; and secondly the paper adjusts for three factors similar to the FF factors (equation (4)). The results are reported in Panel E[10]. Results indicate that when adjusting for market

[10] Closing prices are used , and infrequent trading stocks are excluded from the sample.

risk with a single-factor model, the average weekly profit is statistically significant for all sub-samples, except for the large stock sub-sample. Furthermore, contrarian profits decline as one moves from the smallest stock sub-sample to large stock sub-sample, a result more in line with the results for the US market. When risk adjustment is performed by means of the three FF factors, profits for all sub-samples become positive[11] and statistically significant at the 5% level, and have an inverse relationship with size, i.e. the smaller the firms the larger the profit. Even for the large stock sub-sample profits are now positive, but the highest profits are the ones for the two extreme sub-samples, with the smallest sub-sample leading with gains that are almost double of that in the largest stock sub-sample.

Results this far indicate that contrarian profits are possible in the LSE, and tests suggest that contrarian strategies may produce statistically (p) and economically (?) significant profits, irrespective of how stock returns are defined. In addition, the two most "profitable" sub-samples appear to be the two extreme size sub-samples. Furthermore, profits decline as one moves from the smallest stock sub-sample to larger stock sub-samples. The paper’s findings so far on short-term profitability are in line in most cases with JT for the US market, and consistent with long-term findings for the UK market (Dissanaike, 1997, Van Der Put & Veld, 1997, etc).

[11] The increase in profits when risk-adjusted returns are employed could be related with the increase in the number of stocks that are negatively correlated as one moves from one sample to the other (tables 3a and 3b). Another reason, could be that (as will be seen in Table 5), all contemporaneous coefficients for HML and some for SMB are negative, indicating that controlling for these variables should increase contrarian profits (see for example Chordia & Shivacumar, 2002). Furthermore, if past losers are less risky than past winners (and we show that consistent with De Bondt and Thaler, 1985, and Dissanaike,

5. Decomposition of Contrarian Profits - Methodology

Results in the previous section indicate that contrarian strategies are profitable in the UK. An important question that arises at this stage is regarding the sources of these profits. In this section the paper proceeds to decompose the UK contrarian profits to various sources, in the spirit of JT. That is, contrarian profits are decomposed to sources due to common factor and firm-specific reaction, allowing it to be over- or underreaction in each case, facilitating the evaluation of the economic significance of any overreaction or delayed reaction. This methodology also allows the evaluation of the extent to which over- or under-reaction to firm-specific information has the same impact on contrarian profits as the delayed reaction to common factors.

A K-factor model is employed to describe stock returns, allowing equity prices to react both instantaneously and with a lag to factor realizations as follows:

$$r_{i,t} = \mu_i + \sum_{k=1}^{K} (b^t_{0,i,k} f_{t,k} + b^t_{1,i,k} f_{t-1,k}) + e_{i,t} \tag{7}$$

where:

μ_i is the unconditional expected return of the i-th stock,

$f_{t,k}$ is the unexpected k-th factor realisation at time t,

$b^t_{0,i,k}$ is the time t sensitivity of stock i to the contemporaneous k-th factor realisation,

$b^t_{1,i,k}$ is the sensitivity of stock i to the lagged k-th factor realisation at time t, and

$e_{i,t}$ is the estimated residual representing the firm-specific component,

---

1997, they are indeed less risky), then taking into account for risk should have a positive effect on

JT also assume that factor sensitivities are uncorrelated with factor realizations, that is $E(b^t_{0,i,k} \mid f_{t,k}, f_{t-1,k}, k=1..K) = b_{0,i,k}$ & $E(b^t_{1,i,k} \mid f_{t,k}, f_{t-1,k}, k=1..K) = b_{1,i,k}$. Futhermore, without loss of generality, they consider orthogonal factors so that $E(f_{t,i} f_{t,j}) = 0$, for $i \neq j$ and $E(f^2_{t,k}) = s^2_{f_k}$. Since $f_{t,k}$ is the unexpected factor realisation cov($f_{t,k}$, $f_{t-1,j}$) = 0, $\forall$ k & j, and since the co-movements in stock returns are entirely captured by the common factor cov(e_{it}, $e_{j,t-1}$) = 0, $\forall\ i \neq j$. This is similar to a conventional multi-factor model that also allows non-zero lagged factor realizations. If stock i reacts with a delay to common factor k then $b_{1,i,k} > 0$, while if stock i overreacts to the factor then $b_{1,i,k} < 0$. Also, overreaction to firm-specific information induces negative serial correlation in e_i, while underreaction will induce positive serial correlation in e_i. Given this return generating process, the cross-serial covariance between the returns of i and j is $\text{cov}(r_{i,t}, r_{j,t-1}) = \sum_{k=1}^{K} E(b^t_{1,i,k} b^{t-1}_{0,j,k}) s^2_{f_k}$. Equation (7) allows for cross-serial covariances to be assymetric: for example, if j reacts instantaneously to $f_{t,k} \forall k$ but i reacts partially with a delay to at least one factor (i.e. $b^t_{1,j,k} = 0$ and $b^t_{1,i,k} > 0$), then $\text{cov}(r_{i,t}, r_{j,t-1}) > 0$, but $\text{cov}(r_{j,t}, r_{i,t-1}) = 0$. In this case j leads i, since j's return predicts i's return but the reverse is not true (JT, p. 997). Under the assumption that equation (7) is the return generating process, contrarian profits are decomposed as follows:

$$E(p) = -E\left(\frac{1}{N}\sum_{t=1}^{N}(r_{i,t-1} - \bar{r}_{t-1}) r_{i,t}\right) = -s^2_m - \Omega - \sum_{k=1}^{K} d_k s^2_{fk} \tag{8}$$

where:

$$s^2_m = \frac{1}{N}\sum_{i=1}^{N}(m_i - \bar{m})^2 \tag{9}$$

$$\Omega \equiv \frac{1}{N}\sum_{i=1}^{N}\text{cov}(e_{i,t}, e_{i,t-1}) \tag{10}$$

---

contrarian profits. The reason is that the losers (winners) risk adjusted profits will be higher (lower).

$$d_{t,k} \equiv \frac{1}{N} = \sum_{i=1}^{N} (b_{0,i,k}^{t-1} - \overline{b}_0^{\,t})(b_{1,i,k}^{t} - \overline{b}_1^{\,t}) \text{ where } d_k \equiv E(d_{t,k}) \qquad (11)$$

Where, $\overline{b}_{0,k}^{\,t}$ and $\overline{b}_{1,k}^{\,t}$ are the cross-sectional averages of $b_{0,i,k}^{t}$ and $b_{1,i,k}^{t}$, $-s_m^2$ is the cross-sectional variance of expected returns, -O is the negative of the average serial covariance of the idiosyncratic component of returns (and is determined by stock price reactions to firm-specific information). If stock prices tend to overreact to firm-specific information and correct the overreaction in the following period, - O will be positive. The last term in (8) is the component of contrarian profits attributable to differences in the timeliness of stock price reactions to common factors. When $d_k < 0$ stock price reactions to the k^{th} factor realization contribute positively to contrarian profits and negatively when $d_k > 0$. In their decomposition of US contrarian profits JT employ a single (market) factor model. However, as discussed above, FF argue that a three-factor model is a better description of stock returns, and is capable of capturing long-term contrarian profits in the US market. Thus, in this paper we decompose contrarian profits using a multi-factor model rather than just a single-factor decomposition.[12]

In the above specification the lead-lag structure is likely to be biased downward and the contribution of firm-specific overreaction is likely to be biased upward if factor sensitivities are not constant. That is, for two stocks: one that reacts instantaneously all the time, and another that reacts instantaneously half of the time but with a lag the other half of time, the unconditional estimates of equation (7) for the second stock will be an average of both time periods. This will underestimate the lead lag effect

[12] Note that, for comparability of results, in section 6.4 contrarian profits are also decomposed using a single-factor model.

contribution (by $0.187 s_f^2$) and overestimate the overreaction contribution (by $0.125 s_f^2$) based in equation (8). In order to deal with this issue and at the same time allow for possible time-variation in factor sensitivities, the following decomposition of contrarian profits, *p*, is also employed. Assuming equation (7) describes the Return Generating Process, and that errors are normally distributed and $corr(e_{i,t}, e_{i,t-1}) = r, \forall i$, the expected contrarian profit at time t conditional on $f_{l,t-1}$ (where *l* is the squared demeaned laged r_m, SMB, HML) will be:

$$\mathrm{E}(p_t \,|\, f_{l,t-1}, e_{i,t-1}) = s_m^2 - d_t f_{l,t-1}^2 - r q_{t-1} \tag{12}$$

where: $$q_t = \frac{1}{N}\sum_{i=1}^{N} e_{i,t}^2 \tag{13}$$

The difference of the decomposition in (8) with the approach in (12) is obvious: the former does not consider time-variation in factor sensitivities, since (8) uses a single number *O* (the average autocovariance of the error term) related to the firm-specific component. In addition, the variance of each factor s_{fk}^2 used in relation to the common factor component, is constant. However, the later decomposition in (12) considers non constant factors such as the demeaned $f_{l,t-1}^2$ and q_{t-1}:

$$\mathrm{E}(p_t \,|\, f_{l,t-1}, e_{i,t-1}) = s_m^2 - d_t f_{l,t-1}^2 - r \left(\frac{1}{N}\sum_{i=1}^{N} e_{i,t}^2\right)_{t-1}$$

Intuitively, the above expression allows not only for changes in factor sensitivities, but also determines whether these changes in factor realizations have a bigger impact on contrarian profits. At the same time if firm-specific news are responsible for contrarian profits, increased cross sectional dispersion of the firm-specific component shall increase contrarian profits. For example, for the three-factors that we have already considered, the contribution of each different component of contrarian profits can be estimated with the following time-series regression:

$$p_t = a_0 + a_1(r_{m,t-1} - \bar{r}_m)^2 + a_2(SMB_{t-1} - \overline{SMB})^2 + a_3(HML_{t-1} - \overline{HML})^2 + gq_{t-1} + u_t \quad (14)$$

In (14) $\bar{r}_m$ is the average common factor return, $\overline{SMB}$ and $\overline{HML}$ are the average returns of the SMB and HML factors respectively. An estimate of the contrarian profits due to delayed reactions to common factors is given by the product of a_i (where i = 1, 2, 3) and the variance of the common factor ($a_i s_f^2$, where f = m, SMB, HML) while an estimate of contrarian profits due to overreaction is given by:

$$g\left(\frac{1}{T}\sum_{t=1}^{T} q_{t-1}\right) \quad (15)$$

Section 6 presents the results for both of the above decompositions, and for different samples and specifications of returns.

6. Decomposition of Contrarian Profits - Results

6.1. Results using all stocks in the sample (closing prices)

As a first step in the analysis of the factors driving contrarian profits, the profits are decomposed using all stocks in the sample and closing prices to create returns. The following sub-sections will decompose profits with a sample adjusted for infrequent trading and with bid prices, in order to unveil whether there is an impact on the factors affecting profits after considering microstructure biases. To this end, Tables 5-7 report the results of the decomposition of contrarian profits as described in Section 5. More specifically Table 5 reports the results from estimating equation (16), (a multifactor version of (7)), with the three-factors similar to FF (as explained earlier):

$$r_{it} = a_i + b_{0,m} r_{m,t} + b_{1,m} r_{m,t-1} + b_{0,SMB} SMB_t + b_{1,SMB} SMB_{t-1} + b_{0,HML} HML + b_{1,HML} HML_{t-1} + e_{i,t} \qquad (16)$$

Equation (16) is estimated separately for a) all stocks and the whole sample period, and b) for each stock in each sub-sample and each year. Table 5 reports the average sensitivities of stock returns to the current and lagged factor realizations as well as the estimate of the cross-sectional covariance (d). As can be seen the average slope coefficient on the contemporaneous market factor is 0.555 and for the lagged market factor is 0.173, suggesting that UK equity returns react more strongly to contemporaneous market factor realizations. This is true for all sub-samples and the reactions are statistically significant. However, stock prices do not fully react contemporaneously to common factor realizations, but part of the effect is incorporated in prices with a lag. As regards the other two factors, UK equity returns also seem to react more strongly to the contemporaneous rather than the lagged factor.

Note that for the smaller sub-samples the reactions to the contemporaneous SMB factor are much stronger, indicating their stronger relationship with this risk premium compared to larger stocks. For both current and lagged SMB realizations the reactions are also statistically significant. As regards to the HML factor UK equity returns seem to react weakly to lagged factor realizations and react strongly and negatively to current factor realizations. The cross-sectional covariance is negative ($\delta < 0$) for all sub-samples and the SMB and HML factors, indicating that (delayed) reactions to these factors could contribute positively to contrarian profits in LSE. However, d is positive for most sub-samples for the market factor, indicating that reactions to this factor could contribute negatively to contrarian profits in LSE.

The results in Table 6 provide an estimate of the part of contrarian profits that are due to reactions to each of the three-factors ($-\hat{d}s_f^2$ x 10^3, where f = M, SMB, HML). Furthermore, the Table provides an estimate of the profits that are due to overreaction to firm-specific information ($-\Omega$), and the unexplained part of the profits ($-s_a^2$). It can be seen that the magnitude of the contribution to the profits of the delayed reactions to the three-factors is relatively small. For the all stocks sample, it is 0.000 for the market factor, 0.009 for the SMB factor, and 0.003 for the HML factor and on average it is higher for smaller stocks. Note also that it is negative for most sub-samples as regards to the market factor (i.e. reactions to this factor contribute negatively to contrarian profits). However, the contribution to profits due to overreaction to firm-specific info is much higher: 0.069 for the all stocks sample, and inversely related to size, in line with JT.

In order to account for possible time variation in factor sensitivities the paper applies the decomposition of profits as described in equations (12) to (15). Note that to create the firm-specific related factor $?_t$, the estimated residuals from equation (16) are employed. The results are presented in Table 7 (Panels A and B). The slope coefficients (a_1, a_2, and a_3) provide an estimate of the contrarian profits due to the reactions to the market, SMB and the HML factors respectively, and the coefficient *?* provides an estimate of profits due to overreaction to firm-specific information (Panel A). It can be seen that they are statistically significant for most sub-samples and the all-stock sample, however the market factor estimates are negative.

Panel B provides estimates of contrarian profits due to delayed reactions to common factors and overreaction to firm-specific information. For example, the contrarian profit for the smallest stock sub-sample due to firm-specific overreaction (last column in Panel B) is 0.073. Since the average weekly contrarian profit for this sub-sample is 0.156 (Table 4, Panel A, 2^{nd} column) the contrarian profit due to firm-specific overreaction should be 0.073 / 0.156 = 0.467. In other words 46.7% of contrarian profits for the smallest stock sub-sample is due to firm-specific overreaction. This ratio is provided in the Table for all sample groupings and factors in brackets. For example, for the all stocks sample, 121.96% of contrarian profits appears to be due to firm-specific overreaction, 24.31% due to delayed reaction to the HML factor, 46.57% due to delayed reaction to the SMB factor, and -40.31% due to reaction to the market factor. Note that, for the US and the all stocks sample, JT find the contribution of firm-specific information to contrarian profits to be approximately 104%. The fact that the factors contribute together about 150% of contrarian profits for the all-stock sample could be due to not adjusting for microstructure biases.

To summarize the results in this sub-section, when closing prices for all available stocks are employed, UK stocks seem to react more strongly to the contemporaneous factors. The delayed reactions to the SMB and HML factors however, seem to contribute positively to contrarian profits while the delayed reactions to the market factor appear to contribute negatively to contrarian profits. However, overreaction to firm-specific information seems to contribute the most to contrarian profits and delayed reaction appears to have a smaller impact. This result holds even when time-variation in factor sensitivities is considered.

6.2. Results using frequently trading stocks in the sample (closing prices)

Can the above findings be due to market frictions such as infrequent trading? Tables 8-10 report the same results as in sub-section 6.1, however, this time infrequent trading stocks are excluded from the sample (as described earlier). More specifically, Table 8 reports the results from estimating equation (16) and it is interesting to note that, when compared to the results in Table 5, the new results appear very similar. That is, returns react stronger to contemporaneous factor realizations (the reaction is also statistically significant) and also react negatively to the HML contemporaneous factor realizations. Furthermore, the delayed reactions to the SMB and HML factors appear to contribute positively to contrarian profits, whilst reactions to the market factor appear to contribute negatively to contrarian profits in all cases, (indicating that the two cases where the contribution was positive in Table 5 were due to infrequent trading). The decomposition of profits in Table 9 indicates a very similar pattern as before (Table 6), although each factor's contribution is now lower.

However, excluding infrequent trading stocks seems to affect the decomposition when time varying factor sensitivities are considered. As can be seen from Table 10 (Panel A) now only the coefficients on the SMB and HML factors are statistically significant for all cases. For example, the *t*-statistic on the coefficient of the SMB factor for the all stocks sample is 6.301 and the *t*-statistic on the coefficient of the HML factor is 7.697. Note that the coefficient *?* has a *t*-statistic of 1.397, i.e. it is statistically insignificant for the all stocks group. Overreaction to firm-specific information seems to be significant only for the smallest sub-sample at the 5% and for the largest sub-sample at the 10%. Recall also (Table 4, Panel C) that a contrarian strategy produces a profit with frequent trading stocks only for the two extreme sub-samples. These results taken together with results in Table 10 (Panel B) indicate that with frequent trading stocks, only the extreme size sub-samples produce profits and that the sources of these profits come in similar proportions from reactions to the SMB and HML factors and overreaction to firm-specific information. The large values for the all-sample group is due to the fact that they are related to a profit that is not very different from zero. As a result, the small magnitude of the profits drives the contributions to such high levels when employed in the ratio that is used to determine the contribution, and should not cause concern. Furthermore, the all-stock group for the frequently trading sample is represented by only 660 firms out of the almost 2000 firms originally in the data set, and should be approached cautiously. This is not a problem with the subsamples however, which are annually rebalanced (unlike the all-stock group), and problematic stocks are removed only for that year and are reconsidered for the other years.

The findings in this sub-section seem to suggest that excluding infrequent trading stocks from the sample alters results only when time variation is allowed. In this case, profits come from both delayed reactions to the SMB and HML factors and overreaction to the firm-specific news. This indicates that part of the contribution of the overreaction effect may come from infrequently trading stocks, and that it is important that we account for this problem.

6.3. Results using all stocks in the sample (bid prices)

Kaul and Nimalendran (1990) find that the bid-ask error component explains over 50% (23%) of the small (large) firm variance, thus, the return reversal could be partly due to bid-ask errors. Kaul and Gultekin (1997) also find that for NASDAQ all profits are due to the bid-ask bounce, while for AMEX and NYSE, on average half of the profits are due to bid-ask errors. However, Loughran and Ritter (1996) use NYSE and AMEX data and find that it is risk and overreaction and not bid-ask bias that explain profits. JT also find that the bid-ask bias does not affect results. The evidence is conflicting, and to this end, the current section investigates whether results presented so far are affected from the bid-ask problem.

Profits are decomposed using bid-to-bid rather than closing prices. The results are presented in Tables 11-13, and indicate that using bid prices changes things (as in the previous section), only when time-variation is allowed. More specifically, the findings in Table 11 are very similar (albeit with slightly smaller betas) to the findings in Table 5: returns react stronger to contemporaneous factor realizations (the reaction is also statistically significant) and also react negatively to the HML contemporaneous factor realizations. In addition, as in Table 5, the reactions to the SMB and HML factors appear to contribute positively to contrarian profits, whilst reactions to the market factor appears to contribute negatively to contrarian profits. The decomposition of profits in Table 12 indicates a very similar pattern as before (in Table 6), although the contribution of each factor to profits is slightly lower.

For time varying factor sensitivities results change, and as can be seen from Table 13 (Panel A) the coefficients on the SMB and HML factors appear statistically significant for most sub-samples, while the market factor is significant only for the large sub-sample (*t*-statistic: 3.735). For example, the *t*-statistic on the coefficient of the SMB factor for the largest stock sub-sample is 4.620 and the *t*-statistic on the coefficient of the HML factor is 11.059. Note that the coefficient ? is statistically significant for all sub-samples and the full sample. The above significance for SMB and HML, combined with the insignificance of the market factor, indicates that had the three-factor model not been used a lot of significant information would have been lost. Panel B provides estimates of the contrarian profits due to both reactions to common factors and firm-specific information. Contrarian profits due to firm-specific overreaction are significantly larger compared to Table 7, especially for smaller firms.

Findings in this sub-section indicate that when using bid prices the results change only for time varying factor sensitivities. In this case, profits come mainly from overreaction to the firm-specific component of returns that contributes positively towards profits. The bid-ask bias does not provide a complete explanation for contrarian profits, and it does not reduce the contribution of the firm-specific component. In the case of the medium stocks (Table 13, Panel B) the firm-specific contribution is cancelled out by the SMB and HML factors negative contribution, while for the large sub-sample some of the firm-specific contribution is reduced.

6.4. Results using a single-factor model

In their 1995 decomposition of US contrarian profits JT use a single-factor model. However, as seen so far, the SMB and HML factors do contribute a lot of information, and not including these factors could have distorted the findings. This would happen because to the extent that the missing factors are not correlated to the market factor, most of the missing information will affect the residuals and thus the firm-specific component of returns as defined in the study. Furthermore, it would be interesting to compare the UK findings in this paper with the US findings in the JT paper. To this end, the decomposition described in Section 5 is repeated with a single (market) factor model and the results are presented in this sub-section. Tables 14 & 15 present the findings for a sample of all stocks available and closing prices, while Tables 16 & 17 present the findings for a sample of frequently trading stocks. Finally, Tables 18 & 19 present the findings for all stocks using bid-to-bid rather than closing prices.

From Tables 14 & 15 it can be observed that using a single-factor model for all stocks and closing prices, stock reactions are stronger for the contemporaneous period, but part of the reaction is incorporated in prices with a lag. These (delayed) reactions appear to contribute negatively to contrarian profits (positive δ). The estimates of contrarian profits due to the common factor realizations are small and negative, whilst the part of profits due to overreaction is much larger (especially for the smaller sub-samples). However the results seem to indicate that there could be a negative contribution of the firm-specific component to profits, unlike the results in Table 6, and it is probably related to the distortion caused by leaving out the two significant SMB and HML factors. Allowing for time-variation, 154.42% of the profits are due to firm-overreaction and approximately -28.14% is due to the common factor reaction.

Notice that leaving the two additional factors out of our model adds about 32% of irrelevant structure to the firm-specific component (increasing its contribution to 1.544 from 1.2196). Furthermore, the differences between the contributions of each factor vary significantly from sub-sample to sub-sample when using the single-factor model.

When only frequently trading stocks are considered and closing prices are used to create returns (Tables 16 & 17), stocks react slightly stronger to the common factor realizations, which still contribute negatively to contrarian profits in most cases. The estimates of contrarian profits due to common factor realizations are small and negative, whilst the part of profits due to overreaction is much larger (especially for smaller firms). Comparing with the results in Tables 8 and 9, it is clear that although the lagged betas are quite similar in value, and the average of the contemporaneous beta is not very different, there is a significant downward shift in the contemporaneous betas of the three smaller sub-samples. Furthermore, the firm-specific reaction contribution is now lower for all sub-samples and the all-firms group, indicating that the lack of the two additional factors has in fact affected the residual of the single-factor version of equation (16) (see Table 15 notes for details).

This is a very important indication that using a single-factor model when more factors are actually relevant could bias results. Allowing for time-variation confirms this finding. For example, the contribution of firm-specific overreaction to contrarian profits of the smallest firms appears to be 176% whilst the contribution of market reactions is around 2% (compared to 90% and -17% respectively for the three-factor model, Table 10). Similarly, the contribution of firm-specific overreaction to contrarian profits of largest firms appears to be 46% whilst the contribution of market reactions is around 10% (from 20% and 6% respectively, Table 10). That is, excluding the SMB and HML factors takes out about 17% and 18.5% respectively of contribution information (Table 10 Panel B), of which 4% and 26% is added to the common and firm-specific factor respectively (Table 17).

Finally, in Table 18 (bid-to-bid prices), although the reaction of the stocks to the lagged factor is similar to the one in Table 11, the contemporaneous betas are now decreased (increased) for larger (smaller) sub-samples. This shows the downward (upward) bias introduced again from the single-factor model in the contemporaneous beta estimates. The contributions of the common factors are not very different from Table 12, but the firm-specific component contribution is once again much lower. This is due to the negative effect of the SMB and HML factors (see negative sign in Table 11 for all HML and some SMB contemporaneous betas) that are now not included in the model.[13] Allowing for time-variation in factor sensitivities confirms this finding.

Overall, the beta coefficients with the single-factor model follow similar patterns with the ones for the three-factor model, and suggest that UK stock returns react stronger to the contemporaneous market factor rather than the lagged factor in all cases. The market factor contributions are not very different than for the three-factor model. However, the firm-specific contributions are smaller on average for the single-factor model, consistent with the fact that the two (missing) factors have negative slopes in most cases, and not including them in the model affects the firm-specific component

[13] And thus affect the firm-specific component that is related to the error of equation (16), and it's single-factor version.

negatively. On average, these results persist irrespective of market frictions such as bid-ask-bias and infrequent trading, and show that the single-factor model would have biased the estimates of firm-specific contribution, and the bias would range from about 24% for all stock up to 67% for frequently trading stocks. JT also find a stronger reaction to the contemporaneous market factor and a part of the effect to be incorporated in prices with a lag. However, the magnitudes of the profits and the contributions vary as discussed earlier. Furthermore, JT find that (delayed) common factor reactions contribute positively to contrarian profits, thought the decomposition indicates that for the UK the resulting lead-lag effect contributes negatively in most cases to contrarian profits. As in JT most of contrarian profits is due to overreaction to firm-specific information. These results are robust even after allowing time-variation in factor sensitivities (i.e. when taking the demeaned factors to allow for the measurement of the different effect of changes in factors on profits). Put simply, the effect of using a single-factor model instead of a multifactor model appears mainly on the firm-specific component, which in most cases is biased, and the magnitude of the bias is up to 67%. It can thus be suggested that studies employing single-factor models should be cautious about their findings relevant to the magnitude of the firm-specific overreaction, and crosschecked with multifactor models.

7. Concluding Remarks

Evidence of contrarian profits implies return predictability and rejection of informational efficiency of asset prices in the weak form. This paper employs data for all stocks listed in the LSE (that agree with the criteria set), in order to investigate the existence of short-term contrarian profits and the sources of these profits in the main UK capital market. More specifically, the first important question the paper attempts to address is whether UK returns are predictable from past / historical information. The main result that emerges from the empirical analysis indicates that zero-investment contrarian portfolios produce significant profits. In fact, contrarian profits persist even after the sample is adjusted for market frictions, such as infrequent trading and bid-ask bias, and irrespective of whether raw or risk-adjusted returns are used to calculate contrarian profits. Furthermore, these profits appear statistically and economically significant, and are more pronounced for extreme market capitalization stock portfolios (smallest - highest). Thus, investors can employ short-term contrarian strategies in the LSE for the smallest or largest firms in the market; the paper's suggestion however is that they focus in the largest ones that are more liquid and transparent (avoiding large transaction costs at the same time).

The second important question the paper attempts to address deals with the sources of these profits. The results indicate that UK stock prices do not fully react contemporaneously to the FF factor realizations, and that delayed reactions contribute to contrarian profits. However, the magnitude of this contribution is small, whilst the magnitude of the contribution of investor overreaction to firm-specific information to profits is far larger. Furthermore, the overreaction contribution grows as one moves from the smaller to the larger stock sub-samples. It is thus the firm-specific reaction that UK investors can cash in, and not the common factor reaction (in line with JT).

Another interesting finding is that even when the sample is adjusted for infrequent trading and bid-ask bias the main conclusion is the same (although magnitudes vary). However, when only frequently trading stocks are employed the magnitude of the contribution to profits from investor overreaction to firm-specific information is reduced while the magnitude of the contribution to profits of delayed reactions is increased. This suggests that part of the contribution of the overreaction effect may come from infrequently trading stocks, and thus consideration of this effect should be taken before concluding on the firm-specific overreaction component contribution.

The implications of the above findings are multiple. With regards to financial theory, the results do not support market efficiency, since the future may be predicted based on the negative serial correlation of stock returns. Furthermore, risk does not explain the results as efficient market advocates would suggest, and in fact, the paper finds that past losers are less risky than past winners (consistent with De Bondt and Thaler, 1985 for the US, and Dissanaike, 1997 for the UK). At the same time, the paper finds that infrequent trading and the bid ask bias do not explain UK contrarian profits, but only a portion can be devoted to infrequent trading. This is further evidence against market efficiency, since another suggestion of efficient market supporters, that microstructure biases explain results, is challenged. Efficient market advocates have also suggested that results might be data specific for the US, but as can be seen here, they are not, and the overreaction hypothesis is also present for the UK data employed in this paper. There also seems to be a size-effect, not only for the smallest firms as would be expected, but for the extreme sized firms, i.e. the smallest and largest, contrary to Clare and Thomas (1995) suggestions that overreaction is related only to small firms.

In terms of literature, the findings are in general in line with the suggestions of overreaction hypothesis. For example most of the profits (but not in every single case) come from firm-specific news like JT suggest, but these are much lower than they argue. This is probably related to the possible bias introduced by using the single-factor model. In addition, for the UK, the market factor contributes negatively towards contrarian profits some times, and not positively like JT find for the US. Furthermore, our results in general are in line with other UK long-term contrarian studies by Poterba and Summers (1988), Brouwer, Van Der Put & Veld (1997), Richards (1997), Dissanaike (1997), and Balvers, Wu, and Gilliland (1999). As regards the model used, the paper's results suggest that the three-factor model is superior to the single-factor model, although not perfect itself (for example, Davis, Fama, and French (2000) suggest that the FF three-factor model is only an incorrect representation of reality although a quite good one. Thus, the results of this paper must be viewed under this light). One of our contributions to literature is that we also quantify the effect and find that it mostly distorts the firm-specific component contribution.

With respect to market participants, this paper provides evidence that contrarian strategies in the LSE are not only profitable for longer-term strategies (as previous studies have shown), but they are also profitable for shorter-term strategies. Furthermore, the profits are not due to taking on excess risk directly (as seen from the risk adjusted returns), or indirectly (since profits exist for the largest, more liquid, stocks as well), or to microstructure biases. Furthermore, investors can form their strategies based only in past information broadly and cheaply available in newspapers, such as past prices (to determine losers or winners) and Market Values (to determine the largest firms). With respect to regulators, the paper indirectly suggests that any rule that decreases information asymmetries would work towards the reduction of overreaction.

As regards future research, given that results are very sensitive to the model used for the analysis, it might thus be a good idea to repeat tests using the three-factor model for the JT data on US stocks. This will enhance the validity of this paper's UK findings on the superiority of the three-factor model, by applying the model to a different dataset for which single-factor results exist. Furthermore, although the three-factor FF model provides a better description of stock returns than a single-factor model, it does not capture all relevant information. It would thus be interesting to also employ other multifactor models that capture macroeconomic factors like interest rates, inflation etc, that have been accepted as factors that could affect stock returns.

References

Bacmann, J-F., Dubois, M., 'Contrarian Strategies and Cross-Autocorrelations in Stock Returns: Evidence From France' *Social Science Research Network Electronic Library* (SSRN), & *European Financial Management Association* 1998 Meeting.

Ball, R. and Kothari, S.P., 'Non-stationary expected returns: Implications for tests of markets efficiency and serial correlation in returns' *Journal of Financial Economics*, Vol. 25, 1989, pp. 51-74.

Balvers, R., Wu Y., and Gilliland, E., 'Mean reversion across national stock markets and parametric contrarian investment strategies', *The Journal of Finance*, Vol. 55, 1999, pp. 745 – 772.

Banz, R. W., "The Relationships Between Return and Market Value of Common Stocks", *Journal of Financial Economics*, 7, 1981, 3-18.

Barberis, N., Shleifer, A., and Vishny, R., 'A model of investor sentiment' National Bureau of Economic Research (NBER) working paper 5926, February 1997.

Baytas, A., Cakici, N., 'Do markets overreact: international evidence', *Journal of Banking and Finance,* Vol. 23, 1999, pp. 1121-1144.

Bowman, R., Iverson, D., 'Short-run overreaction in the New Zealand stock market', *Pacific-Basin Finance Journal*, Vol. 6, 1998, pp. 475-491.

Brouwer, I., Van Der Put, J., and Veld, C., 'Contrarian investment strategies in a European context', *Journal of Business Finance & Accounting*, Vol. 24, 1997, pp. 306-386.

Chan, K.C., 'On the contrarian investment strategy' *Journal of Business*, Vol. 61, 1988, pp. 147-164.

Chopra, N., Lakonishok, J., & Ritter, J., 'Do stocks overreact?' *Journal of Financial Economics* Vol. 31, 1992 p.p. 235-268

Clare, A. and Thomas, S., 'The Overreaction hypothesis and the UK Stock returns', *Journal of Business Finance and Accounting*, Vol. 22, 1995, pp. 961-973.

Conrad, J.,Kaul, G., 'Long-term market overreaction or biases in computed returns?' *Journal of Finance*, Vol. 48, 1993, pp. 1-38.

Conrad, J. and Kaul, G., 'The returns to long term winners and losers: bid-ask biases in computed returns', *Journal of Finance*, Vol. 48, 1993, pp. 39-63.

Davis, J., Fama, E., and French, K., 'Charechteristics, covariances, and average returns: 1929-1997', *Journal of Finance*, Vol. 55, 2000, pp. 389-406

Da Costa, J. Newton, C.A., 'Overreaction in the Brazilian stock market', *Journal of Banking and finance*, Vol. 18, 1994, pp. 633-642.

De Bondt, W.F.M. and Thaler, R.H., ‘Does the stock market overreact?’, *Journal of Finance*, Vol. 40, 1985, pp. 793-805.

De Bondt, W.F.M. and Thaler, R.H., ‘Further evidence on investor overreaction and stock market seasonality’, *Journal of Finance*, Vol. 42, 1987, pp. 557-581.

Dissanaike G., ‘Do stock market investors overreact?’, *Journal of Business Finance & Accounting*, Vol. 24, 1997, No 1, pp. 27-50.

Fama, E., ‘The Behavior of Stock Market Prices’, *Journal of Business*, Vol. 38, 1965, pp. 34-105.

Fama, E., and French, K.R. ‘Multifactor Explanations of Asset Pricing anomalies’, *The Journal of Finance*, Vol. 52, 1996, pp. 55-84.

Grinblatt, M., Keloharju, M., ‘The investment behaviour and performance of various investor types: a study of Finland’s unique data set’, *Journal of Financial Economics*, Vol. 55, 2000, pp. 43-67

Jegadeesh, N., ‘Evidence of predictable behavior of security returns’, *Journal of Finance*, Vol. 45, 1990, pp. 881-898.

Jegadeesh, N. and Titman, S., ‘Overreaction, delayed reaction, and contrarian profits’, *The Review of Financial Studies*, Vol. 8, 1995, pp. 973-993.

Kaul, G., Conrad, J. and Gultekin M., ‘Profitability of short-term contrarian strategies: implications for market efficiency’, *Journal of Business & Economic Statistics*, Vol. 15, 1997, pp. 379-386.

Kaul, G., and Nimalendran, M., ‘Price reversals, bid-ask errors or market overreaction?’, *Journal of Financial Economics*, Vol. 28, 1990, pp. 67-93.

Kryzanowski, L., and Zhang, H., ‘The contrarian investment strategy does not work in Canadian markets’ *Journal of Financial and Quantitative Analysis*, Vol. 27, 1992 pp. 383-395.

Lehman, B., ‘Fads, Martingales and market efficiency’, *Quarterly Journal of Economics*, Vol. 35, 1990, pp. 401-428.

Lo, A.W. and MacKinlay, A.C., ‘When are Contrarian Profits due to Market Overreaction?’, *Review of Financial Studies*, Vol. 3, 1990, pp. 175-205.

Poterba J., & Summers H L., ‘Mean reversion in stock prices. Evidence and implications’ *Journal of financial economics*, vol. 22, 1988, pp. 27-59.

Richards, A., ‘Winner-loser reversals in national stock market indices: can they be explained?’, *Journal of Finance*, Vol. 53, 5, 1997, pp. 2129-2144.

Zarowin, P., ‘Size, Sesonality and Stock Market Overreaction’, *Journal of Financial and Quantitative Analysis*, Vol. 25, 1990, pp. 113-125.

Table 1
Total Number of Firms in the Sample and Market Values per year

Year	Min Value	Max Value	Mean Value	Standard Error	Standard Deviation	Total number of firms
1985	0.03	63908.49	255.1624	64.07501	2186.076	1164
1986	0.03	66349.63	270.0225	61.88033	2185.173	1247
1987	0.04	50232.23	316.029	53.26607	1957.845	1351
1988	0.04	37661.02	310.5211	42.17414	1611.471	1460
1989	<0.01	40510.89	310.9541	41.77737	1654.827	1569
1990	<0.01	42404.25	376.6412	45.0914	1828.844	1645
1991	<0.01	34655.77	313.3649	36.15513	1449.365	1607
1992	<0.01	26962	373.1171	40.5028	1590.477	1542
1993	<0.01	24963.15	455.0192	45.46436	1762.001	1502
1994	<0.01	30041.87	568.5602	54.27537	2116.739	1521
1995	<0.01	28257.65	525.9799	50.66479	2000.457	1559
1996	<0.01	65188.08	640.5103	72.05224	2871.261	1588
1997	0.04	39147.56	640.5264	66.04175	2574.781	1520
1998	0.04	51451.2	795.1016	88.86772	3379.311	1446
1999	0.04	74902.88	882.729	115.0587	4211.842	1340
2000	0.35	119814.1	1234.571	196.3658	6788.124	1195

Notes to Table 1:
Values in million of Sterling

Table 2
Descriptive Statistics of Stock Returns

	All Stocks	Smallest Stocks	Small Stocks	Medium Stocks	Large Stocks	Largest Stocks
			Panel A: Descriptive Statistics (Closing Prices)			
Mean	0.00050	0.00101	-0.00003	-0.00002	0.00048	0.00089
Standard Error	0.01662	0.01784	0.01697	0.01697	0.01796	0.01973
Minimum	-0.16978	-0.14958	-0.17176	-0.16546	-0.17956	-0.18397
Maximum	0.06778	0.07827	0.08295	0.07557	0.09478	0.10306
Skewness	-2.30835	-1.53943	-2.05311	-2.0446	-1.86742	-1.82349
Kurtosis	20.5054	14.00213	18.46336	16.54123	17.78007	18.95179
Jarque-Berra	15149.6	7048.275	12268.07	9956.03042	11318.997	12772.641
			Panel B: Descriptive Statistics (Bid Prices)			
Mean	0.00029	-0.00008	-0.00014	-0.00021	0.00049	0.00062
Standard Error	0.01926	0.000765	0.00071	0.00076	0.00079	0.00082
Minimum	-0.20309	-0.20147	-0.18557	-0.22177	-0.19913	-0.18624
Maximum	0.08144	0.08501	0.06837	0.08443	0.10826	0.11884
Skewness	-2.68446	2.00923	-2.34711	-2.65513	-2.21395	-1.55343
Kurtosis	25.0880	17.62133	18.60344	26.00095	21.34257	14.61788
Jarque-Berra	19746.97	9636.45	10859.65	20775.33	14015.79	6588.39

Table 3a
Serial Correlations & Significance (All Firms)

	Order of serial correlation			
	1st	**2nd**	**3rd**	**4th**
Panel A: Raw Returns (Stocks with Negative Serial Correlation)				
Number of Stocks	453	621	918	980
5%	119*	219*	424*	491*
10%	153**	282**	507**	567**
Panel B: Risk Adjusted Returns (Stocks with Negative Serial Correlation)				
Number of Stocks	643	813	1018	977
5%	200*	298*	435*	430*
10%	252**	387**	525**	519**
Panel C: Three-factor adjusted Returns (Stocks with Negative Serial Correlation)				
Number of Stocks	739	962	1144	1042
5%	239*	348*	480*	407*
10%	296**	448**	590**	531**

Notes to Table 3a:
Firms that have negative serial correlation are reported in the table.
* denotes firms with significant negative serial correlation at the 5% level
** denotes Firms with significant negative serial correlation at the 10% level
Note also that there are many firms negative serial correlation significant at the 15%.

Table 3b
Serial Correlations & Significance (Frequently Trading Firms)

	Order of serial correlation			
	1st	**2nd**	**3rd**	**4th**
Panel A: Raw returns (Stocks with Negative Serial Correlation)				
Number of Stocks	171	225	354	368
5%	46*	78*	162*	185*
10%	62**	103**	194**	209**
Panel B: Risk adjusted Returns (Stocks with Negative Serial Correlation)				
Number of Stocks	278	333	396	356
5%	100*	133*	179*	157*
10%	121**	173**	221**	196**
Panel C: Three-factor adjusted Returns (Stocks with Negative Serial Correlation**)**				
Number of Stocks	293	367	425	367
5%	107*	142*	183*	144*
10%	133**	181**	240**	192**

Notes to Table 3b:
Firms that have negative serial correlation are reported in the table.
* denotes firms with significant negative serial correlation at the 5% level
** denotes Firms with significant negative serial correlation at the 10% level
Note also that there are many firms negative serial correlation significant at the 15%.

Table 4
Contrarian Profits (*p*), and £ Profits (*?)*

	All Stocks	Smallest Stocks	Small Stocks	Medium Stocks	Large Stocks	Largest Stocks
Panel A: Closing prices (all stocks)						
p x 10³	0.07625	0.15630	-0.01585	0.03611	-0.06839	0.33848
	(2.320)*	(2.753)*	(-0.749)	(0.426)	(-4.480)*	(2.495)*
	0.00221	0.00704	-0.00014	-0.00294	-0.00285	0.00487
?	(1.561)	(3.366)*	(-0.121)	(-2.690)*	(-2.675)*	(1.429)
Panel B: Bid to Bid Prices						
p x 10³	0.02886	0.05741	0.07459	-0.09078	-0.04829	0.09572
	(1.046)	(1.032)	(0.613)	(-5.255)*	(-3.323)*	(5.556)*
	0.00201	0.00168	0.00394	-0.00474	-0.00213	0.00357
?	(0.908)	(1.063)	(0.699)	(-4.032)*	(-1.860)**	(3.035)*
Panel C: Excluding Stocks that Trade Infrequently						
p x 10³	-0.00127	0.08120	-0.03391	-0.04713	-0.06867	0.10132
	(-0.101)	(1.953)**	(-1.528)	(-2.143)*	(-5.138)*	(7.056)*
	0.00052	0.003325	-0.00117	-0.00420	-0.00210	0.00315
?	(0.574)	(2.265)*	(-0.977)	(-3.502)*	(-2.231)*	(3.656)*
Panel D: Single-Factor Risk Adjusted Returns (Excluding Stocks that Trade Infrequently)						
p x 10³	0.00243	0.21672	0.060575	0.03346	-0.00404	0.11950
	(0.197)	(5.185)*	(2.995)*	(1.703)**	(-0.263)	(8.537)*
	-0.00029	0.00544	0.00289	0.00015	0.00005	0.00332
?	(-0.448)	(4.454)*	(3.169)*	(0.153)	(0.084)	(6.447)*
Panel E: Three-factor Risk Adjusted Returns (Excluding Stocks that Trade Infrequently)						
p x 10³	0.01777	0.25554	0.09693	0.058466	0.028521	0.12992
	(1.647)**	(6.097)*	(4.874)*	(3.109)*	(1.997)*	(10.369)*
	0.00009	0.00567	0.00381	0.00086	0.00084	0.00368
?	(0.151)	(5.094)*	(4.517)*	(1.007)	(1.369)	(7.938)*

Notes to Table 4:
See equation (5) for calculation of contrarian profits. Panel A: Results for all firms using closing prices Panel B: Results for all firms using bid-to-bid prices. Panel C: Results after removing firms that trade infrequently. Panel D: Single-factor risk adjusted returns for frequently trading firms, employing the residual from: $r_{i,t}=a_0+b_{0r}r_{m,t}+e_{i,t}$. Panel E: Three-factor adjusted returns for frequently trading firms, employing the residual from: $r_{i,t}=a_0+b_0r_{m,t}+b_1SMB_t+b_0HML_t+e_{i,t}$. Contrarian Euro profits (?) are estimated as: $y_{t,k} = \frac{\sum_{1=1}^{N_{t-1}} w^{+}_{i,t} r_{i,t}}{\sum_{1=1}^{N_{t-1}} w^{+}_{i,t}}$, where $w^{+}_{i,t} = -\frac{1}{N_{t-1}}(r_{i,t-1} - r_{m,t-1})$ if $r_{i,t-1} < r_{m,t-1}$ or 0 otherwise. t-statistics reported in parentheses: $t=\frac{\bar{p}}{e.s.e(\bar{p})} \sim t_{n-k}$ $t=\frac{\bar{y}}{e.s.e(\bar{y})} \sim t_{n-k}$, on repeated sampling (* indicates significance at the 5% level; ** indicates significance at the 10% level).

Table 5
Average estimates of stock return sensitivities (3 factors - all stocks)

	$\bar{b}_{o,M}$	$\bar{b}_{1,M}$	$\hat{d}_{M}$
Smallest Stocks	0.645805	0.139315	0.030969
	(38.313)*	(9.564)*	
Small Stocks	0.517984	0.179426	0.029238
	(42.459)*	(17.164)*	
Medium Stocks	0.515874	0.205527	0.010743
	(45.940)*	(21.967)*	
Large Stocks	0.512568	0.221385	0.039508
	(51.945)*	(26.204)*	
Largest Stocks	0.583226	0.119636	-0.04126
	(57.963)*	(14.508)*	
Average	**0.555091**	**0.173058**	**0.0138396**
All Stocks	0.625758	0.217838	-0.000081
	(72.999)	(40.984)*	
	$\bar{b}_{o,SMB}$	$\bar{b}_{1,SMB}$	$\hat{d}_{SMB}$
Smallest Stocks	0.777966	0.045671	-0.37027
	(35.275)*	(2.299)*	
Small Stocks	0.450008	0.065278	-0.17492
	(27.278)*	(4.285)*	
Medium Stocks	0.375741	0.040581	-0.11955
	(25.846)*	(2.948)*	
Large Stocks	0.172548	-0.006644	-0.10118
	(13.122)*	(-0.548)*	
Largest Stocks	-0.233638	0.020433	-0.10900
	(-19.566)*	(2.003)*	
Average	**0.308525**	**0.033064**	**-0.17498**
All Stocks	0.3753162	0.032499	-0.04100
	(30.917)*	(4.416)*	
	$\bar{b}_{o,HML}$	$\bar{b}_{1,HML}$	$\hat{d}_{HML}$
Smallest Stocks	-0.17028	0.047119	-0.36745
	(-6.272)*	(1.859)**	
Small Stocks	-0.154438	0.008381	-0.15711
	(-7.599)*	(0.440)	
Medium Stocks	-0.214113	0.036601	-0.10690
	(-12.260)*	(2.291)*	
Large Stocks	-0.192566	0.010898	-0.07827
	(-12.207)*	(0.763)	
Largest Stocks	-0.175245	0.047428	-0.14577
	(-12.348)*	(3.782)*	
Average	**-0.181328**	**0.030086**	**-0.1711**
All Stocks	-0.143107	0.025595	-0.01442
	(-12.685)*	(3.549)*	

Notes to Table 5:

The coefficients $\bar{b}_0$ and $\bar{b}_1$ reported in Table 5 are obtained from equation (16), which is estimated for the full sample, as well as for each year and each stock in each sub-sample separately. SMB is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks, and HML is the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks. This provides estimates of a_i, b_0, b_1, for each stock, for the full sample, as well as for each year, each sub-sample, and each factor. Then, $\bar{b}_0$ and $\bar{b}_1$ are calculated as the averages of b_0 and b_1.

* Indicates significance at the 5% level. ** Indicates significance at the 10% level

Table 6
Decomposition of contrarian profits (3 factors - all stocks)

	$-\hat{d}s^2_M$ **x10³**	$-\hat{d}s^2_{SMB}$ **x10³**	$-\hat{d}s^2_{HML}$ **x10³**
Smallest Stocks	-0.014620	0.085752	0.078105
Small Stocks	-0.013803	0.040511	0.033395
Medium Stocks	-0.005071	0.027686	0.022722
Large Stocks	-0.018651	0.023433	0.016638
Largest Stocks	0.019477	0.025245	0.030985
All Stocks	0.000038	0.009496	0.003065
	$-\Omega$ x10³	$-s^2_a$ x10³	
Smallest Stocks	0.240971	-0.207935	
Small Stocks	0.110115	-0.151600	
Medium Stocks	0.033356	-0.129992	
Large Stocks	0.015432	-0.108121	
Largest Stocks	0.097521	-0.073256	
All Stocks	0.069006	-0.016238	

Notes to Table 6:
The term $-\hat{d}s^2_M$ provides an estimate of the part of contrarian profits due to market reactions. The term $-\hat{d}s^2_{SMB}$ provides an estimate of the part of contrarian profits due to reactions to the size factor, while the term $-\hat{d}s^2_{HML}$ provides an estimate of the part of contrarian profits due to reactions to the book-to-market factor. The negative of the average autocovariance of the error term, Ω, defined as $\Omega \equiv \frac{1}{N}\sum_{i=1}^{N} \text{cov}(e_{i,t}, e_{i,t-1})$, provides an estimate of contrarian profits due to overreaction to firm-specific information. The negative of the cross-sectional variance of expected returns ($-s^2_a$) provides an estimate of the profits that are not due to the previous terms.

Table 7
Decomposition of contrarian profits with time-varying factor sensitivities
(3 factors - all stocks)

Panel A: Estimated coefficients

	a_0 x 10^3	a_1 x 10^3	a_2 x 10^3	a_3 x 10^3	g x 10^3
Smallest Stocks	0.05662 (0.840)	-40.04323 (-1.045)	104.87354 (0.918)	104.76158 (2.455)*	17.53029 (2.949)*
Small Stocks	-0.01593 (-0.677)	-87.06687 (-6.507)*	118.18356 (2.961)*	109.20998 (7.327)*	-2.44207 (-1.176)
Medium Stocks	-0.05919 (-2.670)*	-48.28303 (-3.829)*	29.96345 (0.797)	114.94104 (8.183)*	1.057801 (0.541)
Large Stocks	-0.07135 (-4.408)*	-39.49639 (-4.291)*	47.23366 (1.721)**	38.70094 (3.774)*	-2.57271 (-1.801)**
Largest Stocks	0.14647 (0.923)	-46.69936 (-0.519)	234.44236 (0.873)	27.37841 (0.273)	38.07464 (2.719)*
All Stocks	-0.03938 (-1.079)	-64.98927 (-3.060)*	153.04215 (2.414)*	87.02743 (3.719)*	22.31376 (6.835)*

Panel B: Contributions to contrarian Profits

	$a_1 s^2_M$ x 10^3	$a_2 s^2_{SMB}$ x 10^3	$a_3 s^2_{HML}$ x 10^3	$g(\frac{1}{T}\sum_{t=1}^{T} q_{t-1})$ x 10^3
Smallest Stocks	-0.018903 [-0.12094]	0.024288 [0.15539]	0.022268 [0.14247]	0.072918 [0.46652]
Small Stocks	-0.041103 [2.59282]	0.027370 [-1.72656]	0.023214 [-1.46436]	-0.010158 [0.64078]
Medium Stocks	-0.022793 [-0.63116]	0.006939 [0.19215]	0.024432 [0.67653]	0.004400 [0.12184]
Large Stocks	-0.018645 [0.27262]	0.010939 [-0.15994]	0.008226 [-0.12028]	-0.010701 [0.15647]
Largest Stocks	-0.022046 [-0.06513]	0.054295 [0.16041]	0.005820 [0.01719]	0.158373 [0.46790]
All Stocks	-0.030680 [-0.40314]	0.035443 [0.46572]	0.018499 [0.24307]	0.092815 [1.21959]

Notes to Table 7:
t-statistics appear in parentheses.
* indicates significance at the 5% level; ** indicates significance at the 10% level
Numbers in bracket are ratios of each component relative to the average contrarian profit.

Table 8
Average estimates of stock return sensitivities
(3 factors - Excluding Stocks that Trade Infrequently)

	$\bar{b}_{o,M}$	$\bar{b}_{1,M}$	$\hat{d}_{M}$
Smallest Stocks	0.71499 (39.289)*	0.18112 (12.028)*	0.019470
Small Stocks	0.59483 (42.131)*	0.19466 (16.524)*	0.005410
Medium Stocks	0.519739 (44.825)*	0.21745 (21.454)*	0.034093
Large Stocks	0.51266 (45.878)*	0.19244 (19.128)*	0.005151
Largest Stocks	0.62417 (53.816)*	0.09750 (10.728)*	0.006508
Average	**0.59328**	**0.17663**	**0.014126**
All Stocks	0.69257 (47.435)*	0.21087 (23.577)*	0.001809
	$\bar{b}_{o,SMB}$	$\bar{b}_{1,SMB}$	$\hat{d}_{SMB}$
Smallest Stocks	0.73247 (29.390)*	0.03472 (1.543)	-0.442480
Small Stocks	0.46953 (24.561)*	0.02429 (1.431)	-0.199248
Medium Stocks	0.29251 (18.893)*	0.02780 (1.833)*	-0.086220
Large Stocks	0.04481 (2.933)*	-0.03328 (-2.476)*	-0.132895
Largest Stocks	-0.24567 (-17.654)*	0.02229 (1.680)**	-0.099521
Average	**0.25873**	**0.015164**	**-0.192073**
All Stocks	0.10692 (5.307)*	-0.01203 (-1.079)	-0.024860
	$\bar{b}_{o,HML}$	$\bar{b}_{1,HML}$	$\hat{d}_{HML}$
Smallest Stocks	-0.19542 (-6.089)*	0.03713 (1.333)	-0.245868
Small Stocks	-0.23211 (-10.125)*	0.02626 (1.273)	-0.113819
Medium Stocks	-0.22789 (-11.648)*	0.01544 (0.846)	-0.16576
Large Stocks	-0.22591 (-11.995)*	0.00263 (0.166)	-0.134634
Largest Stocks	-0.18089 (-11.809)*	0.06009 (4.188)*	-0.177955
Average	**-0.21244**	**0.02831**	**-0.167607**
All Stocks	-0.13225 (-7.356)*	0.033371 (2.847)*	-0.004598

Notes to Table 8:
See Notes to Table 5

Table 9
Decomposition of contrarian profits
(3 factors - Excluding Stocks that Trade Infrequently)

	$-\hat{d}s_{M}^{2}$ **x10^{3}**	$-\hat{d}s_{SMB}^{2}$ **x10^{3}**	$-\hat{d}s_{HML}^{2}$ **x10^{3}**
Smallest Stocks	-0.009191	0.094054	0.056941
Small Stocks	-0.002554	0.042352	0.026359
Medium Stocks	-0.016095	0.018327	0.038389
Large Stocks	-0.00243	0.028248	0.031180
Largest Stocks	-0.003072	0.021154	0.041213
All Stocks	-0.000854	0.005284	0.001065
	$-\Omega$ x10^{3}	$-s_{a}^{2}$ x10^{3}	
Smallest Stocks	0.229988	-0.215994	
Small Stocks	0.086188	-0.147579	
Medium Stocks	0.045987	-0.122829	
Large Stocks	0.025111	-0.099133	
Largest Stocks	0.114961	-0.060084	
All Stocks	-0.014067	0.015580	

Notes to Table 9:
See Notes to Table 6

Table 10
Decomposition of contrarian profits with time-varying factor sensitivities
(3 factors - Excluding Stocks that Trade Infrequently)

Panel A: Estimated coefficients

	a_0 x 10^3	a_1 x 10^3	a_2 x 10^3	a_3 x 10^3	g x 10^3
Smallest Stocks	-0.08704 (-1.558)	-31.76949 (-1.169)	321.96496 (3.938)*	135.73168 (4.544)*	31.89859 (2.086)*
Small Stocks	-0.06984 (-2.400)*	-63.96142 (-4.519)*	212.44737 (4.989)*	115.44263 (7.421)*	-3.15911 (-0.397)
Medium Stocks	-0.06270 (-2.111)*	-50.23478 (-3.478)*	131.40186 (3.024)*	79.18700 (4.988)*	-3.15243 (-0.388)
Large Stocks	-0.09724 (-5.356)*	-29.70145 (-3.364)*	66.40358 (2.500)*	35.14729 (3.622)*	7.90679 (1.591)
Largest Stocks	0.03768 (2.017)*	13.53981 (1.490)	74.14643 (2.712)*	88.15862 (8.826)*	8.46819 (1.656)**
All Stocks	-0.06122 (-3.773)*	-9.52502 (-1.194)	151.22545 (6.301)*	67.51784 (7.697)*	6.25909 (1.397)

Panel B: Contributions to contrarian Profits

	$a_1 s_M^2$ x 10^3	$a_2 s_{SMB}^2$ x 10^3	$a_3 s_{HML}^2$ x 10^3	$g(\frac{1}{T}\sum_{t=1}^{T} q_{t-1})$ x 10^3
Smallest Stocks	-0.014997 [-0.18470]	0.074564 [0.91826]	0.028851 [0.35530]	0.078865 [0.97122]
Small Stocks	-0.030195 [0.89027]	0.049201 [-1.45065]	0.024538 [-0.72350]	-0.007810 [0.23028]
Medium Stocks	-0.023715 [0.50316]	0.030432 [-0.64567]	0.016832 [-0.35713]	-0.007794 [0.16537]
Large Stocks	-0.014021 [0.20420]	0.015378 [-0.22396]	0.007471 [-0.10880]	0.019548 [-0.28469]
Largest Stocks	0.006392 [0.063086]	0.017172 [0.16948]	0.018739 [0.18495]	0.020936 [0.206638]
All Stocks	-0.004497 [3.54317]	0.035023 [-27.59678]	0.014352 [-11.30867]	0.015475 [-12.193690]

Notes to Table 10:
See Notes to Table 7.

Table 11
Average estimates of stock return sensitivities (3 factors - bid prices)

	$\bar{b}_{o,M}$	$\bar{b}_{1,M}$	$\hat{d}_M$
Smallest Stocks	0.56146	0.17786	0.06899
	(25.999)*	(9.214)*	
Small Stocks	0.43360	0.18709	0.02413
	(28.161)*	(13.384)*	
Medium Stocks	0.44890	0.17653	0.03727
	(32.272)*	(14.598)*	
Large Stocks	0.42106	0.15309	0.05193
	(32.536)*	(13.719)*	
Largest Stocks	0.53717	0.06328	-0.00422
	(40.160)*	(6.279)*	
Average	**0.48044**	**0.15157**	**0.03562**
All Stocks	0.53131	0.21904	0.011206
	(57.680)*	(32.562)*	
	$\bar{b}_{o,SMB}$	$\bar{b}_{1,SMB}$	$\hat{d}_{SMB}$
Smallest Stocks	0.57928	0.02202	-0.28507
	(20.425)*	(0.848)	
Small Stocks	0.30902	-0.00051	-0.16922
	(15.545)*	(-0.026)	
Medium Stocks	0.23284	-0.03813	-0.12323
	(13.561)*	(-2.283)*	
Large Stocks	-0.00851	-0.10720	-0.05745
	(-0.530)	(-6.985)*	
Largest Stocks	-0.27599	-0.06166	-0.09064
	(-18.607)*	(-4.831)*	
Average	**0.16733**	**-0.03710**	**-0.14512**
All Stocks	0.21212	0.00804	-0.01051
	(16.690)*	(0.924)	
	$\bar{b}_{o,HML}$	$\bar{b}_{1,HML}$	$\hat{d}_{HML}$
Smallest Stocks	-0.20999	0.11393	-0.26007
	(-5.940)*	(3.502)*	
Small Stocks	-0.19981	0.07843	-0.20122
	(-7.643)*	(3.260)*	
Medium Stocks	-0.20925	0.07511	-0.15368
	(-9.282)*	(3.807)*	
Large Stocks	-0.25390	0.04720	-0.02543
	(-12.774)*	(2.735)*	
Largest Stocks	-0.16958	0.08790	-0.16618
	(-9.447)*	(5.610)*	
Average	**-0.20851**	**0.08051**	**-0.16132**
All Stocks	-0.15326	0.04394	-0.00278
	(-12.329)	(5.709)	

Notes to Table 11:
See Notes to Table 5.

Table 12
Decomposition of contrarian profits (3 factors - bid prices)

	$-\hat{d}s_{M}^{2}$ **x10³**	$-\hat{d}s_{SMB}^{2}$ **x10³**	$-\hat{d}s_{HML}^{2}$ **x10³**
Smallest Stocks	-0.032568	0.066020	0.055281
Small Stocks	-0.011391	0.039190	0.042771
Medium Stocks	-0.017594	0.028539	0.032666
Large Stocks	-0.024515	0.013305	0.005405
Largest Stocks	0.001992	0.020991	0.035323
All Stocks	-0.005290	0.002434	0.000591
	$-\Omega$ x10^3	$-s_{a}^{2}$ x10^3	
Smallest Stocks	0.264064	-0.194724	
Small Stocks	0.066139	-0.129557	
Medium Stocks	-0.009948	-0.115085	
Large Stocks	0.019544	-0.088714	
Largest Stocks	0.111820	-0.058128	
All Stocks	0.047847	-0.011494	

Notes to Table 12:
See Notes to Table 6.

Table 13
Decomposition of contrarian profits with time-varying factor sensitivities
(3 factors - bid prices)

Panel A: Estimated coefficients

	a_0 x 10^3	a_1 x 10^3	a_2 x 10^3	a_3 x 10^3	g x 10^3
Smallest Stocks	-0.32663	-15.77024	-8.15782	65.22539	114.06395
	(-3.436)*	(-0.462)	(-0.078)	(1.728)**	(4.626)*
Small Stocks	-0.80117	-64.64017	-435.05206	95.44440	299.59368
	(-3.869)*	(-0.869)	(-1.903)**	(1.161)	(5.577)*
Medium Stocks	-0.09860	7.45052	112.32887	88.55877	-13.56615
	(-3.459)*	(0.727)	(3.570)*	(7.823)*	(-1.835)**
Large Stocks	-0.02731	33.34247	21.30174	26.69069	-14.95185
	(-1.099)	(3.735)*	(0.777)	(2.705)*	(-2.320)*
Largest Stocks	-0.01631	-12.20981	136.67044	117.67789	17.06446
	(-0.608)	(-1.268)	(4.620)*	(11.059)*	(2.455)*
All Stocks	-0.06429	-18.83851	48.69727	130.73763	34.32832
	(-1.279)	(-1.035)	(0.870)	(6.501)*	(2.622)*

Panel B: Contributions to contrarian Profits

	$a_1 s_M^2$ x 10^3	$a_2 s_{SMB}^2$ x 10^3	$a_3 s_{HML}^2$ x 10^3	$g\left(\frac{1}{T}\sum_{t=1}^{T} q_{t-1}\right)$ x 10^3
Smallest Stocks	-0.007445	-0.001889	0.013864	0.368507
	[-0.12969]	[-0.03291]	[0.24151]	[6.41923]
Small Stocks	-0.030515	-0.100754	0.020288	0.967899
	[-0.40909]	[-1.35071]	[0.27198]	[12.97566]
Medium Stocks	0.003517	0.026014	0.018824	-0.043828
	[-0.03874]	[-0.28656]	[-0.20735]	[0.48278]
Large Stocks	0.015740	0.004933	0.005673	-0.048305
	[-0.32593]	[-0.10215]	[-0.11748]	[1.00024]
Largest Stocks	-0.005764	0.031652	0.025014	0.055130
	[-0.06022]	[0.33068]	[0.26133]	[0.57597]
All Stocks	-0.008893	0.011278	0.027790	0.110905
	[-0.30818]	[0.39081]	[0.96299]	[3.84315]

Notes to Table 13:
See Notes to Table 7.

Table 14
Average estimates of stock return sensitivities
(1 factor - all stocks - closing prices)

	$\bar{b}_o$	$\bar{b}_1$	$\hat{d}$
Smallest Stocks	0.33925	0.14286	0.05118
	(29.544)*	(13.626)*	
Small Stocks	0.3567	0.16157	0.03308
	(40.684)*	(21.513)*	
Medium Stocks	0.39253	0.20647	0.01210
	(47.649)	(29.205)*	
Large Stocks	0.48387	0.23161	0.03116
	(62.239)*	(37.835)*	
Largest Stocks	0.76018	0.11804	-0.00602
	(99.282)	(21.943)*	
Average	**0.46651**	**0.17211**	**0.0243**
All Stocks	0.50407	0.23532	0.00912
	(74.441)*	(57.382)*	
	$-\hat{d}s^{2}_{M}$ x10^3	-Ω x10^3	$-s^{2}_{a}$ x10^3
Smallest Stocks	-0.02416	0.19316	-0.21611
Small Stocks	-0.01562	0.06423	-0.17389
Medium Stocks	-0.00571	-0.01450	-0.12766
Large Stocks	-0.01471	-0.02727	-0.08749
Largest Stocks	0.00284	0.08653	-0.05477
All Stocks	-0.00431	-0.04587	-0.01272

Notes to Table 14:

The coefficients $\bar{b}_0$ and $\bar{b}_1$ are obtained from a simple version of equation (16), specifically by: $r_{it} = a_i + b_{0,i} r_{M,t} + b_{1,i} r_{M,t-1} + e_{i,t}$, which is estimated for the full sample, and for each year and each stock in each sub-sample separately. This provided estimates of a_i, b_0, b_1, for the full sample, and for each year and each stock in each sub-sample and the full sample as well. Then, $\bar{b}_0$ and $\bar{b}_1$ are calculated as the averages of b_0 and b_1 for each sub-sample and each stock for each year. An estimate of the potential contribution to contrarian profits of the differences in the timing of stock price reactions to the common factors is provided by $\hat{d}$, which was estimated as: $\hat{d} = \frac{1}{N}\sum_{i=1}^{N} E\{(b_{0,i} - \bar{b}_o)(b_{1,i} - \bar{b}_1)\}$.

The term $-\hat{d}s^{2}_{M}$ provides an estimate of the part of contrarian profits due to common factor reactions. The negative of the average autocovariance of the error term, Ω, defined as $\Omega \equiv \frac{1}{N}\sum_{i=1}^{N} \text{cov}(e_{i,t}, e_{i,t-1})$, provides an estimate of contrarian profits due to overreaction to firm-specific information. The negative of the cross-sectional variance of expected returns ($-s^{2}_{a}$) provides an estimate of the profits that are not due to the previous two terms. t statistics in parentheses

Table 15
Decomposition of contrarian profits with time-varying factor sensitivities
(1 factor - all stocks - closing prices)

	α_0 x 10^3	α_1 x 10^3	γ x 10^3	$a_1 s^2_M$ x 10^3	$g(\frac{1}{T}\sum_{t=1}^{T} q_{t-1})$ x 10^3
Smallest Stocks	0.0916	-46.9385	20.4694	-0.0221587	0.08718589
	(1.431)	(-1.315)	(3.450)*	[-0.1417682]	[0.5578021]
Small Stocks	0.0142	-72.1049	1.0540	-0.0340393	0.00448933
	(0.603)	(-5.479)*	(0.481)	[2.1472557]	[-0.2831946]
Medium Stocks	-0.2610	-49.8252	74.8214	-0.0235215	0.3186889
	(-2.836)*	(-0.971)	(8.773)*	[-0.6513232]	[8.8246743]
Large Stocks	-0.0466	-34.8854	-1.177	-0.0164687	-0.0050132
	(-2.706)*	(-3.636)*	(-0.738)	[0.2407909]	[0.0732990]
Largest Stocks	0.1565	-26.3175	45.4736	-0.0124240	0.19368698
	(1.021)	(-0.308)	(3.201)*	[-0.0367055]	[0.5722306]
All Stocks	-0.0197	-45.3706	27.5902	-0.0214186	0.1175157
	(-0.551)	(-2.253)*	(8.242)*	[-0.2814]	[1.5442]

Notes to Table 15:
The coefficients α_0, α_1, and γ are obtained from the following decomposition of contrarian profits, p_t: $p_t = a_0 + a_1 (r_{M,t-1} - \bar{r}_M)^2 + g q_{t-1} + u_t$, where $q_t = \frac{1}{N}\sum_{i=1}^{N} e^2_{i,t}$, $\bar{r}_M$ is the average common factor return, and $e_{i,t}$ are the residuals estimated from the equation in table 14. The estimate of the contrarian profits due to delayed reactions to the common factor is given by the product of a_1 and the variance of the common factor ($a_1 s^2_M$), while an estimate of contrarian profits due to overreaction is given by: $g(\frac{1}{T}\sum_{t=1}^{T} q_{t-1})$. Numbers in bracket are ratios of each component relative to the average contrarian profit from Table 4,
t-statistics appear in parentheses: * denotes significance at the 5%; ** denotes significance at the 10%

Table 16
Average estimates of stock return sensitivities
(1 factor - Excluding Stocks that Trade Infrequently - closing prices)

	$\bar{b}_o$	$\bar{b}_1$	$\hat{d}$
Smallest Stocks	0.45693	0.18993	0.03161
	(37.321)*	(18.739)*	
Small Stocks	0.45331	0.20369	0.01730
	(47.230)*	(24.807)*	
Medium Stocks	0.45098	0.22177	0.01812
	(51.875)*	(29.586)*	
Large Stocks	0.55565	0.21634	0.01031
	(64.431)*	(30.588)*	
Largest Stocks	0.77693	0.08406	-0.00870
	(90.521)*	(14.863)*	
Average	**0.53876**	**0.183158**	**0.01372**
All Stocks	0.68343	0.22866	-0.00274
	(59.477)*	(30.531)*	
	$-\hat{d}s_M^2$ x10^3	-Ω x10^3	$-s_a^2$ x10^3
Smallest Stocks	-0.01492	0.16219	-0.15707
Small Stocks	-0.00817	0.02930	-0.11287
Medium Stocks	-0.00856	-0.00144	-0.09101
Large Stocks	-0.00487	-0.02105	-0.07776
Largest Stocks	0.00411	0.10844	-0.03942
All Stocks	0.00129	-0.03466	-0.01010

Notes to Table 16:
See Notes to Table 14.

Table 17
Decomposition of contrarian profits with time-varying factor sensitivities
(1 factor - Excluding Stocks that Trade Infrequently - closing prices)

	α_0 x 10^3	α_1 x 10^3	γ x 10^3	$a_1 s_M^2$ x 10^3	$g(\frac{1}{T}\sum_{t=1}^{T} q_{t-1})$ x 10^3
Smallest Stocks					
	-0.07556	3.47468	60.19677	0.001640	0.153759
	(-1.346)	(0.132)	(4.138)*	[0.0187538]	[1.7579196]
Small Stocks					
	-0.05931	-39.87044	17.12576	-0.018822	0.043744
	(-1.971)*	(-2.833)*	(2.197)*	[0.5549528]	[-1.2897476]
Medium Stocks					
	-0.05377	-34.94105	9.06450	-0.016495	0.023153
	(-1.798)**	(-2.498)*	(1.170)	[0.3499747]	[-0.4912415]
Large Stocks					
	-0.09183	-21.99570	13.03128	-0.010384	0.033285
	(-5.073)*	(-2.598)*	(2.779)*	[0.1512219]	[-0.4847463]
Largest Stocks					
	0.04280	23.14706	18.39582	0.010927	0.046988
	(2.213)*	(2.560)*	(3.672)*	[0.1078497]	[0.4637592]
All Stocks					
	-0.05133	7.55276	18.23177	0.003566	0.046569
	(-3.034)*	(0.944)	(4.125)*	[-2.8095208]	[-36.6949001]

Notes to Table 17:
See Notes to Table 15.

Table 18
Average estimates of stock return sensitivities
(1 factor - all stocks - bid prices)

	$\bar{b}_o$	$\bar{b}_1$	$\hat{d}$
Smallest Stocks	0.36440	0.16429	0.08283
	(23.341)*	(12.612)*	
Small Stocks	0.36167	0.17975	-0.00284
	(30.470)*	(18.206)*	
Medium Stocks	0.40991	0.18181	0.04042
	(37.685)*	(22.439)*	
Large Stocks	0.49642	0.19381	0.032115
	(47.303)*	(24.847)*	
Largest Stocks	0.71893	0.07795	-0.00297
	(64.189)*	(11.113)*	
Average	**0.47027**	**0.15952**	**0.02991**
All Stocks	0.47293	0.20751	0.01087
	(55.709)*	(42.044)*	
	$-\hat{d}s^2_M$ x10^3	-Ω x10^3	$-s^2_a$ x10^3
Smallest Stocks	-0.03910	0.16167	-0.16147
Small Stocks	0.00134	0.00471	-0.11015
Medium Stocks	-0.01908	-0.06292	-0.09822
Large Stocks	-0.01516	-0.03578	-0.07391
Largest Stocks	0.00140	0.10067	-0.04598
All Stocks	-0.00513	0.02210	-0.01054

Notes to Table 18:
See Notes to Table 14.

Table 19
Decomposition of contrarian profits with time-varying factor sensitivities
(1 factor - all stocks - bid prices)

	α_0 x 10^3	α_1 x 10^3	γ x 10^3	$a_1 s_M^2$ x 10^3	$g(\frac{1}{T}\sum_{t=1}^{T} q_{t-1})$ x 10^3
Smallest Stocks					
	-0.33451	-15.03922	116.72895	-0.007010	0.388362
	(-3.620)*	(-0.463)	(5.345)*	[-0.1236740]	[6.7651032]
Small Stocks					
	-0.74588	-101.6280	254.5905	-0.047976	0.847034
	(-3.689)*	(-1.431)	(5.328)*	[-0.6431748]	[11.3553438]
Medium Stocks					
	-0.12815	19.13962	8.01148	0.009035	0.026655
	(-4.394)*	(1.869)**	(1.162)	[-0.0995281]	[-0.2936079]
Large Stocks					
	-0.03405	35.69625	-9.50868	0.016851	-0.031636
	(-1.401)	(4.182)*	(-1.655)	[-0.3489406]	[0.6550762]
Largest Stocks					
	-0.05040	2.47825	42.39335	0.0011699	0.141045
	(-1.777)**	(0.248)	(6.324)*	[0.0122229]	[1.4735615]
All Stocks					
	-0.11035	-13.27944	58.43454	-0.006269	0.194414
	(-2.207)*	(-0.751)	(4.925)*	[-0.2172363]	[6.7369782]

Notes to Table 19:
See Notes to Table 15.