THE UK EQUITY MARKET AROUND THE EX-SPLIT DATE

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ABSTRACT

Using UK stock market data this study unveils positive abnormal returns on and around the ex-split date. These excess returns are partially predictable using the publicly available information prior to the ex-split date. There is also a persistent increase in the post-split volatility of these stocks with the results being robust to the choice of the volatility proxy. Post-split volatility is found to be positively related to trading activity. Contrary to the US findings, volatility dynamics following the stock split are better captured by changes in the daily trading volume rather than by the number of trades.

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Key Words: Stock splits; Ex-split date; Equity abnormal returns; Stock market volatility

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I. INTRODUCTION

Some investors may view stock splits as advantageous, but there is little evidence that they are benefited in any meaningful way. In many cases, stock splits are seen as a sign of management optimism and investors appear to share this view. Based on market efficiency these favorable managerial signals should be immediately incorporated in the stock prices. Nonetheless, expectations based on theoretical frameworks are often contradicted by empirical evidence. The question of interest is, therefore, 'how do markets react when it comes to stock splits?' A number of studies have attempted to explain this event and assess both the short- and long-run performance of stock returns/volatility following the corporate announcements.

Differential behavior between split and non-split stocks has been documented indicating that this non-economic action does affect the shareholders' wealth. Research in the area unveils a rise in risk-adjusted returns following the announcement and ex-split dates (Grinblatt, Masulis & Titman, 1984; Ikenberry, Rankine & Stice, 1996; Desai & Jain, 1997) as well as an increase in equity return volatility (Ohlson & Penman, 1985; Dubofsky, 1991; Koski, 1998). If such an overreaction persists for a period of time, then concerns are raised regarding the speed of price adjustment to information flow, and potentially invalidate Fama's (1998) efficient market approach. In parallel, work on corporate events suggests that markets appear to under-react to news (Daniel, Hirshleifer & Subrahmanyam, 1998).

On the theoretical front, four main hypotheses are put forward to explain market reactions to stock splits. The first one, the signaling hypothesis, postulates that such actions aim to reduce information asymmetries between shareholders and management regarding the firm's financial prospects[1]. The second approach, the optimal price range hypothesis, states that managers believe that when share prices trade within a certain range, their decision to split the stocks will enhance their liquidity. This "optimal" price is typically set at the historical average price of the firm's equity, or of the market/industry as a whole. The third approach, the liquidity hypothesis, can be seen as a hybrid form of the signaling and the optimal price range hypotheses, and posits that post-split liquidity enhancement benefits from both the lower price range and positive signals conveyed during the split announcement. The former is supported by Copeland (1979) who states that there is an optimal price range wherein stocks are most liquid. The fourth approach, the tick size

[1] See Fama, Fisher, Jensen & Roll (1969), Grinblatt, Masulis & Titman (1984), Brennan & Copeland (1988), McNichols & Dravid (1990) for relevant discussions and empirical findings.

hypothesis, suggests that stock splits increase the tick size relative to the stock price thereby boosting the profitability of market making (Schultz, 2000; Angel, 1997).

On the empirical front, Lamoureux & Poon (1987), Schultz (2000) and Angel (2004) find an increase in institutional ownership following a split, while Ikenberry, Rankine & Stice (1996) and Dennis & Strickland (2003) refute these findings. Muscarella & Vetsuypens (1996) report higher liquidity following the stock splits. Others report the opposite (Copeland, 1979; Murray, 1985; Lamoureux & Poon, 1987). Examining the equity performance of firms executing stock splits, Fama, Fisher, Jensen & Roll (1969) and Byun & Rozeff (2003) found insignificant abnormal returns, which contradicts the results of Desai & Jain (1997) and Wu & Chang (1997). Hwang, Keswani & Shackleton (2007) observe that an unexpected stock split yields abnormal return within the first three months, but the effect disappears over longer horizons for both expected and unexpected splits.

The post-split volatility increase has also received extensive attention in the empirical literature, but there is no consensus as yet on the reasons behind this phenomenon. Some researchers have highlighted the role of market microstructure effects, such as bid-ask spread and price discreteness, which introduce noise in volatility measurement (Ohlson & Penman, 1985; Ball, 1988). Another explanation relies on the impact of splits on trading activity, which places the rise in the daily number of (small) trades as the main driver behind the post-split volatility increase (Jones, Kaul & Lipson, 1994; Desai, Nimalendran & Venkataraman, 1998; Kamara & Koski, 2001).

The literature has put forward a number of reasonable explanations for both the rise in the risk-adjusted returns and their volatility following the split event, but the majority of studies have focused on the US market. Thus the objectives of the present work are as follows. First, this is the first study, to our knowledge, considering the equity behavior around stock splits in the UK market. Focusing on the UK market is crucial since a) there is a bi-directional trading and investment relationship between the UK and the US, b) the UK is a financial centre interacting continuously with European, Asian and the American markets, and c) the extent to which the findings for the US firms hold in another major market can be assessed.

Second, the study looks at the excess returns and equity volatility surrounding the ex-date rather than the announcement date. Anecdotal evidence of ex-date abnormal returns has been the impetus of this research. The occurrence of ex-date excess returns is rather surprising, as this date is known in advance and lacks the material information[2] to justify any abnormal market reaction. Yet ex-date abnormal returns have been documented by a few US studies (Dravid, 1987; Julio & Deng, 2006) with mixed explanations.

The third goal of the current research is to provide a robust analysis of the factors affecting the UK equity performance for both returns and volatility following the split event (ex-date). The ability to identify these factors is of great importance to market participants, fund managers and academic scholars, as they have a notable impact on portfolio selection, asset allocation, financial pricing, and corporate strategy.

Finally, turning to the methodological framework, a GARCH based approach (Cohray & Tourani Rad, 1996) is employed as the platform for scrutinizing excess returns. In order to examine the volatility behavior, two different volatility proxies, both adjusted for microstructure biases (Kaul & Nimalenndran, 1990), are employed. Since volatility estimates embrace both systematic and unsystematic exposure, an adjustment is made to ensure that analysed proxies mirror the idiosyncratic component of the firm's return volatility. This adjustment has not been previously applied to the analysis of volatility behavior around the event dates.

In what follows, the paper presents the hypotheses tested in Section II. The data and methodology employed are described in Section III. Section IV discusses the empirical findings, and Section V concludes the paper.

II. HYPOTHESES FORMULATION

Under the signaling hypothesis, a stock split announcement can signal further growth in corporate earnings and increase in share prices. The market is expected to react positively to these favorable signals pushing prices up and generating positive abnormal returns around the announcement date. The potential occurrence of further abnormal returns on the ex-split dates would be rather intriguing given the theoretical absence of new information to justify any market under/overreaction. Thus, *ceteris paribus*, corporations executing stock splits are equalized by the amount of signaling information available on the ex-date in an event-wide sense. Possible factors which might affect the ex-date market reaction are the size of the split ratio as a determinant of the positive signal strength stemming from the signaling hypothesis; the market value of equity as an indicator of the firm's prosperity and stability;

[2] Information is material if it has an impact on securities prices when it becomes publicly available for the first time. If it has no impact on prices, it is largely irrelevant, although it may cause portfolio adjustments that leave prices unchanged.

and the favorable "optimal price" determined by the optimal price range hypothesis. On the basis of the discussion so far, the following constitute our testable hypotheses:

H_1 There is no significant abnormal return around the ex-split date

H_2 If H_1 is rejected, the abnormal return is identical for all firms in the sample

H_3 If H_1 and H_2 are rejected, market reaction around the ex-date, e.g. the presence of abnormal returns over [-1 +1], can be predicted via publicly available information

H_4 If H_3 is true, the same information can predict the occurrence of returns over different time horizons around the ex-date

The above hypotheses, concerning abnormal returns around the ex-split date, are tested within an event study framework. A probit model is deployed for predicting the occurrence of abnormal returns across the event window based on firm-specific variables (H_3 to H_4).

Stock market volatility around the ex-split date is the second component of the present research. Several hypotheses are proposed to explain the volatility behavior, yet no consensus has been reached. Some scholars argue that the rise in volatility following the stock split might be explained by the expanded shareholder base creating increased trading activity and hence volatility (Lamoureux & Poon, 1987). Empirical findings examining the relations between trading activity and volatility behavior advocate the rise in the daily number of trades[3] after the ex-date as the key driver of the post-split volatility increase. Others argue that microstructure biases, such as bid-ask bounce and price discreteness, inflate the estimate of volatility thereby rendering the comparison of pre- and post-split volatility misleading (Ohlson & Penman, 1985; Dubofsky, 1991; Kryzanowski & Zhang, 1993; Ball, 1988). On the other hand, some studies have documented that the post-split volatility increase is still evident and significant even when controlling for the microstructure biases (Koski, 1998; Desai & Jain, 1997; Conroy, Harris & Benet, 1990). Based on the empirical evidence the following hypotheses are added into our analysis:

H_5 There is a post-split increase in the stock return volatility

H_6 Trading activity can explain both pre- and post-split equity returns volatility

H_7 If H_5 and H_6 are true, then trading activity measures can explain the post-split volatility increase

[3] For further discussion see Jones, Kaul & Lipson (1994), Desai & Jain (1997). Kamara and Koski (2001) relate the increase in the post-split volatility to the increase in the number of small rather than large trades.

H_8 If H_7 is true, the "daily number of trades" (transactions) measure can better capture the post-split volatility increase than the "daily trading volume" (traded shares) measure, in line with the US empirical findings

Following Ohlson & Penman (1985) the standard deviation of returns, over the relevant pre-/post-split horizon, and the mean squared daily returns are both used to proxy the latent volatility process. Using both volatility measures, the second set of hypotheses (H_5 to H_8) is tested via a cross-section Ordinary Least Squares (OLS) regression analysis.

III. DATA AND METHODOLOGY

The dataset spans the January 1990 - May 2007 period and consists of firms based in the UK and listed in the London Stock Exchange. Reverse stock splits are not considered, while companies with incomplete data are automatically excluded from the sample. Bloomberg Professional is used to identify stock splits, ex-dates, and split ratios. The remaining series, such as daily bid, ask and closing adjusted prices, market capitalization, trading volume, number of trades and market indices are all obtained from Thomson DataStream.

A. Data Analysis

The first set of hypotheses (H_1-H_4) examines the market reaction of UK stocks around the ex-date, while the second set (H_5-H_8) examines the behavior of the ex-date's equity returns volatility. To this end, two data samples are collected accordingly. The first group of data consists of 137 firms that have consistent and available daily data on the adjusted share prices and the firms' market capitalization for the whole period and is employed to test H_1-H_4. The sample is separated into six groups on the basis of the split ratio's size. The total number of companies in each split ratio category and the pertinent statistics are presented in Table 1, Panel A and B.

[Insert Table 1: Panel A - B]

The number of stock splits varies across years/months. Splits are notably less frequent in the post 2000 period[4] and appear to be taking place mostly over the second and third quarters. The most common size of the split ratio is 2:1 (59 firms) followed by 4:1 split ratio (31 firms). The average (median) market value of the firms' equity across the split categories is £2766.39 million (£422.51 million). The highest average market value (£4714.28

[4] This may be possibly attributed to the post-1999 slow economic growth and the accompanied reduced price/earnings fluctuations.

million) is for firms with a split ratio of 2:1, while the lowest (£772.10 million) is for firms splitting at 10:1, but no clear pattern can be inferred between size and split-ratio. Nonetheless, the split ratio increases monotonically with the pre-split share price (on day t = -20) in support of the optimal price range and liquidity hypotheses[5].

In order to analyze the equity volatility around the ex-date a sample of 101 firms, with available data on daily trading volume and number of trades, is employed. The resulting sample is also grouped according to the split ratio's size. The total number of companies in each category and the relevant statistics are presented in Table 1, Panel C[6].

[Insert Table 1: Panel C]

Daily trading activity measures, represented by the trading volume and the number of trades, are obtained over the pre-split [-260 -21] and post-split [+21 +260] periods and averaged across firms. The company average turnover per trade, computed as the ratio of trading volume to the number of trades is reported for both periods.

Examining the measures of trading activity for pre- and post-split windows, one observes a significant increase in the average post-split daily number of trades across all split categories, while the average daily trading volume remains statistically unchanged. The median increase in the number of trades varies over split size categories, but is always statistically significant. This is not true for the median trading volume. For instance, for companies with a 2:1 split ratio the median increase in the post-split number of trades is 65% compared to a mere 15% increase in trading volume. These findings are in line with the optimal price range and liquidity hypotheses, which posit that lower share prices following splits allow smaller investors to purchase the round lots, thereby extending the shareholder base. This, in turn, enhances trading activity and liquidity.

Contrary to the measures of trading activity, the average turnover per trade declines after the split event. The median drops significantly across all split categories and the mean does so in 3 out of 5 cases, while it remains statistically unchanged for the others. The largest reduction in the median trade size (average shares per trade) is observed for the 4:1 split ratio and is 102%, whereas the largest drop in the mean trade size is 77% for the 5:1 companies. The reduction in the size of the average trade following the stock-split event can

[5] The underlying assumption is that the optimal price is determined by the historical average price of the firm's equity, or of the market/industry as a whole. Thus when the companies with highest share prices announce the highest split ratio, and those with lowest share prices the lowest split ratio, the execution of the split will lead the splitting firms' average price to be brought down to the same price range matching the market/industry average price. For further discussion see Lakonishok & Lev (1987).

[6] There are just 3 companies with trading activity data available in the 5:2 split category and thus this category is removed from the volatility analysis.

be explained (although not conclusively) by the increase in the number of small size shareholders, as corroborated by Schultz (2000) and Angel (2004).

B. Methodology

For the examination of excess equity returns around the ex-split date (H_1, H_2), the paper employs the event-study methodology proposed by Brown & Warner (1985). The standard single index asset pricing model has been employed to derive the pertinent hedge ratios and calculate excess returns (also called abnormal or risk adjusted returns), while to account for the volatility clustering effect a GARCH specification for the variance of returns is used (Cohray & Tourani Rad, 1996). The analysis employs a two-year period (520 trading days) with the ex-split date dividing the sample into two sets (*i.e.* 260 daily observations in both the pre- and post-split periods). The parameters of the market model (c and β) are used to compute the abnormal returns around the event dates, while the estimation window runs from 260 to 41 trading days prior to the split date. Abnormal and cumulative abnormal returns over the event window [$-n_1$ $+n_2$] are computed as

$$AR_{it} = R_{it} - (c + \beta_{mi} R_{mt}) \tag{1}$$

$$CAR_i = \sum_{t=-n_1}^{+n_2} AR_{it} \tag{2}$$

where R_{it} is the return on stock i at time t, and R_{mt} is the return on the FTSE ALL Share market portfolio. The Average Abnormal Return (AAR_t) is calculated as $\frac{1}{N}\sum_{i=1_1}^{N} AR_{it}$ where N is the number of companies in the particular sample. The Cumulative Average Abnormal Return (CAAR) represents the total effect of an event across corporations and across a specified time interval [$-t$ $+t$] and is computed by aggregating the AAR_t. The question raised by hypotheses H_3 and H_4 is whether the occurrence of abnormal returns on the ex-date could be explained on the basis of information publicly available prior to the split. The latter reflects variables that could be able to explain abnormal returns across the event window. A probit modeling framework seems appropriate for this purpose. Let the observed binary indicator Y assume a value of 1 for positive and significant abnormal returns and be driven by a set of exogenous factors as follows

$$Y^* = X'\beta + \varepsilon, \quad \varepsilon \sim iid\ N(0, 1)$$

where Y^* is the latent variable such that $Y = 1$ for $Y^* > 0$ and $Y = 0$ otherwise and X is a vector of regressors including the constant. Thus, we have

$$Pr\,(Y = 1 \mid X) = Pr\,(Y^{*}{>}0 \mid X) = Pr\,(\varepsilon < X'\beta) = \Phi\,(X'\beta) \qquad (3)$$

where Φ is the cumulative standard normal distribution function. So the probability of a significantly positive abnormal return is given by the probit function evaluated as a linear function of X. The parameters β are estimated by maximum likelihood. The authors would like to issue a word of caution regarding the interpretation of the coefficients β in this nonlinear framework as β_i does not represent the marginal effect of X_i. Equation (3) postulates that $\partial Pr/\partial X_i = \varphi(X'\beta)\beta_i$ where φ is the standard normal probability density function. Thus, the sign of the impact of each factor X_i on the probability of observing a significantly positive abnormal return is reflected in the sign of the parameter β_i, while the magnitude depends also on the values of the other factors.

The second part of the paper [H_5–H_8] turns to examine the volatility of returns around the ex-split dates. The daily standard deviation of returns and the mean squared daily returns are used as return volatility proxies (Ohlson & Penman, 1985). To account for microstructure bias, due to the bid-ask bounce which inflates volatility estimates[7], the above volatility measures are calculated using bid-bid prices (Kaul & Nimalenndran, 1990). Both volatility proxies are computed over the relevant pre-/post-split periods excluding the 20 days period before and after the split ex-date to avoid any fleeting market microstructure effects around this date. Moreover, since the individual equity returns at time *t* are expected to be correlated with the market factor ($R_{M,t}$), their volatility estimate will also reflect the systematic risk. Hence, an orthogonalization procedure is followed to extract the companies' idiosyncratic volatility component around the event date. The orthogonalization is based on the auxiliary regression of the company's bid-bid return on the market return *i.e.* $R_{i,t} = \beta_0 + \beta_1 R_{M,t} + \varepsilon_t$. The company return is split into a component which is uncorrelated with the market return (the error term) and a second component capturing the sensitivity of the company's return to changes in the market return. The unsystematic risk of the company is captured by the variance of the "whitened" bid-bid returns ε_t and we call the estimates of this: Bias Adjusted Volatility (BAV) as measured by the squared daily returns and Bias Adjusted Standard Deviation (BASD). The volatility measures are calculated separately for the pre- split [-260 -21] and post-split [+21 +260] periods and averaged across companies in order to assess H_5. The average volatilities in the two periods are compared using a *t*-test statistic for H_0: $\mu_{BAV/BASD}(pre) = \mu_{BAV/BASD}(post)$.

[7] Since the London Stock Exchange has no formal tick rules, the bias induced by price discreteness is ignored and no adjustments regarding this bias are made. For further discussion of the tick size relevance for the stock splits see Angel (1997).

The question raised in H_6 is whether trading activity, measured by the daily number of trades and daily trading volume, is capable of explaining the returns volatility behavior both before and after the split event. This is tested, for each of the bias-corrected volatility measures, by conducting two separate cross-section regressions for the pre- and post-split periods as follows:

$$VO^i_{pre\ OR\ post} = a_0 + a_1\ TA^j_{pre\ OR\ \mathrm{post}} + a_n f_n + \varepsilon_t \tag{4}$$

where $VO^i_{\mathrm{pre\ OR\ post}}$ is the i^{th} bias-corrected volatility measure, i =1,2, computed for each company in the sample over the relevant pre- or post-event time horizons [±260; ±21]. Variable TA^j represents j^{th} trading activity measure, j =1, 2, which are the daily number of trades and trading volume, respectively. Variable f_n represents a vector of additional factors which may be useful in explaining the volatility behavior. These include the size of the split factor (*SF*) as a determinant of the positive signal strength, the size of the company (*MV*) and industry dummy variables (*DUMMY*), which take the value of one for the particular industrial group and zero otherwise. The industry dummies are included as returns volatility is likely to differ across industries *ceteris paribus*.

To test H_7 and H_8 the paper examines the relations between changes in the measures of trading activity and equity returns volatility following the ex-date via the following cross-section regression:

$$RVO^i = a_0 + a_1\ RTA^j + a_n f_n + \varepsilon_t \tag{5}$$

where RVO^i is the log ratio of the post- to pre-split bias corrected volatility i for each company. RTA^j is the log ratio of the post-to pre-split average trading activity measure j. Variable f_n subsumes the additional regressors. Provided that the proposed measures of trading activity (RTA^j) are significant and bear the plausible positive sign, H_8 is assessed by comparing the coefficient of determination for each trading activity proxy.

IV. EMPIRICAL RESULTS

In this section the results for each of the aforesaid hypotheses are discussed. The first and second hypotheses refer to the existence of significant excess returns around the ex-split date and for different split size ratios. The Average Abnormal Return (AAR) and Cumulative Average Abnormal Return (CAAR) are estimated[8] over different event windows for each split size category. The findings are reported in Table 2.

[Insert Table 2]

[8] All returns are calculated based on the price adjusted series for a particular company over the examined period. These series are obtained from Thomson DataStream.

Hypotheses 1 and 2 are rejected for all split size categories and all event windows. The AAR obtained on the ex-date (date 0) is always positive and strongly significant across all split size categories - the only exception is the 2:1 split category. Under this category, however, a statistically significant positive AAR is found on the day following the split (+1) and a significant CAAR is found over the horizons [-1 +1], [-3 +3], and [+1 +10]. For longer holding horizons, at least twenty trading days following the event, the stocks in almost all split size categories tend to underperform on average.

The statistically significant positive abnormal returns on the ex-split date are quite surprising due to the lack of material information around that date to justify market overreaction. As argued, firms executing the stock split tend to bring their share price back into some "optimal"/lower price range, something which is not realized until the effective split date. Consequently, the split date price reduction results in the shareholder base expansion and hence an increase in the trading intensity of the smaller individual investors, which in turn inflates prices resulting in abnormal returns on this date. However, assuming that it is the trade intensity, rather than changes in fundamentals, that triggers excess returns on the effective date, this is followed by a stock underperformance over a longer horizon.

Table 3 sets out the probit model estimation results for hypotheses 3 and 4. The endogenous variable (Y_i) is set to one if a positive and significant CAR for the company *i* is observed and zero otherwise. The exogenous variables considered are the split factor, company's market value, variability of equity returns, optimal price factor and industry dummies. The only dummy found significant is the one for financial institutions.

[Insert Table 3]

The Split Factor (*SF*), computed as the logarithm of the split size, is significant over the time horizons [-1 +1], [-3 +3], and [-5 +5] and bears the expected positive sign, which in turn implies that the higher the split ratio the higher the probability of positive abnormal returns. This is in line with McNichols & Dravid (1990) who provide evidence of a positive relation between the abnormal return around the announcement date and the size of the split factor chosen by the firm. Moreover, following the rationale behind the "optimal price range" hypothesis, the splits are used to bring the price to the optimal range favorably accepted by investors. Therefore, a higher split size will indicate that the current share price is much higher than the desired optimal one resulting in a higher amount for round lot investment requirements. The reduction in the share price, following the split, provides access to the small wealth investors to purchase rounds lots. This in turn increases the trading activity while pushing prices up and providing investors with positive abnormal return. In the longer run, the size of the split is no longer informative probably because the turbulent period of the increased trading activity has already passed and the positive signal conveyed in the size of the split factor has been fully incorporated in the share price. Hence, over the longer horizon, investors would base their decisions to purchase a stock on the company's fundamental values.

The second factor examined within the probit model is the size of the company (*MV*) proxied by the logarithm of the market value of the company's equity twenty days before the ex-date. The market value is found to be significantly related to the cumulative abnormal return over the longer horizons up to [+1 +10], but insignificant over the short-run period [-1 +1]. This indicates that over the long-run large firms are more likely to generate positive abnormal returns, which is consistent with Ikenberry, Rankine & Stice (1996) who report negative relations between firm size and the abnormal returns.

The optimal price factor (*OP*) is defined as the logarithm of the ratio of the firm's share price twenty days prior to the split day to the average share price of all companies traded at the same stock exchange (LSE). The optimal price factor has a negative impact, which implies that the smaller the company's share price relative to the market average, the higher the probability to observe a positive abnormal return on the ex-date and over the longer run. This can be explained by the fact that the smaller the difference between the company's share price and the market average share price, the lower the post-split share price relative to the market average. This, in turn, allows more small individual investors to participate in the market game, increasing the trading activity and hence generating abnormal returns. Moreover, the relation between the split size (*SF*) and the abnormal return is opposite to the relation between the abnormal return and optimal price (*OP*) variable. In other words, positive abnormal returns are expected from companies with lower share priced compared to the market average and with a higher split ratio. This leads one to conclude that the company's choice of the split factor is not determined by the average market share price**.** It is rather determined by other motives, such as managerial attempts to bring the share price to the optimal range favorably accepted by investors, and hence increasing the shareholder base, or to bring the price to the company specific historical range.

The standard deviation of the companies' returns over the horizon from 260 to 20 days before the split (*SD*), is significantly negative over most of horizons examined, for example [-1 +1], [-3 +3]. This indicates that the lower the stock returns volatility, the greater the probability to obtain positive and significant abnormal returns over these horizons and can be rationalized by the negative correlation between the returns volatility and the size of the company in our sample. Larger companies are less volatile thereby being more likely to earn positive abnormal returns on the ex-date. The financial institution dummy (*DUMMY*) is found to have a negative and significant effect over the time horizons up to [-20 +20]. This indicates that for these institutions the probability to obtain a positive significant abnormal return around the ex-date is much lower than for companies exercising a stock split and belonging to non-financial industries. This could reflect the relatively wider information availability for financial companies and the more extensive analysts' coverage. The signals conveyed in the split announcement are factored in the share price well before the effective date resulting in a less marked market reaction.

The evidence provided so far suggests that there is some predictive content in company-specific indicators regarding the market overreaction for the splitting companies on the ex-date. The McFadden goodness-of-fit statistic presented in Table 3 indicates that the information publicly available prior to the split can explain to a substantial degree the patterns in the company abnormal returns during the period around the ex-date [-1 +1], with diminishing explanatory power when increasing the time horizon over which the returns are calculated. The latter rejects hypothesis 4.

Turning to equity returns volatility around the ex-split date, the remaining four hypotheses (H_5-H_8) are tested. First, the stock returns volatilities before and after the split are compared. The relevant test statistic leads to the rejection of the null hypothesis stating that the pre- and post-split volatilities are equal, with the results being robust to the choice of the used volatility proxy[9]. This validates hypothesis 5 and is in line the literature (Ohlson & Penman, 1985).

To test the relevance of the measures of trading activity in explaining the post-split volatility increase the cross-section regression in equation (5) is deployed assuming different volatility and trading activity measures. The measures of trading activity used are the daily number of trades (*NT*) and the daily trading volume (*VOL*) defined as the number of shares traded. When the different volatility measures (BASD or BAV) are assumed the regression produces the quantitatively identical results with the statistical inference being invariant to

[9] The average Bias Adjusted Standard Deviation (BASD) of equity returns calculated over the relevant pre-split [-260; -21] and post-split [21; 260] horizons are 0.017 and 0.023 respectively. The *t*-statistics representing the relevant one-tailed *t*-test with the null hypothesis stating that the pre-split standard deviation is equal to the post-split standard deviation is 3.772 with a Heteroskedastic consistent *p*-values based on White's robust standard error being (0.000). This leads to rejection of the null hypothesis. The average Mean Squared Daily Returns over the pre-and post-split horizons are 0.0004 and 0.0007 respectively, with the *t*-statistics being 2.658 (0.009). According to the *p*-value in parenthesis the null is also rejected at one percent level.

the choice of the volatility proxy. Consequently, the study reports the empirical results obtained assuming only one of two measures (namely the Squared Daily Returns) as the volatility proxy. Table 4 outlines the coefficients from the cross-section equation (5) estimated assuming the squared daily returns as the volatility proxy.

[Insert Table 4]

There is a strong positive relationship between the measures of trading activity and returns volatility for both pre- and post-split horizons. For instance, looking at the pre-split period, a 1% increase in the trading volume or number of trades will increase the Bias Corrected Volatility by 0.36%. The adjusted R^2 suggests that the daily trading volume is found to better capture the volatility dynamics than the number of trades.

The market value is found to be significant over all horizons and negatively related to the volatility measure, indicating that the volatility is relatively higher for the smaller companies in both the pre- and post-split periods. When analyzing the post-split period, it is also found that the split size factor (*SF*) is positively related to the volatility of returns. Thus the higher the split factor exercised by the company, the higher the volatility of returns following the ex-date. This is consistent with the "optimal price range" and liquidity hypotheses, since the higher split factor will result in greater share price reduction. This leads to a trading rally and a subsequent volatility rise observed after the ex-date.

Having found significant relations between the measures of trading activity and the returns volatility behavior, the question still remaining is whether these measures are capable of explaining the volatility increase registered after the stock split. To examine the latter the cross-sectional regression (6) is estimated for the entire sample using both trading activity measures. The additional factors used are the size of the company (*MV*), size of the split factor (*SF*), and the trade size measure (*TS*). The latter is defined as $TS = log[(VOL_{post}/NT_{post}) / (VOL_{pre}/NT_{pre})]$. In other words, this measure is simply the log ratio of the post-split turnover per-trade to the pre-split turnover per-trade, both presented in Table 1, Panel C. This measure has not been previously used in this context and it is of interest that it appears to have some explanatory power when used alongside the trading activity measures. The explanation may be based on the post-split price reduction followed by the small investors trading intensity increase and hence the reduction in the size of average trade. Therefore, the diminishing size of the trade following the split event would result in the higher volatility[10].

The estimation output of the cross-section regression (6) with volatility proxied as the mean squared daily returns is reported in Table 5. Column (c) reports the cross-section regression coefficients when combining the TS variable with the daily trading volume (*VOL*) measure[11].

[Insert Table 5 here]

Only three variables, the number of trades (*NT*), trading volume (*VOL*), and trade size (*TS*), are significant in explaining the variations in post/pre-split volatility ratio. The coefficients for both *NT* and *VOL* are positive indicating that the relative volatility increase following the stock split is driven by the relative increase in trading activity. In contrast, the positive coefficient obtained for the *TS* ratio indicates the negative relations between the average daily size of the trade and the volatility increase following the ex-date[12].

The adjusted R^2 reported in Table 5 suggests that the volatility following the stock split is better captured by the changes in the daily trading volume (*VOL*) than changes in the daily number of trades (*NT*). The adjusted R^2 for the cross-section regression in equation (5), reported in Table 4, also favors the trading volume (*VOL*) over the number of trades (*NT*) for explaining the volatility behavior. This establishes that, in contrast to the findings reported for the US market (Jones, Kaul & Lipson, 1994; Desai & Jain, 1997), for the UK market the daily trading volume dominates the daily number of trades in terms of characterizing volatility around the split event.

V. CONCLUSION

Stock splits have received great attention in the finance literature. Various studies have attempted to explain and examine the existence of the excess risk adjusted returns and the increase in returns' volatility following the split. While most papers concentrate on the stock market behavior around the announcement date, the reality of increased risk adjusted returns as well as returns' volatility around the effective date has not been conclusively analyzed. The current work delves into these issues using a sample of stock splits in the UK market.

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[10] Since the post-split turnover per-trade is generally smaller than pre-split turnover per trade, the Trading Size (TS) measure will be less than one, resulting in the logged value being negative. Hence, the inverse relations between this measure and the volatility ratio are expected in the regression.

[11] When combining the trade size (*TS*) with the average daily number of trades (*NT*) the estimated coefficients are virtually the same.

[12] See footnote 9.

The results suggest that the UK firms experience positive abnormal returns on and around the ex-split date. These abnormal returns may be explained on the basis of information publically available prior to the split ex-date. The model proposed in this paper is able to explain approximately 24% of the market abnormal reaction patterns registered on the ex-date. The analysis of the returns volatility behavior shows that even after controlling for microstructure/market biases, there is a statistically significant increase in the volatility figures following the event date. The latter is unaffected by the choice of the volatility proxies employed.

Regression analysis suggests that there is a strong and positive relationship between the measures of trading activity and the returns' volatility over the pre- and post- split horizons. However, when analyzing the changes in volatility behavior, following the split event, the post-split volatility changes appear to be better captured by the changes in the daily trading volume rather than the daily change in the number of trades. This observation provides evidence leading to a disagreement with the findings reported for the US market where the number of trades is found to be the key measure determining the volatility behavior.

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Table 1: Summary Statistics for the Stock Split Sample: 1990 - 2007

Panel A: Distribution of Stock Splits

By Year

	Stock Splits		Stock Splits		Stock Splits
1990	8	1996	4	2002	5
1991	17	1997	12	2003	4
1992	6	1998	12	2004	3
1993	12	1999	11	2005	7
1994	10	2000	7	2006	6
1995	7	2001	4	2007	2

By Month

	Stock Splits		Stock Splits		Stock Splits
January	6	May	19	September	10
February	9	June	17	October	6
March	8	July	21	November	9
April	12	August	12	December	8

By Split Factor

	Stock Splits		Stock Splits		Stock Splits
2 for 1	59	4 for 1	31	10 for 1	9
3 for 1	12	5 for 1	19	5 for 2	7

Panel B: Summary Statistics for Event Study Firms

Two for One Splits

	Mean	Median	Max	Min
Market Value	4714.28	432.74	112464	8.64
Pre-Split Share Price	734.76	755.44	1424.45	68.14

Three for One Splits

	Mean	Median	Max	Min
Market Value	2226.82	320.43	12930.87	5.17
Pre-Split Share Price	838.14	917.5	1453	25

Four for One Splits

	Mean	Median	Max	Min
Market Value	3517.57	938.6	40867.89	5.35
Pre-Split Share Price	965.63	746.91	2171.79	191.84

Five for One Splits

	Mean	Median	Max	Min
Market Value	4019.56	386.31	86728.69	29.51
Pre-Split Share Price	1365.04	1171.17	4074.75	362.6

Ten for One Splits

	Mean	Median	Max	Min
Market Value	772.10	129.63	5213.8	1.12
Pre-Split Share Price	1482.05	1400	4125	2.63

Five for Two Splits

	Mean	Median	Max	Min
Market Value	1347.99	456.98	3990.61	98.06
Pre-Split Share Price	787.5	827.5	1112	385

Table 1: (Continued)

Panel C: Summary Statistics for Volatility Study Firms

Two for One Splits - 41 Companies	Mean	Median	Max	Min
Market Value	6936.08	1740.72	112464	8.64
Pre-Split Share Price	763.21	742.54	1424.45	68.14
Pre-Split No of Trades	155.06	63.08	1287.92	1.64
Post-Split No of Trades	264.23*	104.03*	2018.54	1.63
Pre-Split Trading Volume	3346.32	1217.26	39914.7	12.18
Post-Split Trading Volume	3571.52	1403.51	45530.7	21.89
Pre-Split Turnover per Trade	26.04*	25.36*	90.03	2.27
Post-Split Turnover per Trade	19.29	15.92	68.84	1.99

Three for One Splits - 8 Companies	Mean	Median	Max	Min
Market Value	3121.38	1420.68	12930.87	234.01
Pre-Split Share Price	937.21	824.5	1217	143
Pre-Split No of Trades	192.04	64.87	754.16	14.81
Post-Split No of Trades	270.35**	103.11**	977.88	16.18
Pre-Split Trading Volume	7352.36	1739.83	38854.1	41.4
Post-Split Trading Volume	7501.44	1318.98	37858.8	29.15
Pre-Split Turnover per Trade	60.61	18.62*	373.9	0.94
Post-Split Turnover per Trade	51.76	10.98	333.59	0.59

Four for One Splits - 25 Companies	Mean	Median	Max	Min
Market Value	4449.15	372.9	40867.89	5.35
Pre-Split Share Price	965.63	746.91	2171.79	191.84
Pre-Split No of Trades	188.57	20.58	2217.02	4.32
Post-Split No of Trades	305.18*	30.75*	3149.68	7.26
Pre-Split Trading Volume	2911.62	381.25	25095.4	43.89
Post-Split Trading Volume	3376.3	295.99	29668.6	28.73
Pre-Split Turnover per Trade	27.04*	22.01*	75.39	3.71
Post-Split Turnover per Trade	17.95	10.88	65.03	2.37

Five for One Splits - 19 Companies	Mean	Median	Max	Min
Market Value	4019.56	386.31	86728.69	29.51
Pre-Split Share Price	1365.04	1171.17	4074.75	362.6
Pre-Split No of Trades	129.3	27.97	1192.92	3.2
Post-Split No of Trades	311.48	43.40*	4193.52	5.13
Pre-Split Trading Volume	4099.18	607.57	83872.3	41.03
Post-Split Trading Volume	9995.94	502.77	254107.2	75.25
Pre-Split Turnover per Trade	25.34*	18.22*	78.98	2.93
Post-Split Turnover per Trade	14.31	12.03	60.59	2.14

Ten for One Splits - 5 Companies	Mean	Median	Max	Min
Market Value	1871.78	1604.17	5213.8	5.35
Pre-Split Share Price	1809.1	1355.14	4014.99	2.63
Pre-Split No of Trades	85.54	20.83	294.25	4.62
Post-Split No of Trades	125.06**	30.31**	434.69	4.62
Pre-Split Trading Volume	3176.64	1866.64	7007.74	90.75
Post-Split Trading Volume	3253.98	1893.33	8692.01	117.55
Pre-Split Turnover per Trade	298.22	23.82**	1364.27	6.42
Post-Split Turnover per Trade	114.48	11.38	487.69	5.08

NOTE:

This table reports the summary statistics for the companies used for examining the volatility behavior around the ex-split date. Market Value (in mil. of pounds) represents the average market value of all companies in the sample 20 days before the split; Pre-split Share Price, the average share price 20 days before the split; Pre-/Post-Split No of Trades (in thousands) represent the average companies' number of trades over the [±260, ±21] windows; Pre-/Post-Split Trading Volume (in thousands) is the average daily companies' number of shares traded. The Pre-/Post-Split Turnover per Trade is the ratio of Pre-/Post-Split Trading Volume to the Pre-/Post-Split Number of Trades.

In Panel C, asterisks denotes rejection, on the basis of t-tests and Wilcoxon sign tests, of the one-tailed null hypotheses that the mean and the median values of: 1) The No of Trades and the Trading Volume during the post-split period are greater than those during the pre-split period. 2) The Turnover per Trade over the pre-split period is greater than that over the post-split period. *,** denote significance at the 1% and 5% levels.

Table 2: Cumulative Average Abnormal Return Over the Different Time Horizons: 1990 - 2007

This table reports the values of average abnormal returns (AAR) and cumulative average abnormal returns (CAAR) observed over the relevant time horizon for the companies included in a particular split size category. Two-for-One refers to the category including all companies executing the split factor two-for-one; Three-for-One category includes all companies executing the split ratio three-for-one, etc. *t*-ratios are reported in parenthesis. *, ** denote significance at the 1% and 5% levels.

	Time Horizon														
	AAR			Cumulative Average Abnormal Return (CAAR)											
Size of the Split Ratio	**-1**	**0**	**+1**	[-1 1]	[-3 3]	[-5 5]	[-10 10]	[-20 20]	[-40 40]	[-40 -1]	[1 40]	[-20 -1]	[1 20]	[-10 -1]	[1 10]
Two-for One	0.000	0.000	0.008	0.008	0.014	0.007	0.011	-0.010	-0.021	-0.026	0.004	-0.018	0.007	-0.006	0.017
t - statistic	*0.20*	*0.06*	*3.68**	*2.23***	*2.46***	*0.93*	*1.09*	*-0.77*	*-1.13*	*-1.95*	*0.32*	*-1.90*	*0.76*	*-0.93*	*2.53**
Three-for-One	0.001	0.024	-0.002	0.023	0.007	0.005	0.001	0.026	-0.019	-0.040	-0.004	0.014	-0.012	-0.010	-0.013
t - statistic	*0.13*	*3.01**	*-0.24*	*1.71*	*0.32*	*0.19*	*0.03*	*0.50*	*-0.27*	*-0.78*	*-0.08*	*0.38*	*-0.35*	*-0.41*	*-0.51*
Four-for-One	-0.003	0.009	-0.002	0.004	0.003	0.002	-0.014	-0.020	-0.086	-0.035	-0.060	-0.007	-0.022	-0.014	-0.009
t - statistic	*-1.02*	*3.23**	*-0.77*	*0.83*	*0.44*	*0.16*	*-1.01*	*-1.03*	*-3.25**	*-1.91*	*-3.16**	*-0.53*	*-1.65*	*-1.46*	*-1.00*
Five-for-One	0.002	0.022	-0.003	0.021	0.011	-0.003	-0.036	-0.068	-0.125	-0.030	-0.117	-0.031	-0.059	-0.008	-0.050
t - statistic	*0.94*	*8.44**	*-1.18*	*4.51**	*1.57*	*-0.29*	*-2.89**	*-4.10**	*-5.35**	*-1.81*	*-6.76**	*-2.67**	*-4.85**	*-0.94*	*-5.78**
Ten-for-One	-0.004	0.042	-0.003	0.035	0.045	0.015	-0.001	-0.009	0.056	-0.027	0.040	-0.022	-0.029	-0.026	-0.018
t - statistic	*-0.62*	*6.15**	*-0.44*	*2.89**	*2.41***	*0.64*	*-0.03*	*-0.20*	*0.90*	*-0.61*	*0.91*	*-0.73*	*-0.94*	*-1.15*	*-0.80*
Five-for-Two	0.001	0.061	-0.006	0.056	0.046	0.059	0.073	0.013	0.024	-0.005	-0.033	-0.028	-0.021	-0.007	0.018
t - statistic	*0.15*	*11.79**	*-1.22*	*6.31**	*3.43**	*3.47**	*3.09**	*0.41*	*0.52*	*-0.15*	*-1.00*	*-1.21*	*-0.91*	*-0.42*	*1.12*

Table 3: Probit Regression - Cumulative Abnormal Return Valuation Effect: 1990 - 2007

This table reports probit model estimates of firms' cumulative abnormal return over different time horizons. The models takes the following form: $Pr(Y = 1 \mid X) = f(X'\beta)$
The dependent binary outcome variable Y_i is 1 if there is a positive and significant cumulative abnormal return for firm *i* over the examined horizon and zero otherwise. Independent variables include MV, which is the logarithm of the company market value 20 days prior the split; SF, logarithm of the size of the split factor; SD, standard deviation of equity returns calculated over the [-260; -21] time horizon; OP, logarithm of the stock price 20 days before the split to the average stock price of all firms listed on the LSE; DUMMY, dummy variable which takes a value of 1 for the financial institutions in the sample and zero otherwise. Heteroskedastic consistent *p*-values based on White's robust standard error are in parenthesis.

	Time Horizon											
Model Restriction	[-1 1]	[-3 3]	[-5 5]	[-10 10]	[-20 20]	[-40 40]	[-40 -1]	[1 40]	[-20 -1]	[1 20]	[-10 -1]	[1 10]
Intercept	-5.826	-3.648	-3.829	-3.626	-3.463	-2.202	-2.082	-1.953	-0.436	-2.423	0.153	-1.906
	(0.000)	(0.006)	(0.003)	(0.005)	(0.006)	(0.068)	(0.083)	(0.107)	(0.711)	(0.047)	(0.897)	(0.121)
MV	-0.006	0.068	0.099	0.142	0.093	0.028	0.049	0.032	0.084	0.039	0.051	0.178
	(0.924)	(0.239)	(0.079)	(0.015)	(0.102)	(0.609)	(0.368)	(0.566)	(0.126)	(0.485)	(0.350)	(0.005)
SF	0.798	0.823	0.629	0.289	0.098	0.114	0.118	0.142	0.128	0.021	-0.208	-0.026
	(0.008)	(0.004)	(0.014)	(0.226)	(0.671)	(0.622)	(0.606)	(0.537)	(0.579)	(0.926)	(0.388)	(0.910)
SD	-1.361	-0.663	-0.661	-0.620	-0.679	-0.443	-0.356	-0.327	0.044	-0.498	0.086	-0.226
	(0.000)	(0.011)	(0.009)	(0.014)	(0.006)	(0.063)	(0.133)	(0.171)	(0.849)	(0.039)	(0.711)	(0.342)
OP	-0.394	-0.256	-0.021	-0.298	-0.211	-0.122	-0.065	-0.164	0.007	-0.106	0.073	-0.292
	(0.008)	(0.045)	(0.852)	(0.013)	(0.058)	(0.257)	(0.535)	(0.131)	(0.950)	(0.328)	(0.499)	(0.019)
DUMMY	-1.725	-0.915	-0.806	-0.826	-0.654	-0.378	-0.124	-0.374	-0.167	-0.582	0.071	-0.515
	(0.000)	(0.003)	(0.009)	(0.006)	(0.027)	(0.189)	(0.665)	(0.105)	(0.558)	(0.049)	(0.805)	(0.080)
No of Observations	137	137	137	137	137	137	137	137	137	137	137	137
McFadden R-sq	0.238	0.105	0.098	0.083	0.062	0.024	0.015	0.023	0.022	0.037	0.021	0.069

Table 4: Regression Analysis of Daily Pre-/Post-Split Returns Volatility

This table reports the coefficients from a cross-section regression of the observed mean squared daily returns during the pre-split [-260; -21] period ***OR*** during the post-split [21; 260] period on the different measures of trading activity, average daily number of transactions (Col. a) ***OR*** average daily trading volume (Col. b):
(a) $\boldsymbol{VO}^{i}_{pre\ \mathbf{OR}\ post} = a_0 + a_1\, MV + a_2\, \boldsymbol{NT}_{pre\ \mathrm{OR}\ \mathrm{post}} + a_3 SF + a_4 DUMMY + \varepsilon_t$
(b) $\boldsymbol{VO}^{i}_{pre\ \mathbf{OR}\ post} = a_0 + a_1\, MV + a_2\, \boldsymbol{VOL}_{pre\ \mathrm{OR}\ \mathrm{post}} + a_3 SF + a_4 DUMMY + \varepsilon_t$
Further independent variables are: MV (logarithm of the company market value 20 days prior the split); SF (logarithm of the split factor); DUMMY (dummy variable which takes a value of 1 for the financial institutions and a value of zero otherwise). Heteroskedastic consistent *p*-values based on White's robust standard error are in parenthesis

	Bias Corrected Volatility			
	Pre-Split Period		Post-Split Period	
Model Restriction	(a)	(b)	(a)	(b)
Intercept	-7.607	-8.485	-7.573	-8.081
	(0.000)	(0.000)	(0.000)	(0.000)
MV	-0.298	-0.341	-0.205	-0.310
	(0.001)	(0.000)	(0.023)	(0.001)
VOL		0.362		0.301
		(0.000)		(0.001)
NT	0.339		0.184	
	(0.002)		(0.054)	
SF			0.456	0.414
			(0.031)	(0.038)
DUMMY	-0.605	-0.638	-1.026	-1.027
	(0.033)	(0.022)	(0.000)	(0.000)
No of Observations	101	101	101	101
F-Statistics	5.365 (0.001)	7.077 (0.000)	6.273 (0.000)	8.681 (0.000)
Adjusted R^2	0.116	0.154	0.174	0.235

Table 5: Regression Analysis of Changes in Bias Corrected Volatility

This table reports the coefficients from a cross-section regression of the ratio of the st.dev of returns observed after the split to st.dev of returns prior to the split on the number of regressors:
(a) $\boldsymbol{VO}^{i}_{post} / \boldsymbol{VO}^{i}_{pre} = a_0 + a_1 MV + a_2 \textbf{NT} Ratio + a_3SF + a_4DUMMY + \varepsilon_t$
(b) $\boldsymbol{VO}^{i}_{post} / \boldsymbol{VO}^{i}_{pre} = a_0 + a_1 MV + a_2 \textbf{VOL} Ratio + a_3SF + a_4DUMMY + \varepsilon_t$
(c) $\boldsymbol{VO}^{i}_{post} / \boldsymbol{VO}^{i}_{pre} = a_0 + a_1 MV + a_2 \textbf{VOL} Ratio + a_3SF + a_4\textbf{TS} + a_5DUMMY + \varepsilon_t$
where MV is the logarithm of the company market value 20 days prior the split; VOL Ratio is the logarithm of the ratio of the average daily trading volume after the split to the average trading volume prior the split; NT Ratio is the logarithm of the ratio of the average daily number of trades before the split to the average daily number of trades before the split; SF is the logarithm of the size of the split factor; TS Ratio is the logarithm of the ratio of the post-split daily average size of the trade to the pre - split daily average size of the trade; DUMMY is the dummy variable which takes a value of 1 for the financial institutions and a value of zero otherwise. Heteroskedastic consistent *p*-values based on White's robust standard error are in parenthesis.

	Volatility Measures		
	Bias Corrected Volatility		
Model Restriction	(a)	(b)	(c)
Intercept	1.179	1.143	1.162
	(0.001)	(0.001)	(0.001)
MV	-0.059	-0.050	-0.055
	(0.132)	(0.150)	(0.188)
VOL Ratio		0.539	0.595
		(0.001)	(0.001)
NT Ratio	0.348		
	(0.015)		
SF	-0.199	-0.109	-0.148
	(0.199)	(0.457)	(0.333)
TS			0.444
			(0.024)
DUMMY	-0.263	-0.270	-0.277
	(0.213)	(0.189)	(0.180)
No of Observations	101	101	101
F-Statistics	2.234 (0.071)	3.445 (0.011)	2.926 (0.017)
Adjusted R^2	0.047	0.089	0.088