Systematic liquidity risk and stock price reaction to shocks: Evidence from London Stock Exchange

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Abstract

This study examines the relationship between systematic liquidity risk and stock price reaction to large one-day price changes (or shocks). We base our analysis on 642 constituents of the FTSEALL share index. Our overall results are consistent with Brown et al.'s (1988) uncertain information hypothesis. However, further analysis suggests that stocks with low systematic risk react efficiently to shocks of different signs and magnitudes whereas stocks with high systematic liquidity risk overreact to negative shocks and underreact to positive shocks. Thus, trading on price patterns following shocks may not be profitable, as it involves taking substantial systematic liquidity risk.

1. Introduction

The efficient market hypothesis has been challenged by numerous price anomalies. Price reversals and continuations are perhaps the most important anomalies that have received attention in the last three decades or so. Some studies, including Chan (1988), Park (1995), and Fama (1998), relate price anomalies to the bad model problem whereas others, such as Debondt and Thaler (1985), Howe (1986), and Jegadeech and Titman (1993, 2001), explain these anomalies by investors' irrational reactions to the arrival of news. Debondt and Thaler (1985) suggest that investors overreact to news. However, Jegadeech and Titman (1993, 2001) show that investors underreact to the arrival of new information to the market place. Both overreaction and undereaction hypotheses are supported empirically.

Early studies, including Debondt and Thaler (1985), Chan (1988), Jegadeeh and Titman (1993, 2001), focus on the long-term overreaction and the medium-term undereaction. More recently, Bremer and Sweeney (1991), Lasfer et al. (2003), Spyrou et al. (2007), among others, observe price reversals and continuations over daily intervals. Bremer and Sweeney (1991) report significant price reversals up to two days after negative large one-day price changes (i.e., shocks) whereas Lasfer et al. (2003) and Spyrou et al. (2007) find significant return continuations following both negative and positive shocks.

The extant literature offers various rational explanations to the observed price reversals and return continuations. Zarowin (1990) argue that overreaction is a demonstration of the size anomaly. Chan (1988), Ball and Kothari (1989), Wu (2002), and Wang (2003) relate price anomalies to the estimation errors resulting from the failure to account for time varying risk. Atkins and Dyi (1990), Cox and Peterson, Li et al. (2008), among others, suggests that abnormal returns earned from exploiting investors' overreactions and underreactions to news are not large enough to cover the transaction cost of trading. Moskowitz and Grinblatt (1999) show that industry effects [1] explain the individual stock momentum (return continuation). Daniel et al. (1998), Barberis et al. (1998), and Hong and Stein (1999) employ psychological concepts such as overconfidence, biased self attributation,

[1] Moskowitz and Grinblatt (1999) explain that investors may herd toward (away from) hot (cold) industries causing price pressure that could create return continuation.

conservatism, and representativeness to validate the investor behavior in response to new information signals.

This study is the first to examine role of systematic liquidity risk in explaining the observed price anomalies following large one-day price changes. Our research is mainly motivated by the recent evidence on the role of systematic liquidity risk in asset pricing. Several studies, including, Pastor and Stambaugh (2003), Martinaiz et al. (2005), and Liu (2006), show that the covariation between stock returns and the overall market liquidity represents a systematic risk. Liu (2006) finds that a liquidity augmented CAPM explains variations in stock returns better than the standard CAPM. He also shows that the liquidity augmented CAPM explains several anomalies, including those related the long-term contrarian investment strategy. Furthermore, Lasfer et al. (2003) and Mazouz et al. (2009) use market capitalization as a liquidity proxy. Lasfer et al. (2003) find that smaller capitalization markets take longer time to absorb large one-day price changes. Mazouz et al. (2009) find that large capitalization stocks react more efficiently than small capitalization stocks to both positive and negative shocks. Finally, Atkins and Dyi (1990), Cox and Peterson (1994), and Park (1995) link the price reaction to shocks to the bid-ask spread bounce. They find that the abnormal returns following large one-day price changes do not cover the transaction price movement between the bid and the ask prices.

Our analysis is based on a sample of 642 stock included in the FTSEALL share index constituents list of February 2008. The analysis covers the period from the 1st of July 1992 to the 29th of June 2007. We use proportional quoted bid-ask spread to generate historical liquidity betas.[1] Then, we sort stocks according to their historical liquidity betas and assign these stocks to decile portfolios ranging from the most liquid to the least liquid. We examine the abnormal returns of the stocks in each of the ten portfolios after large price shocks. The abnormal returns are defined as the residuals from the Carhart's (1997) four-factor model. We define positive price shocks as the abnormal returns of 5%, 10%, 20%, or more, while negative price shocks are defined as the abnormal returns of -5%, -10%, -20%, or less.[2]

[1] We also use turnover rate and the Amihud's (2002) illiquidity ratio as alternative liquidity proxies and our conclusions remain unchanged. More details can be obtained from the authors.

[2] Shocks are defined in a various ways in the literature. Howe (1986) defines a shock as a weekly price change of 50% or more. Brown et al. (1998) select stocks that display one-day (market model)

Our preliminary results reveal evidence in favour of Brown et al.'s (1988) uncertain information hypothesis. Specifically, positive shocks are followed by significant return continuations whereas negative shocks are followed by delayed price reversals. In the subsequent analysis, we report strong evidence of the role of the systematic liquidity risk in explaining the price reaction to shocks. Specifically, we show that the observed abnormal returns following price shocks are unique to stocks with high systematic liquidity risk and stocks with low systematic liquidity risk react efficiently to both positive and negative shocks. This evidence is robust to the different liquidity proxies and shock sizes.

The rest of this article is organized as follows. Section 2 reports our literature review. Section 3 describes our dataset. Section 4 presents our research methodology. Section 5 discusses our empirical results. Section 6 concludes.

2. Literature Review

The efficient market hypothesis suggests that stock prices should immediately and accurately reflect all the available information. This hypothesis has been challenged by several price anomalies, including price reversals and continuations. Studies on price reversals and continuations can be dividend into three groups depending on the time horizon in which these anomalies are measured.

The first group of studies focuses on the long-term (typically from 3 to 5 years) price reversals. Debondt and Thaler (1985) were the first to bring the overreaction hypothesis from the psychological science to the field of finance. They argue that since investors overreact to unexpected events, price reversals happen in the long-run (up to 5 years) when the market corrects itself. Several studies, including Debondt and Thaler (1985), Brown and Harlow (1988), Alonso and Rubio (1990), Chopra et al. (1992), Dissanaike (1997), and Mazouz and Li (2007), provide empirical support for the long-term overreaction hypothesis.

Zarowin (1990) argues that the loser-winner effect is more to do with the size effect than investors' overreaction. He shows smaller winners outperform bigger losers, and vice versa. Chan (1988) documents that the betas of the winner

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residual returns in excess of 2.5% in absolute value. Atkins and Dyi (1990) focus on stocks with largest one-day loss or gain in price on 300 trading days selected randomly. Bremer and Sweeny (1991) and Cox and Peterson (1994) define the event day as the one-day price decline of 10% or more. Park (1995) defines the event day as the day in which market adjusted abnormal return is more (less) than +10% (-10%).

and loser portfolios are changing over time and the overreaction anomalies disappear completely after adjusting for the time varying risk. Similarly, Ball and Kothari (1989) detect significant negative serial correlations in the market-adjusted stock returns over a five-year period. They argue that the negative correlations are due to time varying expected returns, which, in turn, are attributable to the time varying relative risks. Ball and Kothari (1989) also show that the profitability of the contrarian strategy disappears after accounting for the time varying risk.

The second group of studies is mainly concerned with the medium-term (usually between 3 to 12 months) underreaction. Jegadeech and Titman (1993) show that investors underreact to firm specific information in the medium term (i.e., 3 to 12 months). They find that a portfolio of stocks with good performance in the past six months generates a cumulative positive return of 9.5% over the next 12 months. Jegadeech and Titman (2001) replicated their original study using data from more recent periods. Their new evidence confirms that the results of their original study were not a product of data snooping. Lewellen and Nagel (2006) document that the neither the unconditional CAPM nor the conditional CAPM can explain the momentum profits. Their tests show that the time variations in betas and equity premiums are not large enough to explain the unconditional pricing errors.

Berk et al. (1999) develop a dynamic theoretical model in which time varying systematic risk and conditional expected returns explain the short-term contrarian and the long-term momentum profits. Wu (2002) shows that a conditional version of Fama and French's (1993) three factor model, relaxed to linearity assumption and imposed to cross-sectional restrictions, can capture the abnormal returns resulting from the medium-term momentum and the long-term reversal. Li et al. (2008) demonstrate that the profitability of the momentum strategies disappears after accounting for the time varying unsystematic risk. Sadka (2006) proposes liquidity risk as a potential explanation of momentum profits. He documents that momentum profits can be viewed as a compensation of the unexpected systematic (market-wide) variations of the variable component rather than the fixed component of liquidity. In other words, the unexpected variations in the aggregate ratio of informed traders to noise traders can explain the momentum profits.

The final group of studies examines investors' reactions to large short-term (up to one month) price changes. Howe (1986) shows that AMEX and NYSE stocks generate weekly abnormal returns of 13.8% (-13%) over ten weeks subsequent to weekly price changes of +50% or more (-50% or less). Lehman (1990) also documents that portfolios with a bad/good performance over a one-week time horizon display an opposite pattern in the following few weeks. Thus, both winner and loser portfolios exhibit significant price reversals. Bremer and Sweeney (1991) also report that stock prices reverse significantly following one-day price decline of -10% or less. They show that the documented price reversal is not related to the well-know calendar effects. However, Cox and Peterson (1994) find that bid-ask spread bounce explains price reversals following daily price declines of 10% or more.

Lasfer et al. (2003) examine the index price reactions to large one-day price changes. They show that investors, in both developed and emerging markets, underreact to the arrival news. Similarly, Spyrou et al. (2007) investigate the short-term price reaction to extreme price shocks in four FTSE indexes. They argue that each index can be considered as a value weighted portfolio of stocks which represent a certain size segment of the market. They find that large capitalization stock portfolios react efficiently to extreme shocks. However, small and medium capitalization stock portfolios underreact to both positive and negative shocks. Spyrou et al. (2007) find that the abnormal returns exist even after adjusting for Fama and French's (1993) factors and considering bid-ask biases and global financial crises. Mazouz et al. (2009) investigate the short-run stock price reaction to large one-day price changes. They report significant abnormal returns following positive price shocks of different magnitudes and negative price shocks of -5% or less. They show that their results are robust across different estimation methods.

Brown et al. (1988) develop the uncertain information hypothesis, which states that both favorable and unfavorable events are followed by significant positive returns. Thus, rational risk-averse investors underreact to good news and overreact to bad news. Brown et al. (1988) argue that investors face uncertainty and as a consequence higher risks and expect higher returns following both positive and negative shocks. They test their hypothesis by examining the behavior of the CRSP equally weighted index and the 200 largest companies in the S&P 500 following shocks. Brown et al. (1988) find evidence in favor of their hypothesis both at the market wide level and individual stock level.

3. Data

Our sample is based on 642 stocks from the FTSEALL share index constituents list of February 2008. The data set of each stock consists of the daily observations of the closing price, the ask price, the bid price, the quantity trading volume, the dollar trading volume, the price-to-book value ratio, the market capitalization, and the number of outstanding shares. The analysis covers a 15-year period starting from the 1st of July 1992 to the 29th of June 2007. All data is downloaded from DataStream.

4. Methodology

To examine the price reaction to large one-day price changes, we estimate the following model:[1]

$$(R_{i,t} - R_{f,t}) = \alpha_i + \beta_{mkt,i} MKT_t + \beta_{hml,i} HML_t + \beta_{smb,i} SMB_t + \beta_{mom,i} MOM_t + \varepsilon_{i,t} \qquad (1)$$

Here, $R_{i,t}$ is the return on stock i on day t; $R_{f,t}$ is the risk-free rate of return on day t; MKT_t is the excess market rate of return; HML_t and SMB_t are Fama and French's (1993) High Minus Low and Small Minus Big factors, respectively; MOM_t is the Carhart's (1997) momentum factor; and $\varepsilon_{i,t}$ is a random error, which captures the abnormal return of stock i on day t, or $AR_{i,t}$. Eq.(1) is re-estimated annually for all stocks with a complete set of return observations across the estimation period. The number of stocks included in our analysis ranges from 270 in 1992 to 520 in 2007.

Following Mazouz et al. (2009), we define a price shock as a residual value in excess of 5%, 10%, and 20% (in absolute values). To avoid the confounding effect, any shocks occurring within a 10-day window following a given shock are ignored. We calculate the cumulative abnormal returns for stock i over a window of S days after a shock, or $CAR_{i,S}$, and the average cumulative abnormal return for all stocks over a window of S days following a shock, or $CAAR_S$, as:

[1] Note that using liquidity augmented Carhat's (1997) model to estimate abnormal returns does not affect our conclusions. These results are available upon request.

$$CAR_{i,S} = \sum_{t=1}^{d} AR_{i,T} \text{ and } CAAR_S = \frac{\sum_{i=1}^{N} CAR_{i,S}}{N} \quad (2)$$

The statistical significance of the $CAR_{i,S}$ and $CAAR_S$ is based on the Newey-West t-statistic.

In this study, we use proportional bid-ask spread as a liquidity proxy. [1] To assess the relative importance of systematic liquidity in explaining the price anomalies following shocks, we adopt the following process: At the 1st of July of each year beginning from 1992, we estimate the historical liquidity beta of each stock in our sample using the most recent five years daily return data. To estimate liquidity beta, we construct a mimicking liquidity factor following Liu (2006)[2] and add this factor to Eq.(1). The coefficient on the mimicking liquidity factor is interpreted as liquidity beta. Then, we sort stocks according to their historical liquidity betas and assign them to decile portfolios. The process is repeated annually. Finally, we use Eq.(2) to calculate the $CAR_{i,S}$ for each stock in every decile portfolio and $CAAR_S$ for all stocks in each decile portfolio.

4. Empirical Results

4.1. Preliminary results

Table 1 presents the CAARs associated with all sample stocks over the entire study period. Our evidence supports the uncertain information hypothesis of Brown et al. (1988). Specifically, we show that investors react asymmetrically to positive and negative shocks. Positive price shocks are followed by significant return continuations. The length of the return continuations depends largely on the magnitude of a shock. Specifically, the continuations persist up to 10 days subsequent to shocks of ≥ +5%, 3 days following shocks of ≥ +10%, and 2 days after shocks of ≥ +5%. However, negative price shocks are followed by significant price reversals starting 2 days following shocks of ≤ -5% and ≤ -10% and 3 days

[1]As a robustness check, we also use turnover rate and Amihud's (1992) illiquidity ratio as alternative liquidity proxies. The use of these liquidity proxies does not affect our conclusions. More details are available upon request.

[2] A mimicking liquidity portfolio is payoff from taking a long position in a portfolio of stocks with lowest proportional bid-ask spread and a short position in a portfolio of stocks with highest proportional bid-ask spread.

after shocks of ≤ -20%. The price reversals continue for up to 10 days after shocks. Thus, investors underreact to good news and overreact to bad news.

[Insert Table 1 about here]

Our results are not entirely consistent with the previous studies, such as Lasfer et al. (2003), Spyrou et al. (2007), and Mazouz et al. (2009). Specifically, Lasfer et al. (2003) shows that developed and emerging markets underreact to both positive and negative shocks. Spyrou et al. (2007) suggest that the price reaction to shocks depend largely on the market capitalization of the underlying stocks. Specifically, the large market capitalization stocks included in the FT30 and FTSE100 react efficiently to shocks whereas medium and small capitalization shocks in the FTSE250 and FTSE SmallCap, respectively, underreact to shocks. Mazouz et al. (2009) examine the price reaction of 424 UK stocks following shocks of different trigger values. They show that investors underreact to positive shocks of all magnitudes and negative shocks of ≤ -5%. They also show that stock prices adjust quickly to negative shocks of ≤ -10%, ≤ -15%, and ≤ -20%.

4.2. Systematic liquidity risk and price anomalies

Table 2 reports the numbers of shocks of liquidity beta sorted decile portfolios. Panel A of Table 2 presents the total number of shocks for stocks in each decile portfolio. The frequency of shocks increases systematically when moving from the most to the least liquid portfolios. For instance, we observe 856 shocks of ≥ +5% in Portfolio 1, the most liquid portfolio, and 2696 shocks of the same magnitude in Portfolio 10, the least liquid portfolio. Smaller shocks of ≥ +5% are more frequent than larger shocks of ≥ +20%. Furthermore, Panel A of Table 2 also show that positive shocks are more common than negative shocks in London Stock Exchange. For instance, Portfolio 10 contains 135 shocks of ≥ +20% and only 98 shocks of -20% or less.

[Insert Table 2 about here]

Panel A of Table 3 reports the CAARs of stocks in decile portfolios following positive shocks. Portfolio1 reacts efficiently subsequent to shocks ≥ +5%, with no significant CAARs observed up to 10 days after shocks. However, Portfolio10 shows highly significant return continuations up to 10 days following shocks ≥ +5%. Overall, we provide strong evidence that high liquid portfolios (Portfolios 1 though 4) react more efficiently to shocks than low liquid portfolios (Portfolios 5 though 10). Thus, the price underreaction following positive shocks is unique to stocks with high systematic liquidity risk.

[Insert Table 3 about here]

Panel B of Table 3 reports the reaction of stocks in the systematic liquidity beta sorted portfolios to shocks ≥ +10%. The reaction to stocks in the Portfolio 1 to shocks ≥ +10% is consistent with the predictions of the efficient market hypothesis. However, Portfolio 10 shows significant positive CAARs up to 3 days following positive shocks of the same magnitude. Once again, the underreaction to positive shocks is only observed in the least liquid portfolios, namely portfolios 9 and 10. From Panel C of Table 3, we can see that Portfolio 10 is only portfolio that underreact to shocks ≥ +20%.

Table 4 presents price reaction of stocks in the 10 liquidity beta sorted portfolios to negative shocks of different magnitudes. Panel A of Table 4 reports CAARs following shocks ≤ -5%. The averages of shocks ≤ -5% range from -7.2% for Portfolio 3 to -8.2% for Portfolio 10. Consistent with the predictions of the overreaction hypothesis, the CAARs associated with the most liquid portfolios (Portfolios 1, 2, and 3) are positive and significantly for up to 3 days following shocks ≤ -5%. However, the CAARs of the least liquid portfolios (Portfolios 9 and 10) are negative 1 day after shocks ≤ -5%. This evidence supports the underreaction hypothesis. The asymmetric response of liquid and illiquid portfolios to shocks confirms the role of systematic liquidity risk in explaining the price reaction.

[Insert Table 4 about here]

Panel B of Table 4 reports the CAARs of stocks in the different liquidity portfolios following shocks of ≤ -10%. The most liquid portfolios, Portfolios 1 through 4, react efficiently to shocks of ≤ -10%. Thus, liquid stocks absorb price shocks immediately. Conversely, consistent with the overreaction hypothesis, the

CAARs of the least liquid portfolio, namely portfolio 10, are significant in days 2 through 10 following shocks ≤ -10%. Panel C of Table 4 suggests that the CAARs of most liquid portfolios (Portfolios 1 through 4) following shocks ≤ -20% are not significantly different from zero. However, Portfolio 10 displays a significant price reversal up to ten days subsequent to shocks ≤ -20%.

Overall, our results confirm the role of systematic liquidity risk in explaining the observe price reaction to shocks. Specifically, the price behavior of liquid stocks following shocks is consistent with the predictions of the efficient market hypothesis. However, illiquidity stocks overreact to negative shocks and underreact to positive shocks with different magnitudes. Since the price reversals and continuations are only associated with illiquid stocks, these patterns may not be exploitable.

5. Conclusion

Several studies, including Bremer and Sweeney (1991), Lasfer et al. (2003), Spyrou et al. (2007), and Mazouz et al. (2009), report significant price reaction to shocks. Atkins and Dyi (1990), Cox and Peterson (1994), and Park (1995) explain the CAARs following price shocks by the bid-ask spread bounces. Brown et al. (1989) argue that these CAARs result from the systematic variations of both risk and return around price shocks. Lasfer et al. (2003) show that price anomalies following shocks are more pronounced in less liquid markets.

Pastor and Stambaugh (2003) and Liu (2006), among others, show that liquidity risk is priced in the US market. This finding has motivated us to examine the role of systematic liquidity risk in explaining the predictability of stock returns following shocks. We find that stocks with high return covariations with the overall market liquidity drive the observe anomalies. Specifically, we show that high liquidity stocks react efficiency to shocks of different signs and magnitudes whereas low liquidity stocks overreact to negative shocks and underreact to positive shocks. Thus, trading on the price patterns following shocks may not be profitable, as it involves taking substantial systematic liquidity risk.

References

Alonso, A. and Rubio, G. (1990). "Overreaction in the Spanish Equity Market". *Journal of Bank Finance*, vol. 14, pp. 469–81.

Amihud, Y. (2002). “Illiquidity and Stock Returns: Cross-Section and Time Series Effects”. *Journal of Financial Markets*, vol. 5, pp. 31- 56.

Atkins, A. and Dyl, E. (1990). "Price Reversals, Bid-Ask Spreads, and Market Efficiency". *Journal of Financial and Quantitative Analysis*, vol. 25, pp. 535-547.

Ball, R. and Kothari, S. P. (1989). "Nonstationary Expected Returns: Implications for Tests of Market Efficiency and Serial Correlations in Returns". *Journal of Financial Economics*, vol. 25, pp. 51–74.

Barberis, N., Shleifer, A., and Vishny, R. (1998). "A Model of Investor Sentiment". *Journal of Financial Economics*, vol. 49, pp. 307-343.

Berk, J., Green, R., and Naik, V. (1999). "Optimal Investment, Growth Options and Security Returns". *Journal of Finance*, vol. 54, pp. 1553–1608.

Bremer, M. and Sweeney, R.J. (1991). “The Reversal of Large Stock-Price Decreases”. *Journal of Finance*, vol. 46, pp. 747-754.

Brown, K. C., Harlow, W. V., and Tinic, M.C. (1988). "Risk Aversion, Uncertain Information, and Market Efficiency". *Journal of Financial Economics*, vol. 22, pp. 355-385.

Brown, K.C. and Harlow, W.V. (1988) “Market Overreaction: Magnitude and Intensity”. *Journal of Portfolio Management*, vol. 14, pp. 6-13.

Carhart, M. (1997). "On Persistence in Mutual Fund Performance". *Journal of Finance*, vol. 52, no. 1, pp. 57–81.

Chan, K. C. (1988). "On the Contrarian Investment Strategy". *Journal of Business*, vol. 61, pp. 147–64.

Chopra, N., Lakonishok, J., and Ritter, J. (1992). "Measuring Abnormal Performance: Do Stocks Overreact?". *Journal of Financial Economics*, vol. 31, pp. 235-268.

Cox, D. R. and Peterson, D.R. (1994). "Stock Returns Following Large One-Day Declines: Evidence on Short-Term Reversals and Longer-Term Performance". *Journal of Finance*, vol. 49, pp. 255-267.

Daniel, K., Hirshleifer, D., and Subrahmanyam A. (1998). "A Theory of Overconfidence, Self-attribution, and Security Market Under- and Over-Reactions". *Journal of Finance*, vol. 53, no. 6, pp. 1839-1886.

DeBondt, W. and Thaler, R. (1985). "Does the Stock Market Overreact?". *Journal of Finance*, vol. 40, pp. 793-805.

Dissanaike, G. (1997). "Do Stock Market Investors Overreact?". *Journal of Business Finance and Accounting*, vol. 24, pp. 27–49.

Fama, E., and French, K. (1993). "Common Risk Factors in the Returns on Stocks and Bonds". *Journal of Financial Economics*, vol. 33, pp. 3-56.

Hong, H. and Stein, J. (1999) "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets". *The Journal of Finance*, vol. 54, no. 6, pp. 2143-2184.

Howe, J. (1986). Evidence on stock market overreaction. Financial Analysts Journal 42, 74–77.

Jegadeesh, N. and Titman, S. (1993). "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency". *Journal of Finance*, vol. 48, pp. 65-91.

Jegadeesh, N. and Titman, S. (2001). "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations". *Journal of Finance,* vol. 56, pp. 699– 720.

Lasfer, M. A., Melnik, A. and Thomas, D. C. (2003). "Short Term Reaction of Stock Markets in Stressful Circumstances". *Journal of Banking and Finance,* vol. 27, pp. 1959-1977.

Lehmann, B. N. (1990). "Fads, Martingales, and Market Efficiency". *Quarterly Journal of Economics,* vol. 105, pp. 1–28.

Lewellen, J. and Nagel, S. (2006). "The Conditional CAPM Does Not Explain Asset-Pricing Anomalies". *Journal of Financial Economics*, vol. 82, pp. 289–314.

Li, X., Miffre, J., Brooks, C., and O' Sullivan, N. (2008) "Momentum Profits and Time-Varying Unsystematic Risk". *Journal of Banking and Finance*, vol. 32, no. 4, pp. 541-558.

Liu, W. (2006) "A Liquidity Augmented Capital Asset Pricing Model", *Journal of Financial Economics*, Vol 82, No 3, pp. 631-671.

Martinez, M., Nieto, B., Rubio, G., and Tapia, M. (2005). "Asset Pricing and Systematic Liquidity Risk: An Empirical Investigation of the Spanish Stock Market". *International Review of Economics and Finance*, vol. 14, pp. 81-103.

Mazouz, K., Joseph, L.N., and Joulmer, J., (2009). Stock Price Reaction Following Large One-Day Price Changes: U.K. Evidence, *Journal of Banking and Finance* 33, 1481-1493.

Mazouz, K. and Li, X. (2007). "The Overreaction Hypothesis in the UK Market: Empirical Analysis". *Journal of Applied Financial Economics*, vol. 17, pp. 1101-1111.

Moskowitz, T. J. and Grinblatt, M. (1999). "Do Industries Explain Momentum?". *Journal of Finance*, vol. 54, pp. 1249-1290.

Park, J. (1995). "A Market Microstructure Explanation for Predictable Variations in Stock Returns following Large Price Changes". *The Journal of Financial and Quantitative Analysis*, vol. 30, no. 2, pp. 241-256.

Pastor, L. and Stambaugh, R. (2002). “Liquidity Risk and Expected Stock Returns”. *Journal of Political Economy*, vol. 111, no. 3, pp. 642-685.

Sadka, R. (2006). "Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk". *Journal of Financial Economics,* vol. 80, pp. 309-349.

Spyrou, S., Kassimatis, K., and Galariotis, E. (2007). "Short-term Overreaction, Underreaction and Efficient Reaction: Evidence from the London Stock Exchange". *Journal of Applied Financial Economics*, vol. 17, no. 3, pp. 221-235.

Wang, K.Q. (2003). "Asset Pricing with Conditional Information: A New Test". *Journal of Finance*, vol. 58, pp. 161–195.

Wu, X. (2002). "A conditional Multifactor Model of Return Momentum". *Journal of Banking and Finance,* vol. 26, pp. 1675–1696.

Zarowin, P. (1990) "Size, Seasonality, and Stock Market Overreaction", *Journal of Financial and Quantitative Analysis*, vol. 25, pp. 125–33.

Table 1: The reaction of FTSEALL share index stocks to shocks

This table presents the average cumulative abnormal returns (CAARs) for 642 constituents of the FTSEALL share index over the period from the 1st of July 1992 to the 29th of June 2007. Abnormal returns (AR_{it}) are obtained from the Carhart's (1997) model (see Eq.(1)). We define a price shock as a residual value in excess of 5%, 10%, and 20% (in absolute values). To avoid the confounding effect, any shocks occurring within 10 day of a given shock are ignored. $CAAR_S$ is the average cumulative abnormal return associated with all stocks over *S* days following a shock. The level of significance of the $CAAR_S$ is assessed using a Newey-West adjusted t-statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Shocks	N	CAAR0	CAAR1	CAAR2	CAAR3	CAAR4	CAAR5	CAAR6	CAAR7	CAAR8	CAAR9	CAAR10
Shock (5%)	11140	0.0758***	0.0065***	0.0067***	0.0070***	0.0063***	0.0065***	0.0062***	0.0054***	0.0054***	0.0054***	0.0054***
Shock (-5%)	8345	-0.0785***	-0.0001	0.0015**	0.0030***	0.0038***	0.0045***	0.0058***	0.0063***	0.0072***	0.0075***	0.0077***
Shock (10%)	2036	0.1437***	0.0097***	0.0083***	0.0059***	0.0032	0.0031	0.0021	0.0005	-0.0002	-0.0007	0.0002
Shock (-10%)	1567	-0.1633***	0.0002	0.0055**	0.0091***	0.0115***	0.0138***	0.0150***	0.0146***	0.0162***	0.0187***	0.0200***
Shock (20%)	249	0.2784***	0.0182***	0.0172**	0.0047	-0.0037	-0.0075	-0.0112	-0.0155	-0.0151	-0.0118	-0.007
Shock (-20%)	311	-0.3193***	0.0042	0.0137	0.0263***	0.0273***	0.0315***	0.0358***	0.0366***	0.0390***	0.0394***	0.0410***

Table 2: The distribution of shocks across liquidity beta sorted portfolios

This table presents the total number of shocks associated with the FTSEALL share index stocks assigned to 10 decile portfolios according to their historical liquidity beta. We use proportional bid-ask spread as a liquidity proxy. PORT denotes portfolio. Our portfolios are ranked from the most liquid, PORT1, to the least liquid, PORT10. The process of generating liquidity betas and ranking the liquidity portfolios is described in Section 4.

	Shocks ≥ 5%	Shocks ≤ -5%	Shocks ≥ 10%	Shocks ≤ -10%	Shocks ≥ 20%	Shocks ≤ -20%
PORT1	856	673	125	119	14	24
PORT2	572	471	78	61	5	8
PORT3	722	604	85	75	9	9
PORT4	841	647	116	105	7	17
PORT5	860	664	126	122	9	27
PORT6	971	636	145	103	9	27
PORT7	869	611	121	111	13	25
PORT8	1167	827	183	153	22	31
PORT9	1634	1072	296	192	27	46
PORT10	2696	2193	767	539	135	98

Table 3: Systematic liquidity risk and price reaction to positive shocks

This table reports the reaction of stocks in the liquidity beta sorted portfolios to positive shocks of different magnitudes. In this study, we use proportional bid-ask spread as a liquidity proxy. To assess the relative importance of systematic liquidity in explaining the price anomalies following shocks, we adopt the following process: At the 1st of July of each year beginning from 1992, we estimate the historical liquidity beta of each stock in our sample, using the most recent five years daily return data. To estimate liquidity beta, we construct a mimicking liquidity factor following Liu (2006) and add this factor to Eq.(1). The coefficient on the mimicking liquidity factor is interpreted as a liquidity beta. Then, we sort stocks according to their historical liquidity betas and assign them to decile portfolios. The process is repeated annually. Finally, we use Eq.(2) to calculate the $CAR_{i,S}$ for each stock in every decile portfolio and $CAAR_S$ for all stocks in each portfolio. $CAAR_S$ is the average cumulative abnormal return associated with all stocks over *S* days following a shock. Portfolios are ranked from the most liquid, PORT1, to the least liquid, PORT10. The level of significance of the CAARs is assessed using a Newey-West adjusted t-statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: CAARs following shocks ≥ 5%

	CAAR0	CAAR1	CAAR2	CAAR3	CAAR4	CAAR5	CAAR6	CAAR7	CAAR8	CAAR9	CAAR10
PORT1	0.0727***	0.0011	0.0016	0.0028	0.0027	0.0033	0.0025	0.0013	0.0028	0.0012	0.0026
PORT2	0.0703***	-0.0009	-0.0033*	-0.0045**	-0.0033	-0.0031	-0.0040	-0.0047*	-0.0050*	-0.0045	-0.0032
PORT3	0.0694***	0.0025*	0.0028	0.0033*	0.0029	0.0040	0.0023	-0.0006	-0.0004	-0.0004	-0.0002
PORT4	0.0714***	0.0018	0.0022	0.0019	0.0004	0.0009	-0.0005	-0.0005	0.0013	0.0003	0.0012
PORT5	0.0722***	0.0033**	0.0034**	0.0055***	0.0045**	0.0029	0.0049**	0.0054**	0.0054*	0.0045	0.0030
PORT6	0.0728***	0.0059***	0.0065***	0.0086***	0.0083***	0.0093***	0.0091***	0.0090***	0.0083***	0.0092***	0.0080***
PORT7	0.0726***	0.0068***	0.0063***	0.0055***	0.0048**	0.0052**	0.0041*	0.0039	0.0034	0.0045*	0.0055**
PORT8	0.0738***	0.0069***	0.0068***	0.0069***	0.0077***	0.0075***	0.0069***	0.0055***	0.0057***	0.0058**	0.0060**
PORT9	0.0757***	0.0071***	0.0084***	0.0092***	0.0090***	0.0099***	0.0102***	0.0098***	0.0097***	0.0104***	0.0099
PORT10	0.0851***	0.0126***	0.0128***	0.0122***	0.0104***	0.0101***	0.0101***	0.0089***	0.0082***	0.0081***	0.0079

Panel B: CAARs following shocks ≥ 10%

	CAAR0	CAAR1	CAAR2	CAAR3	CAAR4	CAAR5	CAAR6	CAAR7	CAAR8	CAAR9	CAAR10
PORT1	0.1386***	0.0062	0.0066	0.0088	0.0012	0.0015	-0.0027	-0.0128	-0.0119	-0.0228	-0.0238
PORT2	0.1288***	-0.0060	-0.0173***	-0.0141**	-0.0168**	-0.0184**	-0.0210***	-0.0191**	-0.0183**	-0.0267**	-0.0280***
PORT3	0.1335***	0.0036	0.0057	0.0074	0.0048	0.0104	0.0068	0.0057	0.0040	0.0044	0.0143
PORT4	0.1363***	0.0034	0.0064	0.0060	0.0048	0.0071	0.0071	0.0077	0.0091	0.0057	0.0036
PORT5	0.1379***	0.0090*	0.0095	0.0070	0.0002	0.0001	0.0035	0.0036	0.0006	0.0019	-0.0078
PORT6	0.1374***	-0.0034	-0.0069	-0.0074	-0.0037	-0.0031	-0.0045	-0.0023	-0.0038	0.0014	-0.0042
PORT7	0.1415***	0.0066	0.0024	-0.0023	-0.0018	0.0006	0.0026	0.0037	0.0061	0.0117	0.0134
PORT8	0.1402***	0.0076***	0.0027	0.0035	0.0059	0.0073	0.0088	0.0054	0.0058	0.0045	0.0072
PORT9	0.1370***	0.0091***	0.0063*	0.0089**	0.0099**	0.0112***	0.0081	0.0061	0.0060	0.0076	0.0069
PORT10	0.1543***	0.0170***	0.0171***	0.0102***	0.0044	0.0023	0.0015	-0.0004	-0.0020	-0.0029	0.0010

Panel C: CAARs following shocks ≥ 20%

	CAAR0	CAAR1	CAAR2	CAAR3	CAAR4	CAAR5	CAAR6	CAAR7	CAAR8	CAAR9	CAAR10
PORT1	0.2897***	0.0009	-0.0121	-0.0167	-0.0346	-0.0583	-0.0729	-0.0770	-0.0667	-0.0698	-0.0935
PORT2	0.2476*	-0.0254	-0.0505	-0.0357	-0.0497	-0.0443	-0.0529	-0.0590	-0.0461	-0.0582	-0.0582
PORT3	0.2744***	-0.0229	-0.0045	-0.0018	-0.0154	-0.0104	-0.0141	-0.0136	-0.0079	-0.0212	-0.0148
PORT4	0.2917**	0.0047	0.0311	0.0283	-0.0098	-0.0177	-0.0463	-0.0037	0.0028	0.0337	0.0415
PORT5	0.3324***	-0.0198	-0.0185	-0.0394	-0.0665**	-0.0923**	-0.0966**	-0.1112**	-0.1066**	-0.0939**	-0.0957**
PORT6	0.2668***	-0.0204	-0.0584	-0.0358	-0.0267	-0.0307	-0.0141	-0.0372	-0.0369	-0.0248	-0.0242
PORT7	0.2438***	0.0054	-0.0071	-0.0250*	-0.0305	-0.0233	-0.0519	-0.0430	-0.0137	0.0054	0.0238
PORT8	0.2521***	0.0122	0.0022	-0.0011	-0.0017	-0.0006	-0.0021	0.0005	-0.0003	0.0019	0.0176
PORT9	0.2659***	0.0286	0.0430	0.0373	0.0273	0.0289	0.0330	0.0415	0.0372	0.0477	0.0499
PORT10	0.2850***	0.0299***	0.0299**	0.0100	0.0035	-0.0003	-0.0021	-0.0120	-0.0160	-0.0159	-0.0103

Table 4: Systematic liquidity risk and the price reaction to negative shocks

This table reports the reaction of stocks in the liquidity beta sorted portfolios to negative shocks of different magnitudes. In this study, we use proportional bid-ask spread as a liquidity proxy. To assess the relative importance of systematic liquidity in explaining the price anomalies following shocks, we adopt the following process: At the 1st of July of each year beginning from 1992, we estimate the historical liquidity beta of each stock in the sample, using the most recent five years daily return data. To estimate liquidity beta, we construct a mimicking liquidity factor following Liu (2006) and add this factor to Eq.(1). The coefficient on the mimicking liquidity factor is interpreted as a liquidity beta. Then, we sort stocks according to their historical liquidity betas and assign them to decile portfolios. The process is repeated annually. Finally, we use Eq.(2) to calculate the $CAR_{i,S}$ for each stock in every decile portfolio and $CAAR_S$ for all stocks in each portfolio. $CAAR_S$ is the average cumulative abnormal return associated with all stocks over S days following a shock. Portfolios are ranked from the most liquid, PORT1, to the least liquid, PORT10. The level of significance of the CAARs is assessed using a Newey-West adjusted t-statistic. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: The CAARs following shocks of -5% or less.

PORT	CAAR0	CAAR1	CAAR2	CAAR3	CAAR4	CAAR5	CAAR6	CAAR7	CAAR8	CAAR9	CAAR10
PORT1	-0.0749***	0.0027*	0.0049**	0.0041	0.0051	0.0051	0.0046	0.0062*	0.0077**	0.0089**	0.0098**
PORT2	-0.0742***	0.0043**	0.0069***	0.0083***	0.0090***	0.0130***	0.0139***	0.0146***	0.0135***	0.0140***	0.0123***
PORT3	-0.0721***	0.0034*	0.0032	0.0056**	0.0048*	0.0035	0.0066**	0.0065**	0.0060*	0.0061*	0.0067**
PORT4	-0.0753***	0.0010	0.0038*	0.0041	0.0045	0.0057*	0.0052*	0.0044	0.0083***	0.0098***	0.0091***
PORT5	-0.0770***	0.0028*	0.0058***	0.0058***	0.0079***	0.0080***	0.0093***	0.0086***	0.0089***	0.0099***	0.0094***
PORT6	-0.0784***	0.0022	0.0028	0.0032	0.0027	0.0015	0.0024	0.0032	0.0041	0.0044	0.0032
PORT7	-0.0764***	-0.0002	-0.0001	0.0006	0.0013	-0.0010	-0.0021	-0.0017	-0.0010	0.0001	0.0024
PORT8	-0.0808***	-0.0019	0.0014	0.0037*	0.0055***	0.0054**	0.0060**	0.0068***	0.0092***	0.0094***	0.0114***
PORT9	-0.0807***	-0.0030**	-0.0016	0.0005	0.0023	0.0030	0.0044*	0.0057**	0.0068**	0.0057**	0.0062**
PORT10	-0.0824***	-0.0027**	-0.0014	0.0012	0.0017	0.0044**	0.0072***	0.0079***	0.0080***	0.0081*	0.0075***

Panel B: The CAARs following shocks of -10% or less.

PORT	CAAR0	CAAR1	CAAR2	CAAR3	CAAR4	CAAR5	CAAR6	CAAR7	CAAR8	CAAR9	CAAR10
PORT1	-0.1572***	0.0055	0.0105	0.0057	0.0075	0.0032	-0.0017	-0.0156	-0.0122	-0.0052	0.0033
PORT2	-0.1623***	-0.0053	0.0002	-0.0039	-0.0082	-0.0060	-0.0026	0.0009	0.0045	0.0011	-0.0017
PORT3	-0.1483***	-0.0088	-0.0101	-0.0068	-0.0096	-0.0070	-0.0050	-0.0062	-0.0007	0.0004	0.0018
PORT4	-0.1522***	-0.0066	-0.0060	-0.0036	0.0026	0.0064	0.0090	0.0060	0.0085	0.0132	0.0065
PORT5	-0.1738***	0.0094**	0.0206***	0.0224***	0.0222**	0.0251***	0.0249**	0.0260**	0.0277**	0.0338**	0.0387***
PORT6	-0.1820***	0.0101**	0.0194***	0.0123	0.0153	0.0175	0.0190	0.0216*	0.0267**	0.0257**	0.0265**
PORT7	-0.1614***	0.0026	0.0050	0.0089	0.0140*	0.0124	0.0123	0.0094	0.0080	0.0075	0.0090
PORT8	-0.1716***	-0.0091	-0.0041	0.0015	0.0066	0.0086	0.0082	0.0073	0.0103	0.0129*	0.0133*
PORT9	-0.1783***	-0.0033	0.0047	0.0104	0.0113*	0.0103	0.0059	0.0092	0.0103	0.0138*	0.0174**
PORT10	-0.1555***	0.0024	0.0074*	0.0150***	0.0184***	0.0240***	0.0289***	0.0304***	0.0303***	0.0324***	0.0325***

Panel C: The CAARs following shocks of -20% or less.

PORT	CAAR0	CAAR1	CAAR2	CAAR3	CAAR4	CAAR5	CAAR6	CAAR7	CAAR8	CAAR9	CAAR10
PORT1	-0.3394***	-0.0308	-0.0198	-0.0234	-0.0288	-0.0272*	-0.0375	-0.0613*	-0.0312	-0.0343	-0.0315
PORT2	-0.3452**	-0.0350	-0.0184	-0.0015	-0.0426*	-0.0405	-0.0284	-0.0407	-0.0710	-0.0651	-0.0681
PORT3	-0.2465***	-0.0829	-0.1183	-0.0924	-0.1124	-0.0728	-0.0447	-0.0284	-0.0374	-0.0301	-0.0209
PORT4	-0.2979***	-0.0097	-0.0159	-0.0178	-0.0319	-0.0260	-0.0230	-0.0217	-0.0168	-0.0296	-0.0442
PORT5	-0.3343***	0.0363**	0.0427***	0.0481***	0.0458**	0.0537***	0.0644***	0.0668***	0.0752***	0.0782***	0.0760**
PORT6	-0.3521***	0.0376**	0.0599**	0.0665***	0.0866***	0.0947***	0.0958***	0.0998***	0.1141***	0.1118***	0.1182***
PORT7	-0.2840***	-0.0208	-0.0112	-0.0033	0.0085	0.0067	0.0076	0.0101	0.0077	-0.0015	-0.0087
PORT8	-0.3627***	-0.0073	0.0015	0.0174	0.0189	0.0227	0.0239	0.0263	0.0290	0.0302**	0.0320**
PORT9	-0.3377***	-0.0072	-0.0083	0.0103	0.0192	0.0200	0.0196	0.0236	0.0276	0.0241	0.0284
PORT10	-0.2953***	0.0237*	0.0413**	0.0593***	0.0589***	0.0615***	0.0700***	0.0727***	0.0675***	0.0745***	0.0787***