Three Essays in Financial Market Predictability

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List of Contents

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List of Tables

Chapter 2

Chapter 3

Chapter 4

List of Figures

Chapter 2

Chapter 3

Chapter 4

Abstract

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Prior studies have shown that returns exhibit certain predictable patterns that are inconsistent with the mainstream finance theory. In this thesis, I explore the behaviour of returns following three different types of market events with a particular focus on behavioural and non-behavioural factors that are attributable to the predictability of post-event returns.

This thesis consists of three self-contained empirical essays. The first essay examines the information role of large S&P500 futures trades (commercial, noncommercial, dealers, asset managers, and hedge funds) in shaping future index returns. I find that commercial firms' net trading level appears positively correlated with future index returns but the relationship is not stable across time. Based on more recent data, hedge funds appear superior in terms of access to information and/or trading ability but this advantage is only preserved at high frequency. Therefore, the current weekly Commitment of Traders (COT) report - published with a three-day delay - prevents timely public access to this type of information. Also, trading signals based on two of the more popular position-based sentiment indicators do not produce significant average returns. Overall, this calls into question the reliability of COT-based trading signals used by market professionals.

The second essay studies the impacts of short sellers' trading in shaping the behaviour of stock returns following extreme price moves using data from stock market in mainland China where short sales were initially prohibited. Extreme price moves occurring under non-prohibitive/prohibitive short-sale constraints are defined as shortable/non-shortable events. I find shortable events exhibit less post-event price drift/reversals than non-shortable ones, indicating an increase in the efficiency of stock prices reacting to unexpected events. Further analysis of short sellers' trading activities on the price event days suggests that they are successful in trading informed price shocks but not in trading uninformed ones. Finally, I find evidence of massive short-covering that amplifies price shocks.

The third essay investigates investors' reaction to stock market rumours using data from China where listed companies are required to clarify rumours appearing in the media. I find that post-clarification abnormal returns exhibit continuation of pre-clarification momentum for rumours that are not denied by the listed companies and reversals for those which are denied. These results suggest that investors are unable to distinguish the reliable rumours from the false ones, as they under-react to rumours containing material information and over-react to those without. Further regression analyses on post-clarification abnormal returns using various subsamples of rumour events show that investors respond more efficiently to rumours when they are more informed about news topics or the rumoured companies.

DECLARATION

I, Haojun Chen, declare that no portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

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I would like to express my gratitude to my supervisors, Professor Michael Bowe and Professor Ian Garrett, and my former supervisor, Dr. Daniela Maher, for their guidance and support throughout my doctoral studies at Manchester Business School. I also need to thank Crity Xu, Xinyong Li, and Josef Tang, for their assistance in gathering a large amount of research data for my papers. At last, I would like to dedicate this thesis to my parents who planted the ambition of becoming a doctor in my mind with their unique and effective approach when I was a child.

Charter 1

Introduction

1.1 Motivation

Fama (1970) argues that in an efficient market prices always fully reflect all available information. This implies that in an efficient market future returns are not predictable based on current information. On the contrary, prior studies have shown that returns exhibit predictable patterns that are inconsistent with the efficient market hypothesis. In particular, Wang (2003) use positions of large S&P500 futures speculators (hedgers) as proxy for investor sentiment and find it a continuation (contrary) indicator for forecasting index returns. Schwarz (2012) reveals that the unexpected changes in large speculators' positions are significantly and positively related to S&P500 futures returns over an intraday horizon following the release of the positioning changes, leading her to conclude that futures returns do not fully reflect information possessed by large speculators. Furthermore, prior studies which focus on the predictability of stock returns following extreme price moves indicate that post-shock returns are predictable from the initial price shocks (see, e.g., De Bondt & Thaler, 1985; Pritamani & Singal, 2001; Chan, 2003; Larson & Madura, 2003; Savor, 2012). In particular, De Bondt & Thaler (1985) document reversals in monthly stock returns after large price moves and hypothesize that investors tend to over-react to new information; and more recently, Savor (2012) find large price moves accompanied by information are followed by drift and no-information ones are followed by reversals. He concludes that investors tend to under-react to news about fundamentals and over-react to other shocks that move prices.

Despite their evidences of market anomalies, the prior studies are not without limitations. First, while there are two futures markets (standard & E-mini S&P500 futures) for trading the S&P500 index, Wang (2003) only considers large traders' trading activities in the standard S&P500 futures market. Schwarz (2012), on the other hand, considers both of the futures markets but within a separate modelling framework. Moreover, giving their timing, both studies only analyse large traders' positioning data from the conventional COT reports in which traders' positions are categorized by entry not by trader type, and thus it is possible that positions of traders whose motivation (hedging vs. speculating) is distinctively different are classified under the same category. On the other hand, in examining the predictability of post-shock returns, prior studies have not considered the effects of short sales and short-constraints, while numerous studies have indicated that the effects play significant roles in shaping the behaviour of stock returns (see, e.g. Diamond & Verrecchia 1987; Chen & Rhee 2010; Boehmer & Wu 2013; Bai & Qin 2015). Furthermore, in gauging the information content of price shocks, studies of Pritamani & Singal (2001), Chan (2003), Larson & Madura's (2003), and Savor (2012) consider rumours as if they are verified news and use them to identify the presence of information for price shocks, while studies of Difonzo & Bordia (1997), Ahern & Sosyura (2015), Chou et al. (2015) have indicated that investors make systematic mistakes in processing rumours. Therefore, it is possible that the under- and over-reaction effects identified in studies of Pritamani & Singal (2001), Chan (2003), Larson & Madura's (2003), and Savor (2012) are attributable to investors' rumour-processing capacity rather than investors' behavioural tendency to under- or over-react.

1.2 Research Focus and Contributions

This thesis consists of three self-contained essays that aim to overcome the limitations of the prior studies. The first essay investigates the predictive role of large (index futures) traders' net positioning measures on future S&P500 index returns. Large future traders whose holdings exceed the reportable level are required to submit their trades to the CFTC for public disclosure. These traders are often considered more informed than the small traders (Chakravarty, 2001; Ke and Petroni, 2004; Schmeling, 2007; Yan and Zhang, 2009). Hence, it is possible that large S&P500 futures traders' positions contain private information regarding future index returns (Wang, 2003a). The essay departs from prior studies of Wang (2003) and Schwarz (2012) by utilizing positioning measures based on both the traditional (commercial/noncommercial) COT report and the new disaggregated COT report (dealer, asset manager, and leveraged fund) and by explicitly considering the potential impact of crisis-related structural breaks on the research outcome. I find that the commercial net positioning level appears to be a short-run significant predictor of future index returns whereas the noncommercial net positioning level appears inversely related to future index returns. However, the presence of the dotcom and subprime crises in my sample significantly impacts on the nature of this predictability, suggesting that the state of the market strongly conditions the results. Specifically, I find that during the dotcom crisis, the link between commercial net positioning level and future (1- and 2-week ahead) returns is strengthened whereas, during the subprime crisis, this link is strongly reversed and thus turns (significantly) negative. I argue that the changing mix of traders (and their trading motives) within the commercial and noncommercial categories may have contributed to the crisis-related impacts on the predictive values of large traders' position levels. Using positioning data from the disaggregated COT report, I find that the mix of commercial/noncommercial positions has changed substantially since the start of the subprime crisis. Particularly, I find that an increasing number of hedge fund positions have since been classified by the CFTC as commercial positions. Moreover, I find that during the dotcom crisis hedgers (commercial) are liquidity demanders while during normal times they are liquidity providers. This can explain the instability of any attempted prediction from one period to another and therefore the lack of reliability of a COT-based sentiment in practical pursuit.

My study calls into question the practitioners' use of COT-based sentiment indexes of the type investigated in Wang (2003) for prediction or the use of hedging/speculative demand proxies based on commercial/noncommercial net positioning levels for academic pursuit. Results from a battery of back-testing procedures on position-based trading signals – including futures trader sentiment index of Wang (2003) and extreme sentiment indicators – do not show reliable statistical significance in favour of the signals.

The second essay of this thesis examines the roles of short sales and short-constrains in shaping the behaviour of post-shock returns. I use stock market data from China where short-selling was initially prohibited but subsequently allowed under a pilot program launched in March 2010. For each stock either initially present or subsequently added to the pilot program, I look for large price moves, which I term price events, in the stock's historical price record. Price events occurring after (before) the stock's affiliation to the program are considered "shortable" ("non-shortable") events. I examine the effect of short sales on the predictability of stock returns following large price moves by running a regression on post-shock abnormal returns with the event-day abnormal price change, which reflects investors' response to the event, as the main predictor and a dummy interaction term for shortable events. I find shortable price events exhibit less price drift/reversals in post-shock returns than non-shortable ones, indicating that there is an increase in price efficiency when short-selling bans are removed. Among the shortable price events, more aggressive short-selling during informed large price drops is associated with less post-shock downward price drift; moreover, extreme levels of short-covering volume are associated with negative reversals on day one immediately following the price event days. Further analysis of the contemporaneous correlation between short-sellers' trading activities and abnormal price changes on the actual event days, reveals that short sellers seek to increase their short exposure as the magnitudes of informed price drops expand and reduce their short exposure as the magnitudes of uninformed price shocks become more extreme. Overall, my results suggest that short sellers are successful and active in trading informed price events in which they exploit short-term underreaction in stock prices to new information. They are less successful in trading uninformed ones in which they bear the risk of suffering losses when overshooting in stock prices becomes extreme. This finding adds to our current understanding of the impacts of short sales on stock returns by highlighting the importance of information content in dictating short sellers' trading. It also contributes to the growing literature on investor over- and under-reaction by showing the roles short-constraints and short sales might have in shaping these anomalies.

The third essay of this thesis studies investors' reaction to stock market rumours using data from China where listed companies are required to clarify rumours appearing in the media. I classify each rumour as either denied (unreliable) or undenied (potentially reliable) based on the content of clarification announcement. Since the rumoured companies are legally accountable for their comments regarding the accuracy of any rumour, denied rumours are considered to be false rumours which contain little information about fundamentals, while the undenied rumours are considered information-based. I use Savor's (2012) regression, with an indicator for denied rumours, to examine the predictability of post-clarification returns from investors' initial reaction. Each cross-section represents one stock-rumour event. I measure investors' initial response to rumours using the abnormal changes in stock prices over two alternative horizons preceding the rumour clarification day. Our regression model incorporates various control variables including increase in volume, firm size, price to book ratio, momentum, and percentage of individual investors. Our results show that post-clarification returns are predictable from investors' initial reactions to rumours. Stock prices continue to drift following clarification for undenied rumours and reverse for denied ones. These results suggest that investors under-react to rumours based on material information and over-react to those without such information. Further regression analyses on post-clarification abnormal returns using various subsamples of rumour events show that the under- and over-reaction effects persist across favourable and unfavourable, bull and bear, and other rumour subsamples. However, abnormal returns are less manifest or insignificant for rumours associated with the designated news media, asset restructurings, and large firms. The latter finding suggests that investors respond more efficiently to rumours when they are more informed about news topics or the rumoured companies. This essay contributes to two distinct branches of the current literature. Prior studies on the predictability of stock returns following large price changes have not considered investors' capacity in processing rumours, while prior studies on stock market rumours have not used the under- and over-reaction effects to examine investors' reaction to rumours. Results of this essay are consistent with the previous analyses conducted by Pritamani & Singal (2001), Chan (2003), and Savor (2012), which show that investors tend to under-react to information-based events, but are at odds with De Bondt & Thaler's (1985) over-reaction hypothesis. The results also provide an empirical support for DiFonzo & Bordia's (1997) experimental finding which shows that investors trade rumours as if they are news. This essay also extents the prior study of Yang & Luo (2014) on stock price adjustment to rumour clarification announcements during the bull and bear market periods in China by showing that the post-clarification regularity is predicted by investors' initial reaction to rumours. Finally, this essay offers an explanation for the contrasting results found in Patel & Michayluk (2016), which claims that the over-reaction effect is absent among large-size companies listed in ASX, and the prior studies of Pritamani & Singal (2001), Chan (2003), and Savor (2012).

Organisation of Thesis

This thesis is structured around three self-contained empirical essays. Each essay has a separate introduction, literature review, background information, discussion of data and methodology, conclusion, and reference list. The equations are independent and are numbered from the beginning of each chapter. But footnotes, tables, figures, page numbers, titles, and subtitles have a sequential order throughout the thesis. The remainder of the thesis is structured as follows. Chapter 2 elaborates the first essay, which investigates the predictive role of large (index futures) traders' net positioning measures on future S&P500 index returns. Chapter 3 presents the second essay, which examines the role of short sales in shaping the behaviour of stock returns following extreme price moves. Chapter 4 contains the third essays, which explores stock returns following rumour clarification announcements. Chapter 5 provides a brief conclusion of the major findings of the thesis.

At last, in the essays I use the terms “we” and “our” rather than “I” and “my” respectively to reflect that each essay is associated with a published or working paper co-authored with my supervisors, Daniela Maher (essay 1), Michael Bowe (essay 2 & 3), and Ian Garrett (essay 2 & 3) at Manchester Business School.

References

Ahern, K.R. & Sosyura, D., 2015. Rumor Has it: Sensationalism in Financial Media. The Review of Financial Studies, 28(7), pp.2050–2093.

Bai, M. & Qin, Y., 2015. Short sales constraints and price adjustments to earnings announcements: Evidence from the Hong Kong market. International Review of Financial Analysis, 42, pp.304–315.

Boehmer, E. & Wu, J.J., 2013. Short selling and the price discovery process. Review of Financial Studies, 26(2), pp.287–322.

De Bondt, W.F.M. & Thaler, R., 1985. Does the Stock Market Overreact? Journal of Finance, 40(3), pp.793–805.

Chan, W.S., 2003. Stock price reaction to news and no-news: drift and reversal after headlines. Journal of Financial Economics, 70(2), pp.223–260.

Chen, C.X. & Rhee, S.G., 2010. Short sales and speed of price adjustment: Evidence from the Hong Kong stock market. Journal of Banking & Finance, 34(2), pp.471–483.

Chou, H.I., Tian, G.Y. & Yin, X., 2015. Takeover rumors: Returns and pricing of rumored targets. International Review of Financial Analysis, 41, pp.13–27.

Diamond, D.W. & Verrecchia, R.E., 1987. Constraints on short-selling and asset price adjustment to private information. Journal of Financial Economics, 18(2), pp.277–311.

Diether, K., Lee, K. & Werner, I., 2009. It's SHO Time! Short - Sale Price Tests and Market Quality. The Journal of Finance, 64(1), pp.37–73.

Difonzo, N. & Bordia, P., 1997. Rumor and Prediction: Making Sense (but Losing Dollars) in the Stock Market. Organizational Behavior and Human Decision Processes, 71(3), pp.329–353.

DiFonzo, N. & Bordia, P., 1997. Rumor and Prediction: Making Sense (but Losing Dollars) in the Stock Market. Organizational Behavior and Human Decision Processes, 71(3), pp.329–353.

Fama, E., 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. The Journal of Finance, 25(2), pp. 383-417.

Larson, S. & Madura, J., 2003. What Drives Stock Price Behavior Following Extreme One - Day Returns. Journal of Financial Research, 26(1), pp.113–127.

Patel, V. & Michayluk, D., 2016. Return predictability following different drivers of large price changes. International Review of Financial Analysis, 45, pp.202–214.

Pritamani, M. & Singal, V., 2001. Return predictability following large price changes and information releases. Journal of Banking & Finance, 25(4), pp.631–656.

Savor, P.G., 2012. Stock returns after major price shocks: The impact of information. Journal of Financial Economics, 106(3), pp.635–659.

Schwarz, K., 2012. Are speculators informed? Journal of Futures Markets 32, 1–23.

Stoll, H.R., Whaley, R.E., 1990. The dynamics of stock index and stock index futures returns. Journal of Financial and Quantitative Analysis 25, 441–468.

Wang, C., 2003. Investor sentiment, market timing, and futures returns. Applied Financial Economics, 13(12), pp.891–898.

Yang, X. & Luo, Y., 2014. Rumor Clarification and Stock Returns: Do Bull Markets Behave Differently from Bear Markets? Emerging Markets Finance and Trade, 50(1), pp.197–209.

Chapter 2

On the predictive role of large futures trades for S&P500 index returns: an analysis of COT data as an informative trading signal

This study examines the information role of large S&P500 futures trades (commercial, noncommercial, dealers, asset managers, and hedge funds) in shaping index returns. Using consolidated data across both standard and E-mini futures contracts, we find that commercial firms' net trading level appears positively correlated with future index returns but the relationship is not stable across time. Based on more recent data, amongst specialist traders, hedge funds appear superior in terms of access to information and/or trading ability but this advantage is only preserved at high frequency. Therefore, the current weekly Commitment of Traders (COT) report - published with a three-day delay - prevents timely public access to this type of information. Also, trading signals based on two of the more popular position-based sentiment indicators do not produce significant average returns. Overall, this calls into question the reliability of COT-based trading signals used by market professionals.

Keywords: Institutional traders; S&P500 futures; Open interest; COT report; Market efficiency

2.1 Introduction

The Commodity Futures Trading Commission (hereafter CFTC) is the independent regulatory agency for futures and options markets in the United States. The agency publishes a weekly report, called Commitment of Traders (COT) report, disclosing the open interest positions of large traders in the futures market. In its original format, the report classifies the reportable (large, above-threshold positions) open interest into commercial and noncommercial positions. The former/latter is traditionally considered as being held by hedgers/speculators. In 2006 CFTC released a new, disaggregated COT report that breaks down futures open interest by trader type instead of generic entries such as commercial vs. noncommercial. It therefore gives public access to futures positions such as those of dealers, asset management firms, and hedge funds.

The COT reports have attracted attention from both academic and professional communities. De Roon et al. (2000) employ the difference between short and long positions obtained from COT reports as a measure of hedging pressure. They specifically test the hedging pressure hypothesis of Keynes (1930) – stipulating that hedgers pay a risk premium to speculators – and discover that both 'own-market' and 'cross-market' hedging pressures are significant factors in shaping futures risk premium and therefore futures returns. A series of studies such as Bessembinder (1992), Leuthold et al. (1994), Wang (2003b), and Tornell and Yuan (2012) support the hedging pressure effect and reiterate the predictive value of large traders' holding positions in commodity futures returns. On the other hand, studies such as Sanders et al. (2004), Bryant et al.

(2006), and Gorton et al. (2012) appear to reject the hedging pressure hypothesis. Studies such as Martikainen and Puttonen (1992), Chu et al. (1999), Blasco et al. (2009), and Li (2009) show that futures markets are generally more efficient in pricing newly arrived information. Moreover, it is well-documented that institutional traders are often perceived as the 'smart money' (Chakravarty, 2001; Ke and Petroni, 2004; Schmeling, 2007; Yan and Zhang, 2009). Hence, it is possible that large S&P500 futures traders' positions contain private information regarding future index returns (Wang, 2003a). Whether this is the case or not, practitioners have been extracting trading signals from the weekly COT reports almost from inception. Jiler (1985) finds statistics based on large traders' positioning data a sensible aid in technical forecasting.[1] Kirkpatrick and Dahlquist (2010) introduce a professional market report that suggests that commercial traders' net long positions – as a percentage of the total net long positions – have a 3-week lead to cash stock positions. Wang (2003a) introduces an oscillating sentiment index based on large futures traders' net holding positions and finds noncommercial sentiment to be a 'price continuation indicator' of future index returns whereas he finds the commercial sentiment a 'contrary indicator'. Kirkpatrick and Dahlquist (2010) claim this type of sentiment oscillator to be highly indicative of the informed traders' beliefs regarding market prospects. The predictive value of large futures traders' positions for market returns is also investigated in other futures markets. For instance, Sanders et al. (2004) investigate the lead–lag relationship between market returns and

[1] William L. Jiler is the former president of Commodity Research Bureau, Inc., creator of the CRB Futures Price index, and is the author of various technical analysis books such as How Charts Can Help You in the Stock Market (1990).

traders' net positions in the energy futures markets and find that market returns lead traders' net positions but not the other way around. Tornell and Yuan (2012) study the information role of currency futures traders' positions on spot exchange rates and find that peaks and troughs of traders' net positions have a significant role in exchange rate forecasting. It follows that, if the public can use large traders' positions data to consistently predict returns, the efficient market hypothesis is seriously in doubt.

In financial futures markets, where the underlying assets are stock indexes, bonds and paper currencies, producers and inventory holders are difficult to conceptualize. Hence, it is possible that the hedging pressure effect may not strongly manifest itself in these markets. Moreover, the role played by large traders in financial futures markets may be different from that in commodity futures markets. Even within the financial futures sector, different contract specifications and market microstructures may lead to a different type of trading behaviour. We therefore focus the scope of this research on a specific, individual futures market and elaborate on the information role of large futures traders' positions in shaping future S&P500 index returns. While several studies exist on the information role of large traders in commodity futures markets, relatively few focus on S&P500 futures. Based on the CFTC's 2011 COT report, the average (consolidated) open interest of S&P500 futures stands at 1,059,666 which far exceeds the average open interest of most other financial futures contracts (except Eurodollar futures). The particularity of S&P500 futures, in addition to its liquidity, is that there are actually two futures markets for trading the index, namely the S&P500 standard and the E-mini markets.[2] Large traders' positions in either market only reflect a proportion of the reportable futures open interest and therefore positions from both markets should be considered, in order to form a joint measure. De Roon et al. (2000) and Wang (2003a), are among the few studies that document the predictive value of large futures traders' positions on S&P500 futures index. Given their timing, these studies only consider positions of standard S&P500 futures contracts. Schwarz (2012) considers both S&P500 futures markets but within a separate modelling framework. We therefore propose a new, consolidated measure of S&P500 futures traders' positions that combines the reportable open interest of both markets and also deals with the situation of cross-market spreads. Using this consolidated measure, we investigate whether its information content has predictive value for S&P500 index returns. The results do not only shed light on the validity of Keynes' hedging pressure hypothesis in this large market but also suggest a more cautious and rigorous approach to the use of position-based indicators in modelling future market returns. While academics and practitioners use data from COT reports as proxy for hedging pressure, speculative interest, or information advantage, few raise the question of construct validity. And yet the way that COT measurements are formulated and their stability/instability through time may have a major impact upon the validity of one's conclusions.

We find that the commercial net positioning level appears to be, prima facie, a significant predictor of S&P500 index returns whereas noncommercial net positioning level appears inversely related to future index returns. Traders' unexpected net

[2] The E-mini contract on S&P500 was introduced in 1997.

positioning measures, which proxy for positioning responses to recent market innovations, are generally found statistically significant only in the short-term (next-day) prediction. The results suggest that the price pressure effect resulting from large traders' unexpected net positioning is significant and, during our study period, noncommercial firms (speculators) generally make price concessions to commercial firms (hedgers) in exchange for trading immediacy. Furthermore, a brief investigation into traders' average earnings for holding a position in the futures market provides additional confirmation that commercial firms (including dealers) generally earn a risk premium from their noncommercial counterparts. However, these results are conditioned on the time period under study. When structural break components – based on the dotcom and subprime crises – are added to our models, significant changes are identified. Our results therefore strongly indicate the presence of structural breaks in the predictive role of COT-based large traders' positioning measures. Using positioning data from the disaggregated COT report, we find that the mix of commercial/noncommercial positions has changed substantially since the start of the subprime crisis. Particularly, we find that an increasing number of hedge fund positions have since been classified by the CFTC as commercial positions. We argue that, as the mix of traders within the commercial and noncommercial categories evolves, the information role of commercial/noncommercial positions shifts accordingly. Our study calls into question the practitioners' use of COT-based sentiment indexes of the type investigated in Wang (2003a) for prediction or the use of hedging/speculative demand proxies based on commercial/noncommercial net positioning levels for academic pursuit. Results from a battery of back-testing procedures on position-based trading signals – including futures trader sentiment index of Wang (2003a) and extreme sentiment indicators – do not show reliable statistical significance in favor of the signals. The structure of this study is the following: Section 2.2 provides the data and methodology, Section 2.3 details the empirical results and their implications, and Section 2.4 concludes.

2.2 Data and methodology

2.2.1 Data, preliminary statistics, and choice of variables

The period under investigation is from the first Tuesday of 1998 (January 6th) until the last Tuesday of April 2012 (April 24th). The period is determined so that COT reports for the E-mini S&P500 futures are available. The reason for choosing Tuesday as the position-reporting day for week t is that COT report generally shows the holding positions of traders on that day.[3] Therefore, the S&P500 open and close values are observed on the same day as traders' positions are observed.[4] To calculate k-week cumulative returns, we use the percentage change from the current index close to its k-week ahead open. We use non-overlapping periods with a 1-day trading session as a break to mitigate serial correlation in returns. Figure 2.1 illustrates this sampling methodology.

[Insert Figure 2.1]

[3] If Tuesday is a holiday then, the COT report for the week will be disclosed on the next business day. Therefore, not all observations in this paper are strictly taken on Tuesday

[4] We also record the close level of S&P500 index on the trading day right after the position-reporting day, for later analysis. Our historical data is obtained from CRSP database.

Our index returns are calculated based on S&P500 spot prices instead of futures settlement prices. The latter are usually constructed based on the rolling-over of the front-month contract prices. Such treatment is problematic in a weekly sampling design as it is difficult to match the price change caused by a front contract renewal with the rollover costs assumed by traders. In S&P500 futures market, the rational price level can be inferred from the spot index. Numerous studies show that there is a relatively efficient process of price discovery between S&P500 spot index and futures. Using minute-to-minute data, Kawaller et al. (1987) find that S&P500 futures prices consistently lead spot prices by 20–45 min. In a similar vein, Stoll and Whaley (1990) suggest that the lead-time is between 5 and 10 min and only occasionally more. Market efficiency in the S&P500 futures (or other index futures contracts) generally increases as barriers to arbitrage are removed. Chu and Hsieh (2002) show that, with the arrival of Standard & Poor Depositary Receipts (SPDRs), mispricing opportunities between spot and futures S&P500 indexes diminish and gains from short (intraday) arbitrage between them are statistically insignificant. In a more recent study, Richie et al. (2008) investigate the mispricing opportunities between S&P500 futures and its underlying spot instruments (i.e. the index or SPDRs) and find that mispricing opportunities only exist in intraday trading and disappear within minutes. Based on such evidence, we argue that, at daily or weekly frequencies, S&P500 spot and futures indexes move concurrently and therefore significant mispricing that could potentially interfere with our results is unlikely.

CFTC is committed to releasing the COT report to the public every Friday at 3:30

p.m. The report shows all the futures holding positions as of the most recent Tuesday. There are two futures contracts for trading the S&P500 index. The E-mini contract, launched in September 1997, is now one of the most widely traded futures in the world.[5] Compared to the classic S&P500 futures, E-mini contracts are traded on a fully electronic system, one with faster execution and smoother order flow. Previous studies either do not consider the E-mini contracts or treat both types of futures contracts separately, as if they are isolated markets. In the S&P500 futures markets, both E-mini and the standard contracts are based on the same underlying index and therefore traders may choose either for trading. Therefore, ignoring one may result in biased measurements.[6] Another problem is that some traders take offsetting positions across standard and E-mini markets. These positions do not reflect traders' net exposure to the S&P500 index but are registered as either long or short position separately, in standard S&P500 and E-mini futures markets. Thus, the measure of traders' positions becomes inaccurate when cross-market spread positions are overlooked. Our consolidated COT measure overcomes this bias by combining traders' positions in both markets. The size of E-mini is 1/5 of the standard contract. We combine traders' positions in the two futures markets by treating five E-mini positions as one standard position. We then calculate the consolidated net positions by taking the difference between the total consolidated long and short positions. Using this aggregation method, the cross-spread positions and their confounding effects are eliminated from analysis. All net position

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[5] The influence of E-mini trades on the S&P500 spot market cannot be ignored. According to the joined investigation led by SEC and CFTC on May the 6th 2010, 'Flash Crash' – the major market indexes' sudden drop by about 9% – was instigated by a very large single sale of E-mini contracts.

[6] Over the last decade, the trading volume of E-mini contracts has increased in parallel with the demand for the standard contract. E-mini contracts may be more appealing to traders who desire high liquidity and fast execution.

figures reported hereafter are consolidated positions.

In 2009, CFTC launched a new weekly COT report called ‘disaggregated report’. This report uses a more insightful classification of traders’ positions. For financial futures, the new disaggregated report discloses positions of *Dealer/Intermediary, Asset Manager/Institutional*, and *Leveraged Fund*. The first group includes index swap dealers, financial brokers and commercial banks. Asset *Manager/Institutional* refers to equity funds. *Leveraged funds,* in the context of S&P500 index futures, are typically hedge funds. According to the notes released by CFTC, the first group of firms is on the ‘sell side’ of the market whilst the remaining firms are on the ‘buy side’.[7] Hereafter we simply use the names dealers, asset managers and hedge funds and refer to these three new categories of traders as the specialist firms. For them, CFTC backdates reports to June 2006.

We use the aggregated long/short positions held by large traders to construct net position measures. The total net position held by category ‘l’ of traders at time t is denoted by NP_t^l and is calculated by subtracting the sum of reportable short positions from the sum of reportable long positions.[8] To account for the market size effect, we normalize the net position series following Schwarz (2012):

$$NPI_t^l = \frac{NP_t^l}{\sum_i Long_t^i + \sum_i Short_t^i} \qquad (1)$$

The denominator, which adds all long and short positions that are broken down in

[7] The notes can be found at: http://www.cftc.gov/ucm/groups/public/@commitmentsoftraders/documents/file/tfmexplanatorynotes.pdf.

[8] Superscript l may be replaced alternatively by the acronyms C, NC, DA, AM and HF to indicate positioning measures of commercial, noncommercial, dealer, asset manager, and hedge fund, respectively.

the COT report for week *t*, serves as a normalizing factor.[9] The measure is closely related to traders' sentiment, as a futures contract has no up-front value. For noncommercial firms, their net positioning reflects their overall speculative interest. A positive/negative reading of the index level suggests that speculators are betting on the long/short side of the market. For commercial firms, their net positioning level index reflects their net hedging positions.

The change in net positions ($NP_t^l - NP_{t-1}^l$) reflects traders' weekly activities since the last position-reporting day. De Roon et al. (2000) and Schwarz (2012) use traders' net positioning changes in order to measure liquidity (price) pressure arising from large traders' order flow. Wang (2003b) finds traders' net positioning changes correlated with past market sentiments. Using Granger causality, Schwarz (2012) shows evidence of correlation between speculators' positioning changes and past market returns in the S&P500 index futures market.

To focus on traders' positioning changes in response to recent market innovations or liquidity pressure, we separate traders' positioning level into an expected and an unexpected component. The former represents the part of positioning that can be explained by traders' past systematic positioning pattern and it is therefore unrelated to traders' response to the latest market innovations and also less likely to generate an unexpected liquidity demand. We define the unexpected component as:

$$UENP_t^l = NP_t^l - F_{t,k}NP_t^l$$

[9] For measures based on the traditional COT report, the denominator adds all long and short positions of commercial and noncommercial firms; for measures based on the disaggregated COT report, the denominator adds all long and short positions of dealer, asset managers and hedge funds.

where $F_{t,k}NP_t^l$ is the forecast of NP_t^l based on past net positioning levels up to time $t - k - 1$. Schwarz (2012) constructs each net positioning forecast using a recursive first-order autoregression. Instead, we adopt the automatic forecasting algorithm developed by Khandakar and Hyndman (2008).[10] As such, we fit a dynamic ARIMA model to the moving window of past net positioning levels $[NP_{t-k-1}^l \dots NP_{t-1}^l]$. The size of the moving window *k* is set to be 150 for commercial and noncommercial net positions and 50 for specialist firms' net positions. We set aside some initial observations for starting our forecasts. For commercial and noncommercial measures we are able to obtain 150 pre-sampling observations from earlier COT reports.[11] For specialist firms' measures, we consume the first 50 observations from our original database. The unexpected net positioning represents traders' positioning response to market innovations since the last position-reporting day (Figure 2.2). To form the corresponding index, we use the same denominator as in Eq. (1). The resulting index is denoted as:

$$UENPI_t^l = \frac{UENP_t^l}{\sum_i Long_t^i + \sum_i Short_t^i} \qquad (2)$$

[Insert Figure 2.2]

Table 2.1 gives a summary of descriptive statistics. The mean values of the commercial and noncommercial net positioning indexes are both negative but commercial firms are, on average, holding almost twice as many net short positions as

[10] Briefly, the algorithm first determines the order of integration by applying the KPSS test on the time series and then searches for the best autoregressive and moving average orders by minimizing the AIC score of the resulting series.

[11] We collect net positions from standard S&P500 futures as the replacement of consolidated net positions during the period when E-mini contract is not available.

noncommercial firms. The first order sample autocorrelation of all net positioning measures is close to one, indicating that large traders' net position holdings are very persistent in week-to-week observations. This further justifies our separation of the level of net positioning into expected and unexpected components. For large commercial players in particular, the forecast represents the expected level of net positions that firms systematically hold in order to keep their business running. The unexpected net positioning indexes, on the other hand, are not serially correlated and have sample means that center on zero.

[Insert Table 2.1]

Figure 2.3 displays the S&P500 and the commercial/noncommercial net positioning indexes – smoothed out by their 30-week moving average – in one chart. The dotted line represents the level of zero net positioning (i.e. $NPI_t^l = 0$). Visually, while commercial and noncommercial trades consistently offset each other, the relationship between the market (S&P500) and these traders' net positioning levels is constantly evolving. At least two apparent structural breaks can be identified. For example, during the dotcom crisis, commercial traders are net short and they regularly change their holdings in the opposite direction of the market. The pattern is, however, reversed as the market evolves. During the subprime crisis, commercial traders are net long and their positioning level drops side-by-side with the market.[12] It appears that, during the dotcom crisis, commercial positions are profitable but during the subprime crisis they are in loss (given their net long holdings at the beginning of the crisis).

[12] The subprime crisis refers to an episode that started as a subprime mortgage crisis but ended up as a global financial crisis.

[Insert Figure 2.3]

Figure 2.4 plots dealer, asset manager and hedge fund net positioning indexes. Asset managers' positions are always net long, which is consistent with the fact that index-tracking funds are often in higher demand than inverse-index tracking funds.[13] Dealers are mostly net short and their trades appear to offset asset managers' net long positions. Hedge funds' positioning strategy appears to be more flexible. They turn to trading on the long side before March 2009 (post subprime rebound) but remain in net short while the market is recovering.

[Insert Figure 2.4]

2.2.2 Methodology

Our objective is to test the predictive power of large futures traders' positioning measures on S&P500 index returns. We begin by studying the predictive role of large traders' net positioning measures as investigated in studies such as De Roon et al. (2000), Wang (2003a), Schwarz (2012), and Tornell and Yuan (2012). De Roon et al. (2000) use large traders' net positioning level as a measure of hedging pressure while Wang (2003a) uses speculators' net positions level as a proxy of sentiment. Giving the timing of these two studies, only large traders' positions in the standard S&P500 futures market are considered. Schwarz (2012) considers both S&P500 futures markets but within a separate modelling framework. Tornell and Yuan (2012) study the information role of currency futures traders' positions on spot exchange rates. None of these studies

[13] The average long/short position ratio of the asset manager group is 5.71.

however consider the effects of crisis periods on the predictability of large traders' net positioning. Our research horizon includes two major turbulent episodes, namely the dotcom and the subprime crises. A gathering literature strand corroborates the fact that a major financial crisis is likely to have a substantial impact on investors' risk preferences, sentiment, and cost of trading (Hoffmann et al., 2013; Nagel, 2012; Ben-David et al., 2011; Gurrib, 2008). Recent studies also emphasize state-dependency in the predictive power of investor sentiment. For example Chung et al. (2012) investigate the predictive power of sentiment in expansion/recession states and find it regime dependent. Wolff (2013) focuses on the impact of the subprime mortgage crisis on the predictive power of investor sentiment and delivers positive results. Kadilli (2013) employs a regime-switching approach to test for the predictive power of investor sentiment (among others) on returns and identifies significant turning points around the dotcom and subprime crises. Following these findings, we therefore cater for regime-change by incorporating two structural break components into our model: one for the dotcom episode, the other for the subprime crisis. In doing so, we aim to test the stability of the predictive power of the COT-based positioning measures. To our best knowledge, this is the first study to incorporate time variation in the predictive power of futures positions. Following Chung et al. (2012), we use an exogenous timing mechanism to separate the crisis and non-crisis states of the market. Given the emerging evidence linking crisis episodes to variation in sentiment prediction and the fact that our principal aim is to test the reliability of traditional COT measures in their current practical and academic pursuits, we believe that regime change founded on economic insight is to be preferred here.

Our dependent variables are k-week ahead cumulative S&P500 index returns measured at k = 1, 2, 4, and 8. The nature of the index futures market and the release cycle of COT report make longer-term prediction irrelevant to our study.[14] To capture the immediate price impact of large futures trades, we also observe the future index returns on the day following the position-reporting day and, for the remainder of this paper, we refer to them as next day index returns. The expected future index return equations are nested in the following form:

$$R_{t,t+k} = aR_{t-k,t} + c_0 + c_1 D_t^1 + c_2 D_t^2 + \beta_0 NPI_t^l + \beta_1 NPI_t^l D_t^1 + \beta_2 NPI_t^l D_t^2 + \epsilon_{t,t+k} \qquad (3)$$

This equation models the interaction between the expected k-week ahead cumulative index returns, denoted by $R_{t,t+k}$, and futures traders' net positioning levels (NPI_t^l) observed at time t. The first-order, lagged return predictor $R_{t-k,t}$ included in the model to account for possible autocorrelation in index returns. The dummy variables D_t^1 and D_t^2 are used to model the time effects of the two major financial crises.[15] The timeline of these two crises is exogenously determined based on a (relative) literature consensus and in agreement with studies such as Kim et al. (2011).[16] Coefficients c_1, c_2, β_1, β_2 measure the additional effects of the financial crises' dummies on the constant and slope coefficients c_0 and β_0 of the model. The last term

[14] The dependent variable – the k-week ahead future returns – may be related to traders' net positioning data released at time $k-1$, $k-2$, etc. However, as the time horizon increases, future returns will be shaped by a series of other factors – including more recent COT reports – and therefore the predictive value of a <k-week old> large traders' net positioning level becomes increasingly redundant.

[15] Specialist firms' net positioning measures are not available until June 2006. As a result, the dotcom dummy D_t^1 is not included in association with the specialist firms' net positioning measures.

[16] According to the authors, the dotcom crisis unfolded from January 2001 to September 2002 whereas the subprime crisis unfolded between December 2007 and June 2009. We adjust the start of the second crisis by two months (earlier) so as to be consistent with the actual peak of the S&P500 index during that time.

ϵ_{t+k} is the zero-mean, random model error term for the k-week ahead cumulative index returns. The distributional properties of S&P500 index return are well known (Cont, 2001). The sample kurtosis for the *1*-week index returns, for example, is 6.27 and volatility clustering is evident. Traditional OLS estimators, under weakly exogenous assumptions, are robust to non-normality of the error term but such robustness comes with loss of efficiency (Wooldridge, 2002). To tackle such problem, we model the conditional variance of ϵ_{t+k} in the following way:

$$\sigma_{t,t+k}^2 = \tau + \rho \cdot \epsilon_{t-k,t}^2 + \varphi \cdot \sigma_{t-k,t}^2 \qquad (4)$$

The conditional variance equation is therefore modeled as GARCH (1, 1) of Bollerslev (1986). We also assume ϵ_t follows the generalized error distribution (GED) described in Nelson (1991). The distribution has a tail-thickness (shape) parameter that can be adjusted to model leptokurtosis. Wilhelmsson (2006) finds significant improvement in the forecast using a leptokurtic error distribution when modelling SP500 index futures returns.

Measures of futures traders' net positioning level are used in De Roon et al. (2000), Wang (2003a), and Schwarz (2012) for modelling futures market returns. S&P500 index traders use the net positioning level chart to identify market continuation and reversal sentiment signals (Kirkpatrick and Dahlquist, 2010). A positive (cumulative) slope coefficient in Eq. (3) would suggest that a high net (long) positioning level tends to be associated with positive future index returns. This in turn could be an indication of the positive risk premium earned by certain traders. Keynes (1930) for instance suggests that it is normal for speculators to earn a risk premium in trading with hedgers because the latter's primary motive for accessing the futures market is seeking insurance. Wang (2003a), on the hand, interprets speculators' excessive returns as an indication of 'superior market timing ability'. Studies such as Schwarz (2012) and Tornell and Yuan (2012) investigate the predictive role of traders' net positioning changes. The former uses speculators' position changes as a proxy for liquidity pressure whereas the latter study the predictive value of both commercial and noncommercial net positioning changes on currency market spot returns. Compared to the net positioning level measure, traders' net positioning changes only reflect their additional positioning since the last observation day and therefore the measure is often used to investigate traders' dynamic response to market innovations (Wang, 2003b; Schwarz, 2012; Sanders et al., 2009). For this very reason, we use the unexpected component of traders' net positioning level. We estimate the predictive value of our unexpected net positioning measure ($UENPI_t^l$) in the following nested model:

$$R_{t,t+k} = aR_{t-k,t} + c_0 + c_1 D_t^1 + c_2 D_t^2 + \beta_0 UENPI_t^l + \beta_1 UENPI_t^l D_t^1 + \beta_2 UENPI_t^l D_t^2 + \epsilon_{t,t+k} \quad (5)$$

The lagged return predictor, the structural break components, and the model error term are under the same specification as in model (3). Any significant, positive (cumulative) slope coefficients in the above equation (β_0, $\beta_0 + \beta_1$, $\beta_0 + \beta_2$) can be interpreted as evidence of price concessions made by the trade counterparty (Schwarz, 2012). The proposition is that traders who find themselves under liquidity pressure will make price concessions in exchange for trade immediacy but the market impact of this type of concessions is expected to be temporary. The liquidity providers are, however, likely to earn positive returns during this transient process. A positive estimate of the same coefficients may also suggest traders are informed ahead of the general public of the change in fundamentals or risk preferences that are priced in the market, especially when the result persists across increasing prediction horizons. Harris and Gurel (1986) study the effect of price pressure in the S&P500 futures market. They find that price pressure has an instant market impact, which is almost fully reversed after 2 weeks. In light of this previous research, we model future market returns in model (5) at 'next-day', *1*-week, and *2*-week prediction horizons.

2.3 Empirical results

2.3.1. Predictive value of large traders' futures positions across time

The estimation results of model (3) and (5) obtained by maximizing the likelihood function under generalized error distribution (GED) are presented in Tables 2.2 and 2.3, respectively.[17] Estimates in Table 2.2 are provided across *1*-, *2*-, *4*-, and *8*-week prediction horizons whereas estimates in Table 2.3 are available for *1*-day, *1*-week, and *2*-week prediction horizons. The nested models are organized around two restrictions. The first restriction (tested by the likelihood ratio LR^1) excludes all terms associated with the net positioning predictor ($\beta_0 = 0,\ \beta_1 = 0,\ \beta_2 = 0$) while the second restriction (tested by the likelihood ratio LR^2) excludes all dummy coefficients ($c_1 = 0, c_2 = 0, \beta_1 = 0,\ \beta_2 = 0$). The resulting models are henceforth labelled as models I and II. We test the restrictions by comparing the likelihood ratio scores of the restricted models

[17] The coefficient estimates for the lagged return predictor and the conditional variance equation are removed to conserve space. The estimates for the conditional variance equation under GARCH (1, 1) are generally significant while the lagged returns coefficients are generally insignificant due to our non-overlapping design.

with the unrestricted one (the full model, III).

[Insert Table 2.2] [Insert Table 2.3]

Results in Table 2.2 show significant links between the commercial positioning level and future S&P500 index returns. The null hypothesis of no significant commercial predictor is rejected at *1*- and *2*-week return horizons. As the prediction horizon increases to *4*- and *8*-week however, the null of no predictive power cannot be rejected. The estimated coefficients for the noncommercial net positioning level are consistently negative across all prediction horizons but are generally insignificant (at 5% level). The estimated coefficients for the commercial net positioning level are generally positive, which suggests that commercial trades are on average more profitable than noncommercial trades. However, when crisis dummies are applied to the prediction model, the predictive role of commercial trades becomes unstable. For example, a 100 basis points increase in the commercial net positioning level index adds around 0.07% to the *1*-week ahead index returns. However, this effect increases by about 5 times during the dotcom crisis, to 0.35%, whereas it decreases by almost twice, to −0.13%, during the subprime crisis. Commercial trades appear therefore significantly profitable during the dotcom episode but are generally unprofitable during the subprime crisis. The restrictions imposed in order to test the structural break components ($c_1 = 0, c_2 = 0, \beta_1 = 0,\ \beta_2$ =0) are consistently rejected (at 1% level) for the *1*–*8*-week prediction horizon, confirming the existence of structural breaks in our model. Consistent with the recent studies of Chung et al. (2012) and Wolff (2013), our estimates of β_1 and β_2 suggest that the predictive power of the commercial net positioning level (sentiment) does indeed depend on the state of the market. Specifically, the direction of this prediction is reversed during the subprime crisis whereas it is strengthened during the dotcom episode. This adverse impact warrants therefore the use of an exogenous, crisis-timing mechanism in our modelling.

Results in Table 2.3 give insight into the predictive role of large traders' unexpected net positioning measures. Likelihood ratio tests suggest that the commercial and noncommercial measures are significant predictors of next-day returns whilst the dealers' measure is significant in predicting *1*-week future index returns during the subprime crisis only. The sign and the statistical significance of the estimates for the commercial/noncommercial predictors in our next-day empirical setting suggest that, under liquidity pressure, noncommercial firms generally give price concessions to commercial firms. This is true during normal times as well as during the subprime crisis. It does not appear to be the case during the dotcom crisis however, when the interaction term for the commercial unexpected net positioning (−0.5373) and its cumulative impact (−0.4419) reverses the price concession effect, perhaps signalling commercials' need for liquidity. This is confirmed by the fact that, for the duration of the dotcom episode, the average ratio of commercial to noncommercial open interest is 41% higher than the average ratio over our study period. As far as specialist firms are concerned, hedge funds' unexpected net positioning measure appears to emulate the predictive role of noncommercial trades, which is in line with hedge funds' typical role as noncommercial (speculative) traders. Likelihood ratio tests indicate however that hedge funds' unexpected net positioning measure is not a significant predictor. Also, the market impact of commercial/noncommercial liquidity tradeoff becomes insignificant as the prediction horizon increases. Such a result is fully consistent with Harris and Gurel (1986) in terms of the temporal nature of the liquidity pressure. The only other result that is statistically supported by both the individual estimates and the LR test (at 5%) is that for dealers' role during the subprime crisis. Although it appears that, during normal times, dealers' unexpected net positioning measure has no significant predictive role for future returns nor is indicative of a significant liquidity supply/demand that is rewarded/acquired, the estimated slope coefficients at both 1-day (0.1715) and 1-week (0.6688) horizon seem to imply a more lasting effect. This suggests that, during the subprime crisis, dealers may sustain an informational advantage regarding the ongoing market trend and therefore position their trades accordingly. In isolation, however, we give little weight to this result. It bears no impact on our main outcome other than to reinforce the conclusion that, as more data becomes available, specialist firms net positioning variables constitute a more insightful research avenue compared to the broad (and often ill-defined) commercial/noncommercial categories. We therefore conclude that the unexpected net positioning measures of specialist firms are generally uninformative to future returns during our period of investigation.

Our empirical findings appear at odds with Wang (2003a) in terms of the predictive role of commercial and noncommercial net positioning measures. Wang finds his commercial (noncommercial) position-based sentiment measures to be negatively (positively) associated with future returns.[18] Our results suggest that, in the short run,

[18] Wang (2003a) uses de-trended futures index returns, which are based on futures settlement prices. Also, his observation period begins in 1993 and ends before the collapse of the dotcom bubble in 2000. E-mini contracts are

commercial net positioning level is a positive indicator of future index returns whereas noncommercial net positioning level is a negative indicator. Our results are generally consistent with the study of De Roon et al. (2000) which documents hedging effects across twenty various futures markets based on the net positioning level. However, their estimate for hedging pressure effect in the S&P500 futures market, though having the same sign as ours, is insignificant. The sign of the estimates for the commercial net positioning level predictors in our model contradicts Keynes (1930) even though, in the index futures market, hedgers are holding on average considerably more net short positions than speculators. Schwarz (2012) runs the index return prediction models separately using E-mini and standard S&P500 futures and finds noncommercial predictors (level and change measures) statistically significant. The signs of the estimated coefficients in Schwarz' empirical models are the same as ours but her models exclude positioning predictors of other trader groups. Our estimates in Table 2.3 corresponding to model (5) are consistent with Fishe and Smith (2012). They also find that hedge funds and, more generally, noncommercial traders tend to belong to the group of liquidity demanders whereas commercial firms are overrepresented in the group of liquidity suppliers. Still, none of the studies addresses the issue of structural breaks. And yet, all likelihood ratio tests in Table 2.2 and most in Table 2.3, restriction II (LR^2), reject the null of no-crisis impact. Such evidence strongly indicates the presence of structural breaks in large traders' positioning data. Another important yet previously overlooked aspect is that of the particular effect a major financial crisis may

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not popular during this period. The difference in measurement and the sampling period have clearly contributed to this incongruence.

have on the predictive role of futures positions. Our estimates for the structural break components in model (3) and (5) indicate that the direction and/or magnitude of the commercial predictors can be reversed/strengthened during a financial crisis and that no reliable conclusion can be derived ex ante given the unpredictable nature of such an event. Therefore, we argue that ignoring these effects may lead to a false representation of the information content of the COT data and its predictive role.

To further supplement the idea of a structural break, we also take a closer look at the level of total futures positions of specialist firms reported in the newer, disaggregated report. Conventional COT reports categorize futures trader positions by entity (commercial/noncommercial) and not by trader type (e.g. dealers and asset managers). It is therefore possible that positions of traders whose motivation is distinctively different are classified under the same category. Figures 2.5 and 2.6 reveal the evolution of specialist firms' total weekly futures positions as a percentage of the total weekly commercial/noncommercial positions.

[Insert Figure 2.5] [Insert Figure 2.6]

The total futures positions per trader type for week t are measured by the sum of traders' long and short positions for the week. We smooth out traders' historical weekly positions by their 30-week moving average and then express them as a ratio to the (smoothed out) total commercial/noncommercial futures positions. The results show that, since the beginning of the subprime crisis, dealers' total positions, as a ratio to total commercial trading positions, has decreased by up to 50% while hedge funds' positions has exceeded the total noncommercial positions by up to 50–60%. This suggests that, over the same crisis period, an increasing number of hedge fund positions have been classified as commercial in the COT report. These ‘commercial’ hedge fund positions however are not the same as traditional commercial positions that, based on the CFTC’s explanatory notes, are generally held by large traders such as banks, financial intermediaries, and securities dealers. In particular, during subprime crisis, hedge funds were under unusually financial distress due to large investor withdrawal (Ben-David et al., 2011). This explains our earlier observation in Figure 3.2 where the relationship between commercial net position levels and the S&P500 index reverses around the subprime crisis. Moreover, the finding is in line with one of the conclusions of the CFTC’s September 2008 Staff Report, stating that commercial/noncommercial classification has become less accurate in reflecting the trading activities since the nature of trading conducted by ‘non-commercials’ has changed significantly over time.[19] Fishe and Smith (2012) arrive at a similar conclusion when investigating 8921 futures traders’ accounts. They find that the information role of hedge funds is different from that of typical commercial hedgers. They also go a step further and suggest that an ex ante classification of traders is inaccurate as long as traders may declare one motive for trade but in fact apply another. This explains our earlier observation in Figure 3.2 where the relationship between commercial net position levels and the S&P500 index reverses around the subprime crisis. Therefore, we argue that whenever positions of traders with different information set, motivation to trade, and liquidity needs are bundled together under the same category, the informative nature of commercial trades

[19] http://www.cftc.gov/ucm/groups/public/@newsroom/documents/file/cftcstaffreportonswapdealers09.pdf

can be expected to change. The remainder of this section shows that the positioning measures of each specialist firm have a unique information role in shaping index returns.

2.3.2. Information advantage

In this section we investigate the potential information advantage a well-defined group of traders might have over their counterparts and its forecasting power (or lack of).[20] We argue that, should this advantage persist in time, its effect would be captured by the relationship between traders' net positions and index returns. Specifically, if traders have sustained information advantage over and above the general public, their net positioning changes should be largely uncorrelated with index returns because a strong correlation will imply that traders' net positioning changes are induced by public information. The intuition is that traders with information advantage have access to changes in fundamentals or risk preferences before the general public; uninformed traders, on the other hand, take actions only when these changes are made available to the general public. For a given group of traders, if the majority of traders within the group are uninformed, we should observe a strong correlation between traders' net positioning changes and contemporaneous index returns. On the other hand, under the assumption that large traders' are not inferior to the public in terms of access or ability to time the index, we regard those traders with net positioning changes that are contemporaneously uncorrelated with the index returns as having a comparative information advantage.

[20] We do not intend to trace down the source of this information advantage (if any) in the current framework.

Figure 2.7 displays, in a scatter diagram, the estimated contemporaneous correlation coefficients between weekly index returns (realized at the market open of the position-reporting day) and the corresponding specialist firms' net positioning changes. We find that asset managers' net positioning changes are mostly correlated with index returns. The estimated coefficient is 0.4827 and the corresponding scatter plot indicates that the relationship can be well approximated by a straight line. We also find a small, negative and significant correlation (−0.1882) between dealers' net positioning changes and index returns. This outcome is consistent with the conjecture that dealers' net positioning changes are mainly motived by their business in OTC and secondary markets. When the market experiences a positive demand shock, dealers may find it more difficult to find customers on the short side and therefore they increase their net short positions in the futures market. This means that a proportion of dealers' net positioning changes is indirectly responsive to public information. Finally, hedge funds' positioning changes are contemporaneously uncorrelated with index return, which suggests that this group of traders may have information advantage over other specialist firms.

[Insert Figure 2.7]

Of course, some could argue that a strong correlation between traders' net positioning changes and contemporaneous index returns is, in fact, a sign of private information on the part of that particular group of traders. They could claim that this group is predicting the market in such an efficient manner that, at weekly frequencies, all one sees is a strong positive correlation when, in fact, this group's net positioning changes are leading the market in daily or intraday frequencies. In response to such an argument, we move forward to investigate the relationship between traders' net positioning changes and daily index returns. We use the traders' unexpected net positioning measure ($UENP_t^l$) this time because this measure represents traders' response to recent market innovations and is finalized at the market close of the position-reporting day. Hence, the unexpected net positioning measure of a relatively better informed class of traders (at daily or intraday trading frequency) should be positively correlated with index returns on the position-reporting day. Figure 8 displays the correlation statistics. The results are consistent with our earlier conjecture about the short-lived information advantage of hedge funds in showing that only the correlation between hedge funds' unexpected net positioning measures and index returns on position-reporting days is significant (at 1% level) and the estimated coefficient is 0.23. The sample correlation between asset manager's unexpected positioning measure and market returns is 0.0397 whereas for dealers the correlation is −0.0937 and is statistically insignificant. This suggests that the strong contemporaneous correlation between asset managers' net positioning changes and weekly index returns reported earlier should be interpreted as evidence of asset managers' index-tracking or portfolio-rebalancing pressure. This may help to explain the negative estimate of 'subprime' coefficient β_2 (−0.3111) in model (5) using the asset managers' unexpected net positioning measure as predictor (Table 2.3). When the market drops sharply, asset managers may have to make price concessions in order to rebalance their portfolios.

[Insert Figure 2.8]

These results are consistent with Fishe and Smith (2012) who, based on a detailed study of over 8000 individual futures accounts, find that hedge funds dominate the intraday informed group while, on the other hand, commercial hedgers such as asset managers are underrepresented herein. Yet, whichever the intraday informed party may be, the public is not informed about the up-to-date holdings of any large futures traders on position-reporting days (these are published only on the coming Friday at 3:30 p.m.), therefore they cannot capitalize on this type of information.[21]

2.3.3. Futures risk premium

An S&P500 futures contract has no value when it is initially traded and therefore the expected return on the contract is the risk premium. Keynes (1930) argues that hedgers, often as producers of commodities, need to protect the value of their inventories and therefore speculators (in commodity futures market) should earn a risk premium for providing them with insurance. Traditional asset pricing models also suggest that hedgers will pay a premium to the counter-trading party (Merton, 1973, 1987). In S&P500 futures market, hedgers can assume long or short positions to achieve their objective and also have access to other risk-transferring alternatives such as trading in SPDRs, index-tracking ETFs, and OTC swap instruments. We should therefore not accept as given the idea that hedgers consistently pay a risk premium to speculators while trading the index. In our setup, hedgers are represented by

[21] It is also possible that hedge funds are more likely to trade in the E-mini market instead of the standard S&P500 index market as the former offers a better infrastructure for liquidity and a speedy execution. We therefore re-run our tests using E-mini net positioning data only. Results are similar to those obtained using consolidated position data and are available upon request.

commercial firms because of their business exposure to movements in the S&P500 index. Our consolidated net positioning data allows us to take a snapshot in time of the kind of risk premium available in the index futures market.

In order to estimate traders' relative average consolidated proceeds, we shall assume traders only adjust their holdings at the market close of each position-reporting day. Under such assumption, the proceeds for traders holding a net position level NP_t^l for week t can be roughly approximated by the product $NP_t^l \cdot (Close_{t+1} - Close_t)$, where $Close_t$ is the index level observed at the market close on position-reporting day t. We are interested in the position-weighted average proceeds, i.e. $\sum_t NP_t^l\,(Close_{t+1} - Close_t)\,/\sum_t |NP_t^i|$, because this measure reflects traders' earnings for positions they hold in the futures market. For dealers, the average earnings stand at 0.5472, compared to −0.294 for asset managers, −0.837 for hedge funds, 0.524 for commercial firms, and −0.7676 for noncommercial firms.[22]

The fact that hedgers (dealers, commercial firms) earnings' proxies, i.e. position-weighted average proceeds, are positive and higher relative to other traders undermines Keynes's (1930) argument that hedgers consistently pay a risk premium in exchange for insurance. This simple calculation seems to suggest that hedgers – dealers and commercial firms in general – may in fact be liquidity providers over our study period and be compensated for their service with higher returns. Such an interpretation corroborates our previous empirical findings, which suggest that – perhaps in demand for immediate trading – noncommercial firms tend to make price concessions to

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[22] Average earnings/losses are calculated based on the second sub-period sample (June 13th 2006–April 24th 2012).

liquidity providers. This result is also in line with evidence from Fishe and Smith (2012) indicating that noncommercial/commercial traders are more likely to demand/supply liquidity. An alternative interpretation is that commercial firms earn on average higher returns because they are relatively better informed. However, such an interpretation is not supported by our empirical findings, which suggest that the predictive role of commercial net positioning level becomes generally insignificant as the prediction horizon increases. Equally, however, this result also argues against the proposition that large speculators in the S&P500 index futures market possess superior information about future index returns. Our study indicates that such superiority, if at all, is unlikely to be maintained and therefore transpire at next-day or weeks-ahead prediction horizons.

2.3.4. Position-based trading signals and their profitability

In this section, we are interested to see how reliable popular position-based sentiment indicators are as trading signals designed to capture information relevant for future index returns. Large traders' net positioning data is often used as a market sentiment measure by financial practitioners (Kirkpatrick and Dahlquist, 2010). Wang (2003a) develops a position-based sentiment index for predicting S&P500 futures index returns. According to Wang (2003a), large speculators' (noncommercial firms) sentiment is a "price continuation indicator" whereas hedgers' sentiment is a "weak contrary indicator". Wang's sentiment index is constructed as follows:

$$\frac{NP_t^l - \mathrm{Min}(NP_t^l)}{Max(NP_t^l) - Min(NP_t^l)}$$

The maximum and minimum net position levels are set based on a moving window of historical observations.[23] The index reveals traders' net positioning level as an oscillator within a minimum–maximum range. Under this setting, the sentiment index will oscillate between 0 and 1. A similar position-based sentiment signal is introduced in Kirkpatrick and Dahlquist (2010) and developed by Ned Davis Research, which claims to have in excess of 1100 institutional clients in over three-dozen countries. This trading signal is also based on an oscillating index, called 'long- term stochastic', and based solely on commercial net positioning level data. The oscillator is similar to Wang's but uses a shorter maximum-minimum moving range and is smoothed out via a 6-week moving average. Practitioners usually configure their trading system by setting two threshold levels for this oscillator. The basic idea is that when the net positioning level is significantly away from the median of the moving range, a trading signal is released.

We explicitly test the position-based trading signals by setting up a back-testing experiment. We follow Wang's sentiment index and the oscillator threshold rules by positioning (long/short) our portfolio at the close of each observation day in response to available trading signals. The position is then liquidated at the close of the new positioning's observation day and the return for the week is recorded. We artificially predetermine the market timing implication (bullish/bearish) of each signal so that the resulting average return is always positive.[24] The Median Rule dictates positioning when Wang's sentiment index is above/below the median of its historical moving

[23] Wang (2003a) uses a 3-year moving window of historical observations. The size of the moving window in our experiment is 150 observations.

[24] We find that treating the commercial position-based signal as bullish and the noncommercial position-based signal as bearish leads to positive average returns while the opposite configuration results in an average loss.

window whereas the 75th & 25th Percentile Rule only requires positioning when the sentiment index moves beyond the 75th or 25th sample percentiles of the index's historical moving window.[25] The back-testing experiment uses weekly data from November 2000 to September 2012 with 618 observations in total. The average weekly index return during this period is 0.00043. The Median Rule is an always-in strategy while the 75th & 25th Percentiles Rule is an ad hoc strategy that does not produce any signals in approximately half of the weeks. Table 2.4 displays the results for each signal type. These suggest that the commercial position-based signals, on average, lead to higher returns than their noncommercial counterparts. More importantly however, none of the trading signals generates average returns that are significant (at 5% level). The more stringent trading rule (i.e. the 75th & 25th Percentiles Rule) does appear to generate a higher average return but the result remains statistically insignificant. Therefore, we find it difficult to accept that the commercial/noncommercial sentiment indexes are contrary/price continuation indicators. Trading signals based on these indexes do not produce significant returns.

[Insert Table 2.4]

2.4 Conclusion

Using consolidated position data, we investigate the information role of large (index futures) traders' net positioning measures on future S&P500 index returns. Our

[25] For example, to follow the Median Rule using the commercial position-based signal, we long the index if Wang's sentiment index is above its historical median value and go short otherwise. As for the 75th and 25th Percentile Rule, positions are taken when the sentiment index travels above the 75th percentile (long) or below the 25th percentile (short).

positioning measures are constructed based on the traditional (commercial/noncommercial) COT report as well as the new disaggregated COT report (dealer, asset manager, and leveraged fund). We depart from previous studies by explicitly considering the potential impact of crisis-related structural breaks on the research outcome. We find that the commercial net positioning level appears to be a short-run significant predictor of future index returns whereas the noncommercial net positioning level appears inversely related to future index returns. However, the presence of the dotcom and subprime crises in our sample significantly impacts on the nature of this predictability, suggesting that the state of the market strongly conditions the results. Specifically, we find that during the dotcom crisis, the link between commercial net positioning level and future (1- and 2-week ahead) returns is strengthened whereas, during the subprime crisis, this link is strongly reversed and thus turns (significantly) negative. This can explain the instability of any attempted prediction from one period to another and therefore the lack of reliability of a COT-based sentiment in practical pursuit. The result is also consistent with the recent studies of Chung et al. (2012) and Wolff (2013) which find the predictive power of their investor sentiment measures to be conditioned by the state of the market. The two crises also affect the nature of the relationship between large traders' net positioning changes – represented here by the unexpected level component – and next-day index returns. Although the direction is reversed, the two crises have, once more, opposing effect on this relationship. Whereas the norm suggests that commercial traders may receive price concessions perhaps in exchange for short-term liquidity, this norm is reversed during the dotcom episode. We argue that the changing mix of traders (and their trading motives) within the commercial and noncommercial categories may have contributed to crisis-related impacts on the predictive values of large traders' position levels. Using positioning data from the disaggregated COT report, we find that the mix of commercial/noncommercial positions has changed substantially since the start of the subprime crisis. Particularly, we find that an increasing number of hedge fund positions have since been classified by the CFTC as commercial positions. Moreover, we find that during the dotcom crisis hedgers (commercial) are liquidity demanders while during normal times they are liquidity providers. We therefore call into question the current use of traditional COT measures in forecasting.

Our evidence does not support Keynes' (1930) hedging pressure hypothesis or speculators' superior market timing ability documented by Wang (2003a). On the other hand, our findings are consistent with Fishe and Smith (2012) in suggesting that commercial traders often provide market liquidity at the demand of their noncommercial counterparties whilst being relatively less informed. Furthermore, results from a contemporaneous correlation analysis between specialist traders' net positioning changes and index returns highlight asset managers and dealers' role as commercial hedgers who position their trades in response to market returns. As for hedge funds, the lack of significant correlation between hedge funds' net positioning changes and contemporaneous weekly returns appears to undermine the idea that they are chasing returns and may suggest a relative information advantage at intraday frequency. This is further corroborated by the fact that hedge funds' unexpected net positioning levels are positively correlated with reporting-day returns. These findings are in line with Fishe and Smith (2012) but the issue of which class of specialist traders is more informed, over precisely what horizon and, more importantly, what is the source of their comparative advantage and its stability through time is far from being settled. As more COT data on specialist trades becomes available, more research is needed in order to answer these questions. Last but not least, we show that trading signals based on a popular position-based sentiment index fail to deliver significant average returns over our period of study.

References

Ben-David, I., Franzoni, F., Moussawi, R., 2011. Hedge fund stock trading in the financial crisis of 2007–2009. Review of Financial Studies 25, 1–54.

Bessembinder, H., 1992. Systematic risk, hedging pressure, and risk premiums in futures markets. Review of Financial Studies 5, 637–667.

Blasco, N., Corredor, P., Santamaría, R., 2009. Information spillovers between derivative markets with differences in transaction costs and liquidity. Applied Economics Letters 16, 1039–1047.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31, 307–327.

Bryant, H.L., Bessler, D.A., Haigh, M.S., 2006. Causality in futures markets. Journal of Futures Markets 26, 1039–1057.

Chakravarty, S., 2001. Stealth-trading: which traders' trades move stock prices? Journal of Financial Economics 61, 289–307.

Chu, Q.C., Hsieh, W.L.G., 2002. Pricing efficiency of the S&P500 index market: evidence from the Standard & Poor's Depositary Receipts. Journal of Futures Markets 22, 877–900.

Chu, Q.C., Hsieh, W.L.G., Tse, Y., 1999. Price discovery on the S&P500 index markets: an analysis of spot index, index futures, and SPDRs. International Review of Financial Analysis 8, 21–34.

Chung, S.L., Hung, C.H., Yeh, C.Y., 2012. When does investor sentiment predict stock returns? Journal of Empirical Finance 19, 217–240.

Cont, R., 2001. Empirical properties of asset returns: stylized facts and statistical issues. Quantitative Finance 1, 223–236.

De Roon, F.A., Nijman, T.E., Veld, C., 2000. Hedging pressure effects in futures markets. Journal of Finance 55, 1437–1456.

Fishe, R.P.H., Smith, A.D., 2012. Identifying informed traders in futures markets. Journal of Financial Markets 15, 329–359.

Gorton, G.B., Hayashi, F., Rouwenhorst, K.G., 2012. The fundamentals of commodity futures returns. Review of Finance 17, 35–105.

Gurrib, I., 2008. Do large hedgers and speculators react to events? A stability and events analysis. Applied Financial Economics Letters 4, 259–267.

Harris, L., Gurel, E., 1986. Price and volume effects associated with changes in the S&P500 list: new evidence for the existence of price pressures. Journal of Finance 41, 815–829.

Hoffmann, A.O.I., Post, T., Pennings, J.M.E., 2013. Individual investor perceptions and behavior during the financial crisis. Journal of Banking & Finance 37, 60–74.

Jiler, W.L., 1985. Analysis of the CFTC Commitments of Traders reports can help you

forecast futures prices. Commodity Research Bureau, http://www.crbtrader.com/pubs/yb/yb1985_cot.asp
Kadilli, A., 2013. A Regime Switching Approach for the Predictability of Returns in International Financial Markets, University of Geneva Working Paper, Available at SSRN: http://ssrn.com/abstract=2291237
Kawaller, I.G., Koch, P.D., Koch, T.W., 1987. The temporal price relationship between S&P500 futures and the S&P500 index. Journal of Finance 42, 1309–1329.
Ke, B., Petroni, K., 2004. How informed are actively trading institutional investors? Evidence from their trading behavior before a break in a string of consecutive earnings increases. Journal of Accounting Research 42, 895–927.
Keynes, J.M., 1930. A Treatise on Money: In 2 Volumes. Macmillan & Company.
Khandakar, Y., Hyndman, R.J., 2008. Automatic time series forecasting: the forecast package for R. Journal of Statistical Software 27, 1–22.
Kim, J.H., Shamsuddin, A., Lim, K.P., 2011. Stock return predictability and the adaptive markets hypothesis: evidence from century-long US data. Journal of Empirical Finance 18, 868–879.
Kirkpatrick, C.D., Dahlquist, J.R., 2010. Technical Analysis: The Complete Resource for Financial Market Technicians, 2nd ed. FT Press, New Jersey, pp. 122–124.
Lasfer, M., Melink, A., Thomas, D., 2003. Short-term reaction of stock markets in stressful circumstances. Journal of Banking and Finance 27, 1959–1977.
Leuthold, R.M., Garcia, P., Lu, R., 1994. The returns and forecasting ability of large traders in the frozen pork bellies futures market. Journal of Business 67, 459–473.
Li, M.Y.L., 2009. The dynamics of the relationship between spot and futures markets under high and low variance regimes. Applied Stochastic Models in Business and Industry 25, 696–718.
Martikainen, T., Puttonen, V., 1992. On the informational flow between financial markets: international evidence from thin stock and stock index futures markets. Economics Letters 38, 213–216.
Merton, R.C., 1973. An intertemporal capital asset pricing model. Econometrica 41, 867–887.
Merton, R.C., 1987. A simple model of capital market equilibrium with incomplete information. Journal of Finance 42, 483–510.
Nagel, S., 2012. Evaporating liquidity. Review of Financial Studies 25, 2005–2039.
Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: a new approach. Econometrica: Journal of the Econometric Society 59, 347–370.
Richie, N., Daigler, R.T., Gleason, K.C., 2008. The limits to stock index arbitrage: examining S&P500 futures and SPDRS. Journal of Futures Markets 28, 1182–1205.
Sanders, D.R., Boris, K., Manfredo, M., 2004. Hedgers, funds, and small speculators

in the energy futures markets: an analysis of the CFTC's Commitments of Traders reports. Energy Economics 26, 425–445.

Sanders, D.R., Irwin, S.H., Merrin, R.P., 2009. Smart money: the forecasting ability of CFTC large traders in agricultural futures markets. Journal of Agricultural and Resource Economics 34, 276–296.

Schmeling, M., 2007. Institutional and individual sentiment: smart money and noise trader risk? International Journal of Forecasting 23, 127–145.

Schwarz, K., 2012. Are speculators informed? Journal of Futures Markets 32, 1–23.

Stoll, H.R., Whaley, R.E., 1990. The dynamics of stock index and stock index futures returns. Journal of Financial and Quantitative Analysis 25, 441–468.

Tornell, A., Yuan, C., 2012. Speculation and hedging in the currency futures markets: are they informative to the spot exchange rates. Journal of Futures Markets 32, 122–151.

Wang, C., 2003a. Investor sentiment, market timing, and futures returns. Applied Financial Economics 13, 891–898.

Wang, C., 2003b. The behavior and performance of major types of futures traders. Journal of Futures Markets 23, 1–31.

Wilhelmsson, A., 2006. GARCH forecasting performance under different distribution assumptions. Journal of Forecasting 25, 561–578.

Wolff, A.F., 2013. Investor sentiment and stock prices in the subprime mortgage crisis. Applied Financial Economics 23, 1301–1309.

Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel Data. The MIT Press, pp. 49–58.

Yan, X., Zhang, Z., 2009. Institutional investors and equity returns: are short-term institutions better informed? Review of Financial

Appendix

Figure 2.1 Returns and the traders' positions sampling design.

'Open' and 'Close' denote the open and close S&P500 index levels. On each position-reporting day large futures traders net positioning levels are observed; S&P500 index open and close levels are also observed on the same day; k-week ahead returns are the percentage change in index level between current Close and k-week ahead Open.

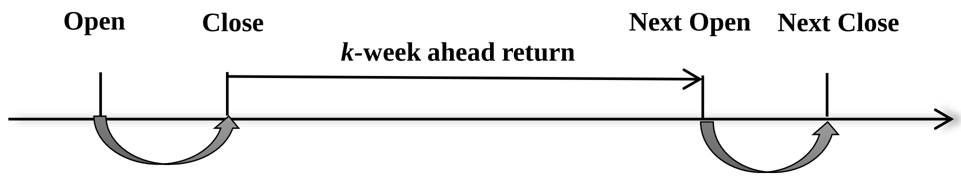


Figure 2.2 Decomposition of traders' net positioning level.

Traders' net positioning level (NP_t) refers to the long-short difference in traders' holding positions, observed on the position-reporting day in week t; $F_{t,k}NP_t$ is the dynamic ARIMA forecast of NP_t using past observations from a moving window [$t - k - 1$, $t - 1$]; $UENP_t$ is the unexpected net positioning level, i.e. the difference between NP_t and the forecast $F_{t,k}NP_t$. The window size is 150 observations for commercial/noncommercial traders and 50 observations for specialist firms.

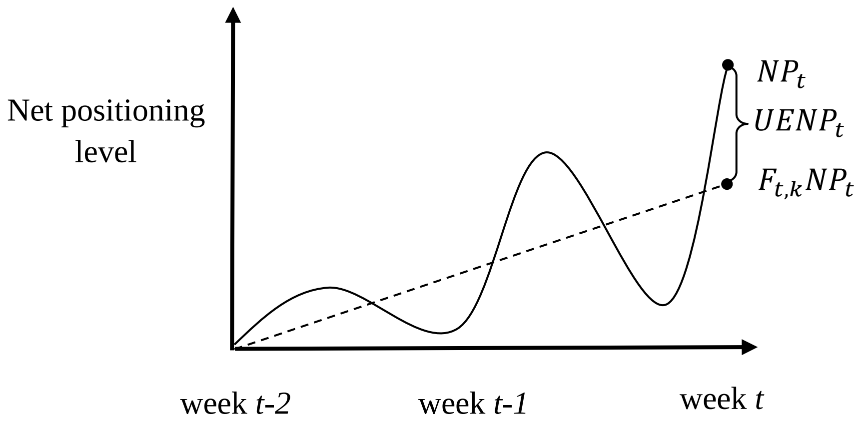


Table 2.1 Summary statistics

Measures	Positions & Returns	Mean	Median	Std.Dev	AC(1)	Unit Root ADF	Unit Root KPSS
NP	Commercial	-29930	-33288	43153	0.966		
	Noncommercial	-15870	-17516	29998	0.955		
	Dealer	-273672	-285800	113966	0.984		
	Asset Manager	328720	332226	82880	0.984		
	Hedge Fund	-82170	-87894	46148	0.956		
△NP	Commercial	-8.119	-152	11215	0.003		
	Noncommercial	-38.495	-36.2	8935	-0.007		
	Dealer	828.873	620.6	17372	0.199		
	Asset Manager	-670.122	115.7	11986	-0.099		
	Hedge Fund	2.991	-780.3	13633	0.017		
NPI	Commercial	-0.0248	-0.0231	0.037	0.971	3.298***	4.280*
	Noncommercial	-0.0138	-0.0155	0.021	0.952	-4.312***	0.242
UENPI	Commercial	-0.000083	-0.000138	0.009	0.052	-25.206***	0.051
	Noncommercial	-0.000124	-0.000096	0.007	0.078	-25.206***	0.111
	Dealer	-0.000126	0.000568	0.014	0.029	-15.453***	0.052
	Asset Manager	-0.000328	0.000032	0.010	-0.011	-16.098***	0.097
	Hedge Fund	0.000488	-0.000703	0.011	0.016	-15.692***	0.033
S&P 500 Index Returns	R_n	0.000344	0.000793	0.013	0.112	-24.341***	0.057
	$R_{t,t+1}$	0.000420	0.002581	0.025	-0.047	-28.576***	0.124
	$R_{t,t+2}$	0.001406	0.003981	0.036	0.050	-18.295***	0.133
	$R_{t,t+4}$	0.002850	0.008646	0.052	0.028	-13.166***	0.081
	$R_{t,t+8}$	0.005803	0.010576	0.073	0.022	-9.335***	0.067

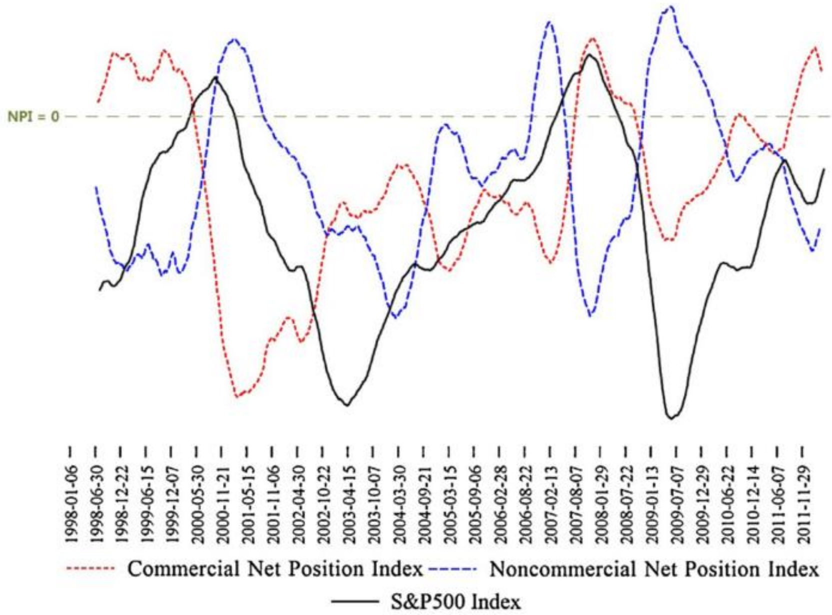
AC(1) is the first-order sample autocorrelation. Unit root analysis is based on ADF and KPSS tests; NP refers to traders' net positioning level; NPI refers to the net positioning level index obtained from normalizing NP; ΔNP refers to the change in traders' net positions level; UENPI refers to the unexpected net positioning index, i.e. the normalized difference between traders' actual net positioning level and the corresponding ARIMA forecast using past observations of traders' positioning levels; R_n refers to the returns of S&P500 index on the trading days immediately after the position-reporting days and calculated as the percentage change in index levels; $R_{t,t+k}$ refers to the k-week ahead S&P500 index returns calculated as the percentage change in index levels.

* Significant at 10% level.

**Significant at 5% level.

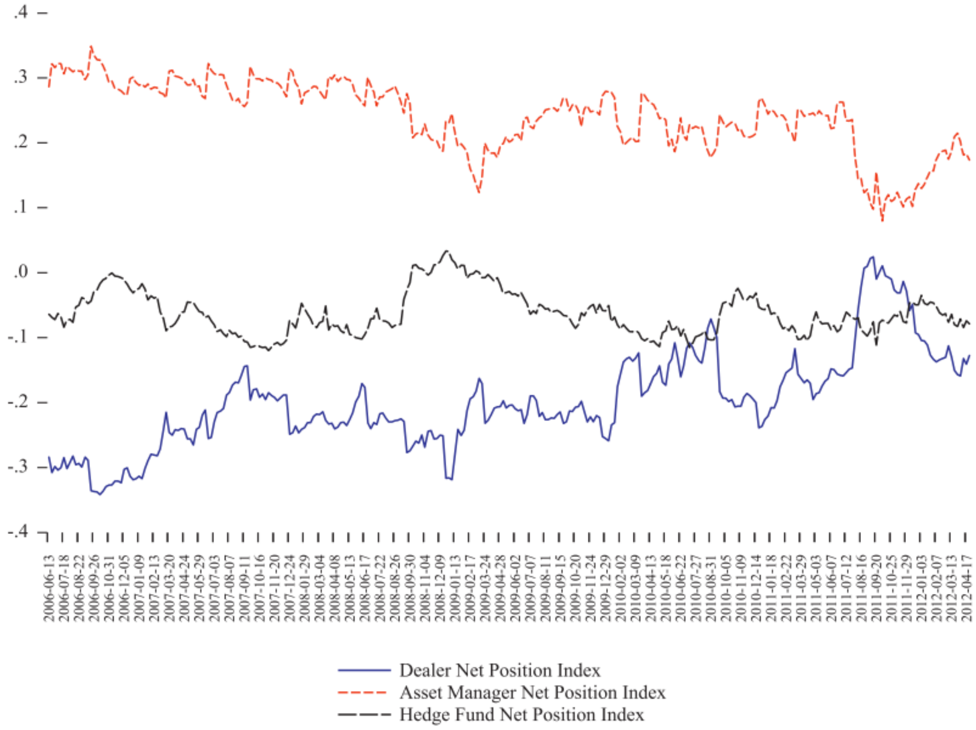
***Significant at 1% level.

Figure 2.3 S&P500, commercial net positioning, and noncommercial net positioning indexes (January 6th 1998–April 24th 2012).



Notes: Commercial and noncommercial net positioning indexes (NPI) are the normalized (by total reportable positions) differences between long and short commercial/noncommercial positions. They measure the level of commercial/noncommercial net positioning in S&P500 futures market. S&P500 index series is measured at the market close. A 30-week moving average has been applied to all series.

Figure 2.4 Dealer, asset manager, and hedge fund net positioning indexes (June 13th 2006–April 24th 2012).



Notes: the three series are the normalized (by total specialist firms' reportable positions) differences between long and short positions for dealer, asset manager, and hedge fund groups. The indexes measure specialist firms' net positioning levels in S&P500 futures market.

Table 2.2 The estimated effect of commercial/noncommercial futures trades on future S&P500 index returns.

Return	Model		c_0	c_1	c_2	β_0	β_1	β_2	LR^1	LR^2
(Panel A) Coefficients in models I, II, and III using commercial (C) and noncommercial (NC) net positioning level measures as predictors for 1 and 2 weeks ahead index returns										
1 week		I	0.0033*** [0.0007]	−0.0057*** [0.0023]	−0.0116*** [0.0025]					
	C	II	0.0048*** [0.0009]			0.0743*** [0.0189]			20.72***	23.24***
		III	0.0054*** [0.0009]	0.0208*** [0.0078]	−0.0141*** [0.0025]	0.0732*** [0.0230]	0.2749*** [0.0911]	−0.2004** [0.1018]		
	NC	II	0.0020** [0.0008]			−0.0518 [0.0319]			5.666	17.16***
		III	0.0028*** [0.0009]	−0.0064*** [0.0024]	−0.0091*** [0.0031]	−0.0633* [0.0335]	−0.0912 [0.1531]	0.1828* [0.1062]		
2 weeks		I	0.0059*** [0.0016]	−0.0138*** [0.0048]	−0.0200*** [0.0048]			−1.6449		
	C	II	0.0082*** [0.0017]			0.1414*** [0.0386]			15.82***	22.29***
		III	0.0093*** [0.0017]	0.0484*** [0.0161]	−0.0234*** [0.0047]	0.1248*** [0.0450]	0.6678*** [0.1989]	−0.5439*** [0.1977]		
	NC	II	0.0033* [0.0018]			−0.0482 [0.0679]			2.19	16.02***
		III	0.0055*** [0.0020]	−0.0148*** [0.0054]	−0.0126** [0.0062]	−0.0373 [0.0745]	−0.1070 [0.2844]	0.3747* [0.2156]		
(Panel B) Coefficients in models I, II, and III using commercial (C) and noncommercial (NC) net positioning level measures as predictors for 4 and 8 weeks ahead index returns										
4 weeks		I	0.0121*** [0.0034]	−0.0296*** [0.0100]	−0.03828*** [0.0092]					
	C	II	0.0155*** [0.0037]			0.2128*** [0.0803]			7.62	14.07***
		III	0.0173*** [0.0041]	−0.0479*** [0.0186]	−0.0481*** [0.0086]	0.2022* [0.1039]	−0.3646 [0.2921]	−0.9916*** [0.2999]		
	NC	II	0.0076* [0.0039]			−0.0968 [0.1363]			4.62	16.15***
		III	0.0113** [0.0046]	−0.0241** [0.0106]	−0.0255*** [0.0081]	−0.1418 [0.1743]	0.8644* [0.5061]	0.9771*** [0.3590]		

Table 2.2 (Continued)

Return	Model		c_0	c_1	c_2	β_0	β_1	β_2	LR[1]	LR[2]
8 weeks	C	I	0.0243*** [0.0075]	−0.0790*** [0.0239]	−0.0767*** [0.0321]					
		II	0.0152 [0.0099]			0.4192** [0.1962]				
		III	0.0288*** [0.0094]	−0.0949 [0.0962]	−0.0806*** [0.0292]	0.2492 [0.2073]	−0.3928 [1.1688]	−0.2019 [0.6467]	1.09	15.51***
	NC	II	−0.0019 [0.0105]			−0.4706 [0.3762]				
		III	0.0223** [0.0090]	−0.0747** [0.0287]	−0.0765** [0.0384]	−0.1292 [0.3226]	0.5883 [2.1250]	−0.0959 [0.9288]	0.27	17.34***

(I) $R_{t,t+k} = aR_{t-k,t} + c_0 + c_1 D_t^1 + c_2 D_t^2 + \varepsilon_{t,t+k}$

(II) $R_{t,t+k} = aR_{t-k,t} + c_0 + \beta_0 NPI_t^l + \varepsilon_{t,t+k}$

(III) $R_{t,t+k} = aR_{t-k,t} + c_0 + c_1 D_t^1 + c_2 D_t^2 + \beta_0 NPI_t^l + \beta_1 NPI_t^l D_t^1 + \beta_2 NPI_t^l D_t^2 + \varepsilon_{t,t+k}$

The model error term $\varepsilon_{t,t+k}$ follows a generalized error distribution with GARCH (1, 1) conditional variance. $R_{t,t+k}$ refers to k-week ahead index returns, calculated as the percentage change in index levels. NPI_t^l refers to the commercial/noncommercial net positioning level index, i.e. the normalized difference of commercial/noncommercial long and short positions. Dummies D_t^1 and D_t^2 mark the dotcom and subprime crises. Standard errors of estimates are inside square brackets. LR[1] and LR[2] are the likelihood ratio statistics for testing restrictions I ($\beta_0 = 0,\ \beta_1 = 0,\ \beta_2 = 0$) and II ($c_1 = 0, c_2 = 0,\ \beta_1 = 0,\ \beta_2 = 0$), respectively, against the alternative of model III.

* Significant at 10% level.

**Significant at 5% level.

***Significant at 1% level.

Table 2.3 The estimated effect of large futures traders' unexpected net positioning levels on future S&P500 index returns.

Return	Model		c_0	c_1	c_2	β_0	β_1	β_2	LR^1	LR^2
(Panel A) Estimated coefficients of models I, II, and III using commercial (C), noncommercial (NC) unexpected net positioning measures (UENPI) as predictors for 1 day, 1 week, and 2 weeks ahead index returns										
1 day		I	0.0014***	−0.0016	−0.0018					
			[0.0003]	[0.0012]	[0.0012]					
	C	II	0.0013***			0.0724**			17.27***	10.83**
			[0.0003]			[0.0360]				
		III	0.0015***	−0.0021*	−0.0017	0.0954**	−0.5373***	0.0813		
			[0.0003]	[0.0011]	[0.0013]	[0.0380]	[0.1326]	[0.1561]		
	NC	II	0.0012***			−0.1296***			13.92***	3.40
			[0.0003]			[0.0454]				
		III	0.0014***	−0.0017	−0.0016	−0.1309***	0.2368	0.0408		
			[0.0003]	[0.0012]	[0.0013]	[0.0477]	[0.2604]	[0.1730]		
1 week		I	0.0033***	−0.0057***	−0.0116***					
			[0.0007]	[0.0023]	[0.0025]					
	C	II	0.0024***			0.0399			4.12	18.59***
			[0.0007]			[0.0784]				
		III	0.0034***	−0.0058***	−0.0113***	0.0426	−0.1274	0.8030***		
			[0.0007]	[0.0022]	[0.0012]	[0.0845]	[0.2291]	[0.2962]		
	NC	II	0.0023***			−0.1336			3.20	16.17***
			[0.0006]			[0.1018]				
		III	0.0033***	−0.0060***	−0.0107***	−0.1073	−0.0945	−0.5768		
			[0.0007]	[0.0023]	[0.0025]	[0.1055]	[0.5222]	[0.3613]		
2 week		I	0.0059***	−0.0138***	−0.0200***					
			[0.0016]	[0.0048]	[0.0048]					
	C	II	0.0040***			−0.1553			0.86	14.40***
			[0.0015]			[0.1904]				
		III	0.0060***	−0.0139***	−0.0203***	−0.1732	−0.0009	0.1557		
			[0.0016]	[0.0048]	[0.0051]	[0.2060]	[0.6060]	[0.6829]		
	NC	II	0.0040***			−0.0682			0.86	15.04***
			[0.0015]			[0.2123]				
		III	0.0059***	−0.0143***	−0.0203***	−0.0530	−0.9080	−0.4049		
			[0.0016]	[0.0050]	[0.0048]	[0.2253]	[1.3543]	[0.6877]		

Table 2.3 (Continued)

Return	Model		c_0	c_1	c_2	β_0	β_1	β_2	LR[1]	LR[2]
(Panel B) Estimated coefficients of models I, II, and III using dealer (DA), asset manager (AM), and hedge fund (HF) unexpected net positioning measures (UENPI) as predictors for 1 day, 1 week, and 2 weeks ahead index returns										
1 day	DA	I	0.0018***		−0.0022*				2.74	4.60
			[0.0005]		[0.0012]					
		II	0.0011**			−0.0050				
			[0.0005]			[0.0405]				
		III	0.0017***		−0.0021*	−0.0311		0.1715*		
			[0.0006]		[0.0012]	[0.0431]		[0.0991]		
	AM	II	0.0011**			0.0269			1.66	3.14
			[0.0005]			[0.0602]				
		III	0.0014**		−0.0020	0.0379		−0.3111*		
			[0.0006]		[0.0013]	[0.0697]		[0.1640]		
	HF	II	0.0012**			−0.0956*			5.84	4.24
			[0.0005]			[0.0513]				
		III	0.0018***		−0.0023*	−0.1268**		−0.0334		
			[0.0006]		[0.0012]	[0.0581]		[0.1059]		
1 week	DA	I	0.0047***		−0.0124**				6.58**	18.11**
			[0.0011]		[0.0027]					
		II	0.0028**			−0.0341				
			[0.0014]			[0.1123]				
		III	0.0053***		−0.0126***	−0.1542		0.6688***		
			[0.0016]		[0.0029]	[0.1243]		[0.2185]		
	AM	II	0.0027*			0.2054			1.59	11.81**
			[0.0014]			[0.1596]				
		III	0.0049***		−0.0127***	0.2027		−0.3197		
			[0.0016]		[0.0031]	[0.1717]		[0.3543]		
	HF	II	0.0026*			−0.1469			1.3	11.54**
			[0.0014]			[0.1471]				
		III	0.0050***		−0.0116***	−0.0890		−0.1558		
			[0.0016]		[0.0030]	[0.1638]		[0.2742]		

Table 2.3 (Continued)

Return	Model		c_0	c_1	c_2	β_0	β_1	β_2	LR[1]	LR[2]
2 weeks	DA	I	0.0049*		−0.0181**				4.65*	5.75*
			[0.0027]		[0.0079]					
		II	−0.0015			0.5410**				
			[0.0035]			[0.2760]				
		III	0.0043		−0.0169**	0.3391		0.4776		
			[0.0034]		[0.0080]	[0.2795]		[0.5464]		
	AM	II	−0.0014			−0.3410			3.16	7.83**
			[0.0035]			[0.4799]				
		III	0.0045		−0.0176**	0.0510		−1.1443		
			[0.0034]		[0.0083]	[0.3576]		[1.0941]		
	HF	II	−0.0014			−0.6527**			3.55	5.0*
			[0.0035]			[0.2945]				
		III	0.0044		−0.0167*	−0.5106		−0.1922		
			[0.0033]		[0.0082]	[0.3401]		[0.5711]		

(I) $R_{t,t+k} = aR_{t-k,t} + c_0 + c_1 D_t^1 + c_2 D_t^2 + \varepsilon_{t,t+k}$;

(II) $R_{t,t+k} = aR_{t-k,t} + c_0 + \beta_0 UENPI_t^l + \varepsilon_{t,t+k}$;

(III) $R_{t,t+k} = aR_{t-k,t} + c_0 + c_1 D_t^1 + c_2 D_t^2 + \beta_0 UENPI_t^l + \beta_1 UENPI_t^l D_t^1 + \beta_2 UENPI_t^l D_t^2 + \varepsilon_{t,t+k}$

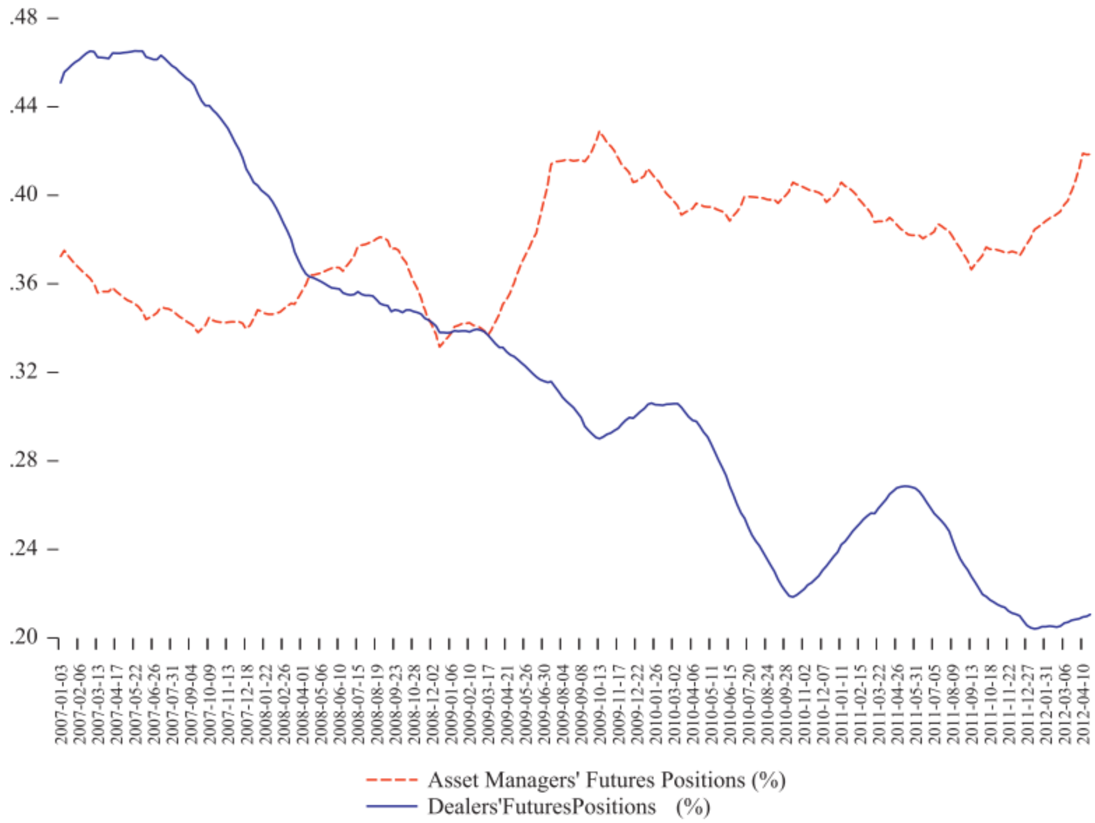
The model error term $\varepsilon_{t,t+k}$ follows a generalized error distribution with GARCH (1, 1) conditional variance. $R_{t,t+k}$ normally refers to k-week ahead index returns (exceptionally, it refers to 1-day ahead index returns), calculated as the percentage change in index levels. $UENPI_t^l$ refers to the unexpected net positioning index, i.e. the normalized difference between traders' actual net position level and the corresponding ARIMA forecast. Dummies D_t^1 and D_t^2 mark the dotcom and subprime crises. Standard errors of estimates are inside square brackets. LR[1] and LR[2] are the likelihood ratio statistics for testing restrictions I ($\beta_0 = 0,\ \beta_1 = 0,\ \beta_2 = 0$) and II ($c_1 = 0, c_2 = 0, \beta_1 = 0,\ \beta_2 = 0$), respectively, against the alternative of model III.

* Significant at 10% level.

**Significant at 5% level.

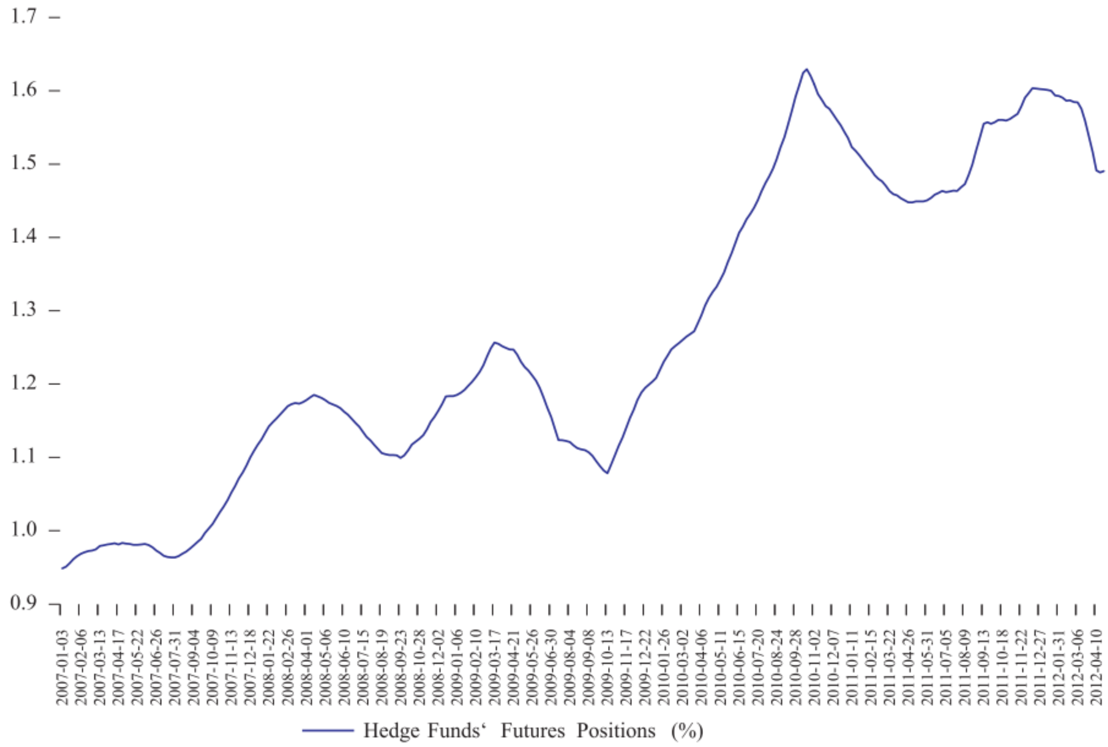
***Significant at 1% level.

Figure 2.5 Dealers and asset managers' holding positions in the S&P500 futures market.



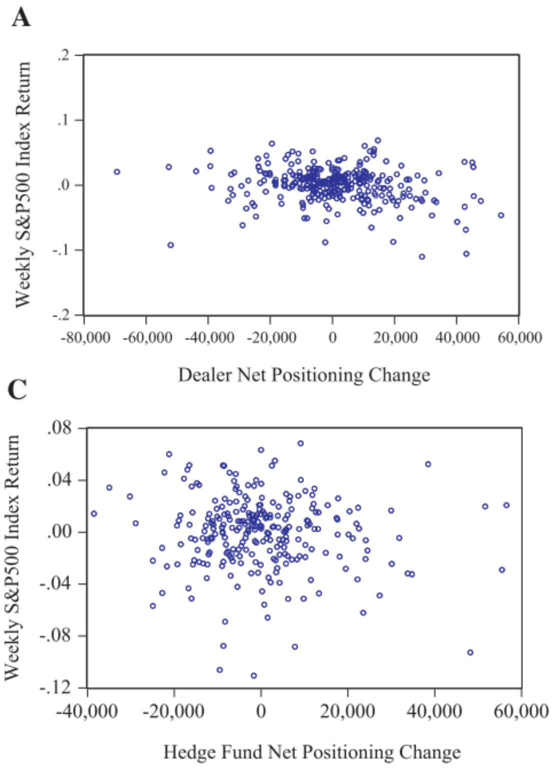
Notes: Dealers and asset managers' holding positions (sum of long and short positoins) are expressed as percentages of the total (long and short) commercial positions at time t.

Figure 2.6 Hedge funds' holding positions in the S&P500 futures market.



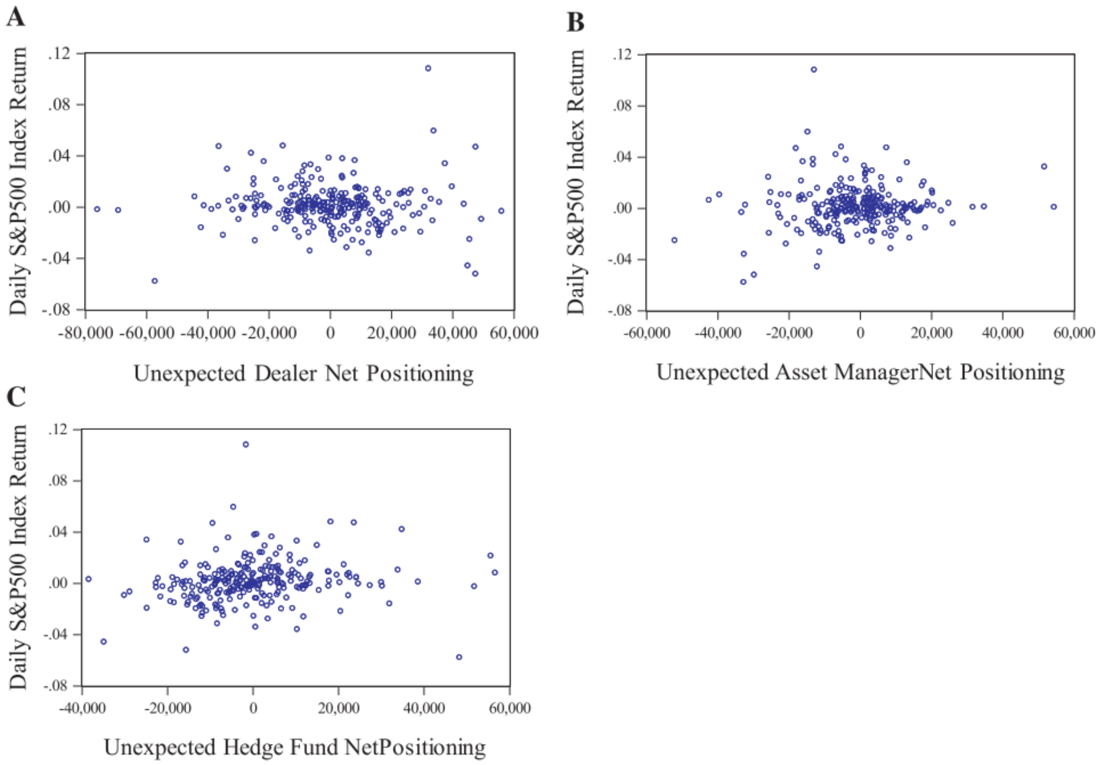
Notes: hedge funds' holding positions are expressed as percentages of the total (long and short) noncommercial positions.

Figure 2.7 (A–C) Contemporaneous correlations between weekly S&P500 index returns and dealer, asset manager and hedge fund net positioning changes.



Notes: S&P500 weekly returns are measured as the percentage change in the index level from the market open of current position-reporting day to the market close of previous position-reporting day. Dealer, asset manager, and hedge fund net positioning changes are calculated as the weekly changes in the reported level of net open interest per class of investors. The correlation coefficients (Spearman rank-order) between net positioning changes and returns are −0.1882***, 0.4827***, and 0.0107 for dealer, asset manager, and hedge fund, respectively. Superscript *** denotes 1% significance in testing the null hypothesis of zero correlation.

Figure 2.8 (A–C) Contemporaneous correlations between reporting-day S&P500 Index returns and the unexpected components of dealer, asset manager and hedge fund net positions.



Notes: S&P500 returns are calculated as the percentage change in the index level from close to open on position-reporting days. The unexpected component of dealer/asset manager/hedge fund net positions is the difference between traders' actual net positioning level and the corresponding ARIMA forecast based on past 50 observations. The correlation coefficients (Spearman rank-order) between unexpected positioning changes and returns are −0.0937, 0.0523, and 0.2300*** for dealer, asset manager, and hedge fund, respectively. Superscript *** denotes 1% significance in testing the null hypothesis of zero correlation.

Table 2.4 Average weekly S&P500 index returns following position-based trading signals.

Trading Signal	Median Rule	75^{th} & 25^{th} Percentile Rule
Commercial sentiment		
Average Return	0.0019	0.0024
Return Std. Dev.	0.02607	0.0278
t-test | *p*-value	1.848* | 0.065	1.602 | 0.11
Number of trades	618	345
Noncommercial sentiment		
Average Return	0.001	0.0016
Return Std Dev	0.02613	0.02868
t-test | p-value	0.936 | 0.35	1.019 | 0.309
Number of Trades	618	340

Notes: Trading signals are identified based on the position-focused market timing rules of Wang (2003a). The median rule gives a positioning signal when Wang's sentiment index is above/below the median of its historical moving window whereas the 75th & 25th Percentile Rule gives a positioning signal when Wang's sentiment index moves beyond the 75th or 25th sample percentiles of its historical moving window. The market timing implication (bullish/bearish) of each signal is artificially predetermined so that the resulting average return is always positive. The *t*-test and the corresponding *p*-value test the null of zero mean returns generated under each trading signal.

* Significant at 10% level.

** Significant at 5% level.

*** Significant at 1% level.

Chapter 3

The Role of Short Sales in Shaping the Behaviour of Stock Returns Following Extreme Price Moves: Evidences from the Chinese Stock Market

This paper examines the impacts of short sellers' trading in shaping the behaviour of stock returns following extreme price moves using data from stock market in mainland China where short sales were initially prohibited. Extreme price moves occurring under non-prohibitive/prohibitive short-sale constraints are defined as shortable/non-shortable events. Consistent with Diamond & Verrecchia (1987)'s hypothesis, we find shortable events exhibit less post-event price drift/reversals than non-shortable ones, indicating an increase in the efficiency of stock prices reacting to unexpected events. Further analysis of short sellers' trading activities on the price event days suggests that they are successful in trading informed price shocks in which they exploit underreaction in stock prices to new information, but not in trading uninformed ones in which they bear the risk of suffering losses when overshooting in stock prices becomes more extreme. Finally, we find evidence of massive short-covering that amplifies price shocks.

Keywords: Predictability of stock returns, Extreme price moves, Short selling, Short Covering, Information, Momentum reversals

3.1 Introduction

In examining the over- and under-reaction anomalies, prior studies have not considered the effects of short sales and short-sale constraints. Moreover, these anomalies are customarily explained in the behavioural finance literatures as a reflection of systematic biases in investors' information processing (De Bondt & Thaler, 1985; Barberis et al., 1998; Daniel et al., 1998; Hong & Stein, 1999; Bloom et al. ,2000; Subrahmanyam ,2005; Li & Yu, 2012). Therefore, they are sometimes considered to constitute evidence against one of the most important assumptions of the efficient market hypothesis. However, to firmly make a case against market efficiency, the challengers must first isolate those non-behavioural effects that can also lead to under-/overreaction in stock prices. For example, reversals following large price moves may simply reflect the impact of liquidity trades, bid-ask bounce, and non-trading (Lo & MacKinlay, 1990; Cox & Peterson,1994; Park, 1995). In this paper, we show that short-constraints act as another non-behavioural effect which may have also contributed to the over- and under-reaction anomalies.

Intuitively, large changes in stock prices reflect investors' responses to unexpected events, and the behaviour of post-event returns reveals the gradual adjustment of stock prices to investors' initial responses. Investor overreaction is like to result in reversals in post-shock stock prices while investor underreaction leads to drift. Diamond & Verrecchia (1987) hypothesize that under rational expectations, short-sale constraints, especially prohibitive constraints, reduce the speed of adjustment of stock prices to information. They argue that under non-prohibitive constraints short-sellers are likely to be informed traders, and thus short-selling helps incorporate information, especially bad news, into stock prices. One implication following from Diamond & Verrecchia's (1987) hypothesis on the behaviour of post-shock returns, is that since short constraints reduce the efficiency of stock prices' reaction to new information, the magnitude of post-shock price drift or reversal should become smaller when the constraints are lessened.

There is inconclusive evidence in the empirical literature regarding the impacts of short sales and short-sale constraints on the speed of adjustment of stock prices to unexpected events. On the one hand, some studies indicate that short sellers act as liquidity providers in liquidity demand shocks and informed arbitrageurs when stock prices deviate from fundamentals, and thus short-sellers' trading improves efficiency in stock prices. (see e.g. Diether *et. al*, 2009; Beber & Pagano, 2013; Boehmer and Wu 2013; Chang et al., 2013). On the other hand , several studies document that short sellers destabilize stock prices when they are being squeezed out or are too aggressive (see e.g. Shkilko et al., 2008; Savor & Gamboa-Cavazos, 2011; Hong et al., 2012). This paper also contributes to this on-going debate by examining the roles of short sales and short-constrains in shaping the behaviour of post-shock returns.

I use stock market data from China. China is an interesting test site, because short-selling was initially prohibited but then subsequently allowed under a pilot program launched in March 2010. This pilot program initially allowed short sales only in 90 elite stocks (in terms of market capitalization and liquidity) of the CSI 300 index, but was then subsequently expanded four times to eventually include 900 stocks, which represent approximately 80% of the total market value of all floating shares in the market. For each stock either initially present or subsequently added to the pilot program, we look for large price moves, which we term price events, in the stock's historical price record. Price events occurring after (before) the stock's affiliation to the program are considered "shortable" ("non-shortable") events.

We examine the effect of short sales on the predictability of stock returns following large price moves by running a regression on post-shock abnormal returns with the event-day abnormal price change, which reflects investors' response to the event, as the main predictor and a dummy interaction term for shortable events. We find that the magnitudes of post-shock price drifts and reversals shrink when short-selling bans are removed. Consistent with the empirical implication of Diamond & Verrecchia's (1987) model, our results suggest that the adjustment of stock prices to unexpected events is more efficient when the underlying stock is shortable. Our results are consistent with the evidence in Chang et al. (2013), who find that after the launch of the pilot program in mainland China, stock prices incorporate more firm-specific information and deviate less from a random walk.

We further investigate whether the reduction in post-shock predictability is associated with short-sellers' trading activities. These trades are disclosed by the stock exchanges in China on a daily basis. We find that intensified short-selling trades are associated with less post-shock downward price drift for price events accompanied by news announcements, and that increases in short-covering trades on price event day are able to predict a decrease in post-shock abnormal returns. An analysis on the contemporaneous correlation between short sellers' trading activities and event-day abnormal returns shows a significant positive relationship between the volume of short-selling (short-covering) trades and the magnitude of price drop (increase) for price events related (unrelated) to news announcements. Moreover, the volume of short-covering trades also increases during large price drops which occur in the absence of news announcements. These results suggest that short sellers' trading improves the speed of adjustment of stock prices to bad news. This finding is consistent with those of Engelberg et al. (2012) who find the predictive power of short-selling trades on future returns is stronger on news days, leading them to conclude that short sellers are "skilled information processors”. Our results are also consistent with those of Boehmer & Wu (2013) and Bai & Qin (2015). Boehmer and Wu (2013) monitor the levels of shorting flow around negative earnings surprises, while Bai and Qin (2015) compare the price reactions of shortable and non-shortable shares to negative earnings surprises. Both studies find short-selling activities reduce the magnitude of post-earnings-announcement drift. Our results also suggest that short-covering trades can either amplify overshooting in stock prices, resulting in stronger post-shock negative reversals, a result consistent with Hong et al. (2012), or accommodate unexplained supply shocks, resulting in weaker post-shock positive reversals.

Finally, the results of this paper complement prior studies by Savor & Gamboa-Cavazos (2011) and Boehmer & Wu (2013). Savor & Gamboa-Cavazos (2011) find short sellers either cannot hold, or are unwilling to hold, their positions when facing adverse extreme price moves. This paper complements this finding by showing that even during unexplained large price drops in which short sellers do not suffer losses they cover more of their outstanding positions as the magnitude of the drop increases. This suggests that short sellers either anticipate the follow-up positive reversals or attempt to avoid exposure to extreme price shocks that are not motivated by new information. Boehmer & Wu (2013) find the volume of short-selling trades positively correlated with the event-day abnormal price changes. We complement this finding by showing that the relationship only applies for price shocks unrelated to new information.

The remainder of the paper is organized as the follows. The next section provides a review the relevant literature; section 3.3 gives a brief introduction to short sales in mainland China; section 3.4 describes the data and methodology; section 3.5 and 3.6 present the descriptive statistics and empirical results respectively; section 3.7 provides robustness checks and section 3.8 concludes.

3.2 Literature Review

The topic of this paper relates to two distinct branches of the current literature. Firstly, this paper contributes to the existing literature on the market impacts of short sales. Early empirical studies on this topic are motivated by the overvaluation hypothesis based on the theoretical framework initiated in Miller (1977) (see also Duffie et al., 2002; Hong & Stein, 2003; Scheinkman & Xiong, 2003). The hypothesis suggest short-constraints discourage investors with bad news from entering the market, making it difficult for stock prices to incorporate negative information. While quite a few studies find evidence supporting the hypothesis (see, among others, Figlewski 1981; Danielsen & Sorescu, 2001; Desai et al., 2002; Jones & Lamont, 2002; Ofek & Richardson, 2003; Chang et al., 2007; Asquith et al., 2005; Boehme et al., 2006; Boulton & Braga-Alves, 2010; Battalio & Schultz, 2011; Harris et al., 2013; Autore et al.,2015), there are several studies that present counter-evidence indicating that the effect of short sales on future stock returns is insignificant (see Brent et al., 1990; Woolridge & Dickinson, 1994; Beber & Pagano, 2013; Boehmer et al., 2013). Diamond & Verrecchia (1987) hypothesize that in a rational expectation framework prohibitive short-constraints reduce information efficiency but do not necessarily lead to overvaluation. According to this model, short-selling bans, which proportionally prohibit both informed and uninformed trades, impede the adjustment of stock prices to information. Furthermore, under non-prohibitive short-constraints, short-sellers are likely to be informed, and thus short-selling activities improve information efficiency. Both implications have gained voluminous support in the empirical literature (see Figlewski & Webb, 1993; Senchack & Starks, 1993; Aitken et al., 1998; Fung & Draper, 1999; Bris et al., 2007; Reed, 2007; Diether et al., 2009; Chen & Rhee, 2010; Saffi & Sigurdsson, 2011; Grundy et al., 2012; Beber & Pagano, 2013; Boehmer & Wu, 2013;

Chang et al., 2013; Jiang & Pang, 2015). In particular, Chen & Rhee (2010) show that the speed of adjustment of stock prices to information is higher among shortable stocks than non-shortable ones in both up and down markets. Boehmer & Wu (2013) find that more short-selling activity is associated with less post-earnings-announcement drift. Bai & Qin (2015) find that shortable stocks exhibit more efficient adjustment to bad news than non-shortable stocks.

The informational role of short-selling trades is the key in understanding the effect of short sales. If short sellers are informed and are active in exploiting the divergence of stock prices from the fundamental values, both the under- and overreaction anomalies should reduce accordingly. A number of studies have indicated that: (i) short-sellers are active in trading on price divergences from fundamental values (Dechow et al., 2001; Francis et al., 2005; Boehmer & Wu, 2013); (ii) are successful in anticipating news events (Christophe et al., 2004; Karpoff & Lou, 2010; Christophe et al., 2010; Chakrabarty & Shkilko, 2013; Blau & Tew, 2014; Drake et al., 2015); and (iii) are skilled in processing information that has not been incorporated into prices (Cohen et al., 2007; Boehmer et al., 2008; Engelberg et al., 2012). In contrast, there is some evidence suggesting that short-sellers may not know what they are doing as arbitrageurs. Woolridge & Dickinson (1994) find that short-selling trades provide liquidity to the market but do not earn abnormal profits. Daske et al. (2005) analyse short-selling orders of NYSE-listed stocks and find no consistent evidence to indicate that short-sellers anticipate price drops on bad news. Blau & Wade (2012) find symmetric short-selling patterns prior to both upgrades and downgrades by analysts. They conclude that pre-recommendation shorting is more speculative than informed.

The effect of short sales on stock returns also depends on how short sellers react to extreme price changes. Shkilko et al. (2008) show that short-sellers can sometimes be too aggressive in driving stock prices down during intraday negative shocks, while Diether et al. (2009) document that short sellers increase their short positions after a period of high returns, suggesting short sellers are contrarians. Boehmer & Wu (2013) find short sellers' trading around large price moves facilitate information discovery and reduce deviation of stock prices from fundamental values, suggesting short sellers are informed during these events. Savor & Gamboa-Cavazos (2011) find short sellers who are trading against overvaluation tend to cover (increase) their positions after experiencing losses (gains) and interpret this result as evidence that short sellers cannot or are unwilling to maintain positions after adverse price movements. Hong et al., (2012) show that short-covering trades made by short sellers who are forced to close their positions produce extra buying pressure that further inflate stock prices.

This paper also belongs to the realm of studies on the behaviour of stock returns following large price moves. Overall, the role of short sales and short-constraints in shaping the behaviour of post-shock returns has not been considered in this branch of literature. De Bondt & Thaler (1985) are the first to propose the overreaction hypothesis positing that investors tend to overreact on new information. The hypothesis predicts that large moves in stock prices will result in reversals and that the magnitude of the reversals is in proportion to the strength of the initial price moves. The prediction of the overreaction hypothesis is supported by a large collection of empirical studies on stock returns following extreme moves (see, Howe, 1986; Zarowin, 1989; Bremer et al., 1997, Bowman & Iverson, 1998; Huang, 1998; Hamelink, 2003; Benou & Richie, 2003; Otchere & Chan, 2003; Wang et al., 2004; Diacogiannis et al., 2005; Zawadowski et al., 2006; Pham et al. 2007; Bharati et al., 2009; Lobe & Rieks, 2011), but this evidence is insufficient to prove investor overreaction, as several studies argue that post-shock reversals can be the results of non-trading (Lo & MacKinlay, 1990), bid-ask bounce

(Atkins & Dyl, 1990; Cox & Peterson, 1994), and investors' aversion to transitional uncertainty (Brown et al., 1988).

A recent focus of the literature is upon the role of information in explaining post-shock reversals and drift. Pritamani & Singal (2001) condition the behaviour of post-shock returns on public news and find significant positive (negative) abnormal returns following positive (negative) price shocks accompanied by news about fundamentals. Chan (2003) shows that price continuation tends to follow large monthly price drops concurrent with bad news. Larson & Madura (2003) use the Wall Street Journal as an indicator towards price moves that are motivated by information. They find reversals that indicate overreaction only in no-information price moves. Tetlock (2010) finds weaker reversals following news days. More recently, Savor (2012) uses analysts' reports as a proxy for indicating information-based/no-information price shocks and develops a regression for post-shock returns to test the impact of information. He finds that information-based price shocks are followed by drift and no-information ones are followed by reversals. In sum, the results from these recent studies contradict the overreaction hypothesis, and instead they suggest that investors tend to underreact to information about fundamentals.

3.3 Short Sales in Mainland China

Since the establishment of two major stock exchanges (SSE & SZSE) in 1991, the stock market in mainland China has experienced spectacular development. It is now the second largest stock market in the world in terms of total market capitalization and trading volume. Despite this, the practice of short-selling is still at an experimental stage in mainland China. While the securities law which allows short sales was passed in 2005, no shares could be borrowed for short-selling until March 2010, when China SEC launched a pilot program lifting the short-selling bans for a list of stocks. Initially, only 90 elite stocks defined in terms of their market capitalization and liquidity were added to the list. The list was expanded multiple times to include more constituent stocks of the major market indexes. As of the end of January 2015, the list contained 900 stocks which account for roughly 80% of the market capitalisation of all floating shares listed on mainland China's stock market.

The short-constraints are particularly stringent for individual traders in mainland China in the sense that only shares held by financial companies are available for lending. Initially, securities companies had to first own the shares in order to lend them to short sellers. The restriction was relaxed on October 2011 when securities companies were permitted to borrow shares from funds, insurance companies, and other certified financial institutions for their short-selling clients. As a result, institutional short sellers always have better access to the stock borrowing market. In addition, in order to participate in short-selling, traders are required to have at least 100,000 RMB as an initial margin and over six months of securities trading experience. Securities brokerage companies may increase these requirements for their clients. The transactions made by short sellers, including the volume and amount of their short-covering and short-selling trades, are disclosed to the public on a daily basis. Naked short sales are banned outright and the uptick rule applies.

3.4 Data and Methodology

3.4.1 Price Events

In order to closely observe the responses of stock prices and short-sellers' activities to unexpected events, we focus our attention on daily stock returns. The sample period under investigation extends from January 2003 to January 2015. The daily return for stock *i* during day *t* is calculated as the percentage change in closing prices (adjusted for dividends and stock splits), and the corresponding abnormal return is defined as the daily return minus the market model estimated return. The coefficients of the market model are estimated over a 250-day estimation window [*t-270, 2-21*] prior to day *t*. The SSE Composite Index is used as the market portfolio index for the model. Fama (1998) argues that since the expected day-to-day changes in stock prices are close to zero, the choice of model for estimating abnormal returns has little impact on statistical inference. Stock price data are obtained from the Wind data terminal.[26]

Once we have calculated abnormal returns, we need to determine whether an event can be classified as a price event. In order to do this, we compare each observation day's abnormal return to its estimation window average. If the absolute difference is larger than three standard deviations based on the estimation window, an event day representing an extreme abnormal price move is identified. This event-selection approach requires at least 540 trading days (i.e., 270 trading days for calculating the first abnormal return and another 270 days for determining a price event) for a stock to be considered. To reduce event-clustering and the effect of market-wide turbulence on our results, stock price events concurrent with a large jump - more than three standard deviation from the estimation window average - in the market portfolio index are excluded our sample.[27] Several prior studies use fixed thresholds, such as 10% daily price change, to define price events (see e.g., Larson & Madura, 2003; Lobe & Rieks, 2011; Savor, 2012). We choose to define a price event relative to volatility for two reasons. First, empirical evidence suggests that stock market volatility shifts over time

[26] Wind (Wind Information Co., Ltd.) is the most popular financial data provider in China. According to the company's webpage, it serves "more than 90% of financial institutions including hedge funds, asset management firms, securities companies, insurance companies, banks, research institutions, and regulatory bodies"; overseas, it serves "75% of Qualified Foreign Institutional Investors (QFII)". The company's data and research are "frequently quoted by Chinese and international media, in research reports, and in academic papers" (http://www.wind.com.cn/En/).

[27] There are 63 large jumps in daily returns of the SSE Composite index between January 2003 and January 2015.

(see e.g., Schwert, 1989; Aggarwal et al.,1999; Cuñado Eizaguirre et al., 2004; Wang & Theobald, 2008; Diamandis, 2008). Therefore, our approach prevents the price-event pool from being dominated by observations from volatile stocks or periods such as the 2007 Chinese Stock Bubble and subsequent correction. Second, the daily price limits imposed in mainland China's stock market would make it impossible to detect price events in day-to-day changes if large fixed thresholds were used.[28] Our event-selection approach is similar to that of Pritamani & Singal (2001), Lasfer et al. (2003), and Boehmer & Wu (2013). To avoid any confounding effects between adjacent price events (Corrado & Jordan 1997), we follow Mazouz et al. (2012) and disregard price events that occur within the 30 trading days that follow a previous event. Lasfer et al. (2012) use two instead of three standard deviations from the estimation-window average as the criteria for selecting price events. This setting would result in many overlaps in event periods in

This leaves 13535 price events after the initial selection process. Figures 3.1 and 3.2 show the distribution of these price events by calendar year and industrial sector. Figure 3.1 shows that the number of price events generally increases over time. This is perhaps not surprising, as more large enterprises have gone public in mainland China over time. Moreover, the number of price events decreases for volatile periods such as the 2007-2009 period of Chinese Stock Bubble and subsequent correction, as the event-selection requirement for a price event automatically rises for these periods. Figure 3.2 shows that Industrials and Materials have the largest number of price events. However, with the exception of the telecommunication service sector, price events are not exclusive to these particular industries, and there is a reasonable distribution of price events across different industrial sectors.

[28] There has been a daily price change limit of ∓10%, except for IPOs, imposed in the mainland China stock exchanges since December 1996.

[Insert Figure 3.1] & [Insert Figure 3.2]

3.4.2 Information Content

Prior studies have revealed that the magnitude of post-shock reversals or drift is predicted by the extent of the initial price shock (Pritamani & Singal, 2001; Larson & Madura, 2003; Tetlock, 2010; Savor, 2012). Moreover, these studies suggest that the information content of a price shock dictates the direction of the post-shock adjustment in stock price. To allow us to investigate this phenomena in our sample, we use Wind's news archive database to examine the information content, if any, of a price event. The Wind database contains all news released by the public companies' board of directors (e.g. earnings and dividend announcements), superintendent agencies, institutional securities analysts, and financial news media. A price event is considered "informed" if at least one news entry explaining the event is found in the database dated on the same day or adjacent days to the event,[29] otherwise the event is identified as an "uninformed" one.

3.4.3 Shortable Events and Short sellers' Trading Activities

To examine the effects of short sales, we first divide the price events into "shortable" and "non-shortable" subsamples according to whether the underlying impacted stocks are covered by the pilot program for short-selling at the time of the events. The record of trades made by short-sellers in each shortable event is available on SSE & SZSE's webpages. Using this data, we develop two measures for the amount of short-covering and short-selling trades associated with a price event. First, we divide

[29] Adjacent days are also considered because a news announcement may be released after market close of the last trade day or, in other scenario, leaked on the event day before its appearance on the media on the next trade day. Savor (2012) also looks for release of analyst report on the event and adjacent trade days to determine whether a price event is motivated by information.

the short volume by the estimated total number of shares held by potential stock lenders.[30] This measure reflects the cost of short-selling for a given stock-event observation and so it indicates how aggressive the short sellers are during the event. Second, we measure the price pressure of short-covering trades for a price event by the ratio of short-covering volume to total trading volume. It is expected that the higher the percentage of short-covering to total trading volume the larger proportion of event-day price change that is attributable to short sellers' covering trades.

3.4.4 Regression Models

Savor (2012) develops a regression model describing the behaviour of post-shock returns following extreme price moves. His framework allows us to test the effect of short sales while controlling for other factors. Our first model is defined as follows:

$$CAR_{p,q} = c + \beta_1 AR_0 + \beta_2\,(SE \cdot AR_0) + \gamma' X + u \quad (1)$$

where $CAR_{p,q}$ is the post-shock cumulative abnormal return calculated by adding the daily post-shock abnormal returns over the holding period $[t+p, t+q]$, AR_0 is the event-day abnormal return, SE is an indicator variable for shortable events and c and u are the constant and model error terms, respectively. The main effect (AR) reflects investors' reaction to the expected event. The coefficient β_1 reflects the magnitude and the direction of the post-shock adjustment in stock prices.[31] The interaction component $(SE \cdot AR)$ is used to test whether shortable price events exhibit a different adjustment in post-shock returns as compared to non-shortable ones. This variable construction follows Savor (2012), who uses the interaction term with an indicator for informed price events to examine the role of information in shaping post-shock returns. The variables

[30] The total number of shares held by potential stock lenders is based on the latest quarter reports of institutional holdings provided by Wind.
[31] De Bondt & Thaler (1985), for example, argue that the stronger the initial price reaction the greater the post-shock adjustment.

contained in X control for any effects stock characteristics may have on cumulative abnormal returns. Following Larson & Madura (2003), Lobe & Rieks (2011), and Savor (2012), we use the price-to-book ratio *(PBR*), momentum (*Mom*), log size (*LS*), and event-day trading volume (*Vol*) as control variables. We measure the price-to-book ratio and log size (current capitalization) before the price event days. Momentum is calculated as the average of daily abnormal returns over the *20*-day pre-event window. Trading volume is scaled by the total volume of floating shares. Previous studies have highlighted the relationship between volume and stock returns (see e.g., Campbell et al., 1993, Lee & Swaminathan, 2000, Pritamani & Singal, 2001; Llorente et al., 2002; and Tetlock 2010). The log size and price-to-book ratio are used to control the size and book-to-market effects (Banz, 1981; Rosenberg et al., 1985). The momentum predictor accounts for any information leakage and momentum effects.

Model (1) is used to examine the empirical implication following from Diamond & Verrecchia's (1987) hypothesis. The estimate for β_2 is expected to be of the opposite sign to the estimate for β_1 in model (1) if the adjustment of stock prices to unexpected events is more efficient for shortable shares than it is for non-shortable shares. To test the impact of short sellers' trading activities on post-shock abnormal returns, we use the following modification of Savor's regression model:

$$CAR_{p,q} = c + \alpha_1 AS_0 + \alpha_2 (UN \cdot AS_0) + \varphi SC_0 + \beta_1 AR_0 + \beta_2 (UN \cdot AR_0) + \gamma' X + u \tag{2}$$

where SC_0 and AS_0 are the measures of event-day short-covering and short-selling trades discussed in the previous section, UN is a dummy variable indicating uninformed events, and the rest of the variables are defined as for model (1). The coefficients α_1 and α_2 measure the impact of short-selling trades conditional on the content of information (informed vs. uninformed) associated with the price events while

φ captures the price effect of short-covering trades.

3.5 Descriptive Statistics

Table 3.1 presents summary statistics for event-day and post-event abnormal returns and the control variables. Post-shock abnormal returns with holding periods starting from the 2nd trading day following the event day are designed to isolate the impacts of liquidity trades, bid-ask bounce, and non-trading (Lo & MacKinlay, 1990; Cox & Peterson,1994; Park, 1995).[32] It can be seen that, consistent with the results in Pritamani & Singal (2001), informed price shocks are followed by drift and the uninformed price events are followed by reversals in all post-shock abnormal returns except for abnormal returns observed on day one following positive uninformed price shocks and on the 5-day horizon following negative uninformed price shocks. One possible explanation for the exception is that the effect of price limits imposed in mainland China's stock market cause a spillover of trading into subsequent days that manifests itself as price continuation in post-shock returns (Chen et al. 2005; Diacogiannis et al., 2005). For example, when price events closing at the daily price limits are excluded from the sample, the mean abnormal return for day one following positive uninformed price shocks is -0.29%, which is significantly different (at 1%) from the mean abnormal return (0.93%) of positive uninformed price events closing at the daily price limits.

[Insert Table 3.1] & [Insert Table 3.2]

[32] Liquidity trades, bid-ask bounce, and non-trading can cause spurious post-shock anomalies because close price is determined by the last transaction price, which may be distorted by microstructure factors. For example, a price event day caused by a supply shock is likely to close at a bid price and the return for day one following the price event, which is calculated as the percentage change in close prices, is like to be positive if the supply shock is transitional. Using post-shock abnormal returns with holding horizons gapping the first day following the price event day therefore isolates these microstructure problems.

Table 3.2 presents the statistics for the subsample of shortable events. The results show that the magnitude of event-day abnormal price changes becomes smaller in both informed and uninformed subsamples when short sales are allowed. This is consistent with prior studies suggesting that short sales improve market liquidity and help in incorporating information into stock prices (see e.g., Woolridge & Dickinson, 1994; Reed, 2007; Boehmer et al., 2008; Boulton & Braga-Alves, 2010; Beber & Pagano, 2013; Chakrabarty & Shkilko, 2013). Furthermore, there is more intensive short-selling for negative informed price shocks, during which short sellers on average short 1.17% of the lendable shares, than for other shortable price shocks. A two-sample *t*-test (with unequal variance) on the levels of event-day short-selling activities (SS_0) between negative informed price shocks and the rest of shortable price shocks in the subsample of Table 3.2 shows a highly significant result (p-value < 0.0001). This suggests that short sellers respond most aggressively to extreme price drops concurrent with news announcements. Finally, the results in Table 3.2 show that there are more short-covering trades (relative to total trading volume) for uninformed price shocks (1.291%) than for informed price shocks (1.205%), but the difference is not statistically significant.

One important finding in this section is that the price limits imposed in mainland China's stock market produce a significant confounding impact on our results. To neutralize the effect, we disregard all price events with closing prices reaching the daily limits. As a result, the number of eligible price events falls to 8732. Based on this final sample of price events, we analyse the effects of short sales on post-shock returns under Savor's (2012) regression framework in the following section.

3.6 Empirical Results

This section presents the OLS estimates for model (1) and (2). In order to reduce heteroscedasticity across the price events of different stocks occurring at different time, both event-day and post-shock abnormal returns are standardized by the corresponding estimation-period standard deviations adjusted for forecast errors (see Boehmer et al., 1991; Campbell et al., 1997, p.158-163).[33]

3.6.1 The Effect of Allowing Short Sales

Table 3.3 presents the estimation results from model (1) for cumulative abnormal returns over different cumulating periods during the 30-trading day post-shock holding period. We analyse informed and uninformed events separately to highlight the role of information in shaping the behaviour of post-shock returns. The *t*-test statistics are calculated using clustered standard errors (Rogers, 1993), where price shocks occurred on the same date are place in one cluster. Estimates for the coefficients of event-day abnormal return (β_1) and its interaction (β_2) with the indicator of shortable events are the focus of our discussion.

[Insert Table 3.3]

The estimates for coefficient β_1 are highly significant in all post-shock holding periods. The results are consistent with those of Savor (2012) and suggest that informed (uninformed) price shocks are followed by drift (reversals), with the extent of the post-shock adjustment predicted by the magnitude of event-day abnormal returns. For the informed price events, the estimates of coefficient β_2 are significant (at 5% level) over post-shock horizons of 5 and 10 days, including the alternative 10-day horizon with one day lag ($CAR_{2,10}$). The sign of the estimates suggests that shortable events exhibit weaker post-shock price drift. This finding supports the empirical implication from Diamond & Verrecchia's (1987) hypothesis and is consistent with the results in Bai & Qin (2015), who find weaker post-earning-announcement drift among the shortable events. For the subsample of uninformed price shocks, the estimates of the coefficient β_2 are significant (at 10% level) in post-shock horizons of 5 and 10 days, including the lagged horizons. Moreover, shortable events appear to exhibit less post-shock reversals as the sign of β_2 is always in the opposite direction to that of β_1. The results in Table 3.3 suggest there is no evidence that allowing short sales further destabilizes stock prices at times of extreme price moves.

One interpretation of the results in Table 3.3 is that the short-selling bans imposed in mainland China prohibit informed traders from entering the market when shorting is the appropriate strategy. This is especially the case when stock prices underreact to bad news and overreact to good news. The effect of this is to reduce the efficiency of stock prices' adjustment to unexpected events. When the bans are removed, the remaining short-constraints favour institutional short sellers who have better access to lendable shares than individual short sellers do. Intuitively, if these short sellers are active in exploiting the under- and over-reaction anomalies, stock prices should react more efficiently to unexpected events. In the following subsections, we examine the impacts of these short sellers' trading activities and their responses to the price events.

3.6.2 The Effects of Short-sellers' Trading Activities

Table 3.4 presents estimation results for model (2). We calculate the t-statistics the same way as in model (1). The estimates for the effects of short-selling (α_1 and α_2) and short-covering trades (φ) on post-shock returns are the focus of our discussion. The coefficient on the short-selling-trades variable, α_1, is significantly positive for all post-shock horizons, suggesting that intensified short-selling is associated with an increase in post-shock abnormal returns for price events related to information. The predictive role of short-selling trades on post-shock abnormal returns for price events unrelated to information, on the other hand, is reflected by the sum of estimates of α_1 and α_2. The estimates for α_2 are negative and close to their α_1 counterparts in magnitude and thus suggest that the predictive value of short-selling trades is practically insignificant (close to zero) for price events unrelated to information. This result indicates that the impact of short-selling trades on post-shock returns is conditional on the information content associated with the price event. Prior studies have documented that an increase in short-selling activities is associated with a decrease in future returns (see e.g., Cohen et al., 2007; Boehmer et al., 2008; Engelberg et al., 2012), but none of these studies examine the relationship in terms of post-shock returns. Our results are consistent Boehmer & Wu's (2013) finding which indicates that highly shorted portfolios exhibit less post-earning announcement drift.

[Insert Table 3.4]

The coefficient reflecting the price pressure of short-covering trades is only significant for day one after the price events. The sign on the coefficient suggests that an increase in short-covering volume (relative to the total volume) is associated with an immediate decrease in post-shock abnormal returns. This result is unexpected as short-covering trades, on average, only account for 1.72% of the daily total volume among the shortable price events. One possible explanation is that the estimates for the effect of short-covering trades are strongly influenced by outliers representing extreme price shocks during which short sellers give price concessions for covering their positions. We re-run the regression with a subsample respectively resulting from trimming 1%, 5%, and 10% of the shortable events from the top and bottom levels of short-covering trades and find the estimates of the coefficient on short-covering trades is still significant.[34] Therefore, the estimates for the effect of short-covering trades indicate that the intensified short-covering activities are associated with high level of demand shocks, which result in reversals in post-shock returns.

If short sellers are active and successful in trading the under-reaction events for exploiting the post-shock downward price drift, their presence should help moderate the mispricing, and thus the subsequent adjustment in stock prices. In this subsection, we show that short-selling activities are associated with reduction in post-drop price drift and short-covering trades are associated with intensified reversals following demand shocks. However, it is still unclear whether short sellers know what they are doing as arbitragers during these price events. In particular, it is of interest in knowing whether short sellers are active in trading the under-reaction events. To clarify these problems, we examine the contemporary relationship between short-sellers' trading and abnormal price changes during the price events in the next subsection.

3.6.3 Short-sellers' Responses to Extreme Price Moves

To understand the informational role of short sales, it is important to know whether short-sellers are informed in making their trades. Table 3.5 presents the contemporaneous correlation between short-selling/short-covering trades and event-day abnormal returns. Spearman's rank correlation test is used in determining the significance of the statistics. Only price events with non-zero short-selling or short-covering activities are considered in the calculation.[35] The volume of short-selling and

[34] Estimation results for the trimmed subsamples are provided in Table 8 of the appendix.
[35] There are a significant number of events with zero short-selling and short-covering activities in subsample of shortable events. The underlying shares for these events are largely held by non-financial companies and therefore the shares cannot be borrowed for short sales. Including these events in our analysis would confound our results as they do not reflect short sellers' responses to the events.

short-covering trades is normalized by the estimated total volume of lendable shares and the amount of outstanding short positions on the event day respectively.[36] Both measures now reflect the intensity of trades and are comparable across the events.

[Insert Table 3.5]

There is a statistically significant positive relationship between the intensity of short selling and the magnitude of informed negative shocks. Since short volume only accounts for a small percentage (less than 1%) of the total trading volume in the Chinese stock market, it is unlikely that the magnitude of price shocks is affected by short activities. In other words, the evidence indicates that short sellers become more aggressive, borrowing more shares, as the magnitude of an informed negative shock increases. It is also shown in the table that the intensity of shorting increases with the magnitude of uninformed price shocks, which suggests that short sellers perceive the over-reaction opportunities, but the corresponding correlation coefficients are too small (less than 0.1) to suggest any economically significant relationships.

As for the short-covering trades, it is shown in the table that short sellers are vulnerable in uninformed price events where they are unwilling, or unable, to hold their positions as the events develop in either an upwards or downwards direction. The intensity of covering is significantly and positively correlated with the magnitude of the price shocks. Moreover, the relationship does not apply among informed price shocks, which suggests that short sellers may anticipate these events. Savor & Gamboa-Cavazos (2011) find short sellers tend to close their positions after experiencing losses. Our results add to this finding by showing that short sellers also tend to retreat during uninformed extreme price drops in which they do not suffer losses. This trading pattern

[36] Short sellers can open and cover a short position on the same trade day in mainland China's stock market. Therefore, the amount of outstanding short positions is calculated by adding new short positions established on the price event day to the number of short interest observed on the previous trade day.

suggests that short sellers are either averse to uncertainty, or able to anticipate the positive reversals following the negative shocks. Interestingly, the statistics also reveal that short-sellers on average cover more than half of the underlying stock's total outstanding short positions during a price event. This finding suggests that these traders tend not to hold their positions overnight during extreme price events. This result explains the insensitivity of short-covering volume to the magnitude of price shocks for informed price events, which are often driven by news released in off-market hours.

3.7 Robustness

The estimation results discussed in the previous section are based on standardized abnormal returns. Our conclusions are unchanged if non-standardized abnormal returns are instead used for estimation; and the corresponding results are presented in Tables 3.6 and 3.7. Overall, the results indicate that the conclusions of this paper are not biased by the use of standardized abnormal returns.

[Insert Table 3.6] & [Insert Table 3.7]

3.8 Conclusion

The behaviour of stock returns following extreme price moves reflects the degree of under-/overreaction of stock prices to unexpected events. In this paper, we provide empirical evidence highlighting the impact of short-sellers' trading activities on the behaviour of post-shock returns using Savor's (2012) regression framework.

We find large price shocks concurrent with news are followed by drift, while price shocks absent of news are followed by reversals. This pattern of post-shock returns, which that investors underreact to price events that are motived by new information and overreact to other event that are not accompanied by news announcements, is stronger and more significant when short-selling is not allowed. Consistent with the Diamond & Verrecchia (1987)'s model, we find shortable price events exhibit less price drift/reversals in post-shock returns than non-shortable ones, indicating that there is an increase in price efficiency when short-selling bans are removed. Among the shortable price events, more aggressive short-selling during informed large price drops is associated with less post-shock downward price drift; moreover, extreme levels of short-covering volume are associated with negative reversals on day one immediately following the price event days. Further analysis of the contemporaneous correlation between short-sellers' trading activities and abnormal price changes on the actual event days, reveals that short sellers seek to increase their short exposure as the magnitudes of informed price drops expand and reduce their short exposure as the magnitudes of uninformed price shocks become more extreme.

Overall, our results suggest that short sellers are successful and active in trading informed price events in which they exploit short-term underreaction in stock prices to new information. They are less successful in trading uninformed ones in which they bear the risk of suffering losses when overshooting in stock prices becomes extreme. This finding adds to our current understanding of the impacts of short sales on stock returns by highlighting the importance of information content in dictating short sellers' trading. It also contributes to the growing literature on investor over- and underreaction by showing the roles short-constraints and short sales might have in shaping these anomalies. Therefore, without controlling the effect of short-constraints, the under and overreaction effects do not constitute sufficient counter-evidence against the efficient market hypothesis. For traders looking at opportunities associated with price shocks, the finding in paper suggests that post-shock reversals and drift are likely to be more profitable among stocks that are either not shortable or difficult to short. For financial market regulators in mainland China, this study provides empirical evidences to support the on-going efforts of reducing short-sale constraints.

References

Aggarwal, R., Inclan, C. & Leal, R., 1999. Volatility in Emerging Stock Markets. The Journal of Financial and Quantitative Analysis, 34(1), pp.33–55.

Aitken, M.J. et al., 1998. Short Sales Are Almost Instantaneously Bad News: Evidence from the Australian Stock Exchange. Journal of Finance, 53(6), pp.2205–2223.

Asquith, P., Pathak, P.A. & Ritter, J.R., 2005. Short interest, institutional ownership, and stock returns. Journal of Financial Economics, 78(2), pp.243–276.

Atkins, A.B. & Dyl, E. a., 1990. Price Reversals, Bid-Ask Spreads, and Market Efficiency. The Journal of Financial and Quantitative Analysis, 25(4), p.535.

Autore, D.M., Boulton, T.J. & Braga-Alves, M. V., 2015. Failures to Deliver, Short Sale Constraints, and Stock Overvaluation. Financial Review, 50, pp.143–172.

Bai, M. & Qin, Y., 2015. International Review of Financial Analysis Short sales constraints and price adjustments to earnings announcements : Evidence from the Hong Kong market. International Review of Financial Analysis, 42, pp.304–315.

Banz, R., 1981. The relationship between return and market value of common stocks. Journal of financial economics, 9(1), pp.3–18.

Barberis, N., Shleifer, A. & Vishny, R., 1998. A model of investor sentiment. Journal of financial economics, 49(3), pp.307–343.

Battalio, R. & Schultz, P., 2011. Regulatory Uncertainty and Market Liquidity: The 2008 Short Sale Ban’s Impact on Equity Option Markets. Journal of Finance, 66(6), pp.2013–2053.

Beber, A. & Pagano, M., 2013. Short-Selling Bans Around the World: Evidence from the 2007-09 Crisis. Journal of Finance, 68(1), pp.343–381.

Benou, G. & Richie, N., 2003. The reversal of large stock price declines: The case of large firms. Journal of Economics and Finance, 27(1), pp.19–38.

Bharati, R., Crain, S. & Nanisetty, P., 2009. Evaluating stock price behavior after events: an application of the self-exciting threshold autoregressive model. Quarterly Journal of Finance and Accounting, 48(2), pp.23–43.

Blau, B.M. & Tew, P.L., 2014. Short sales and class-action lawsuits. Journal of Financial Markets, 20, pp.79–100.

Blau, B.M. & Wade, C., 2012. Informed or speculative: Short selling analyst recommendations. Journal of Banking and Finance, 36(1), pp.14–25.

Bloom, R., Libby, R. & Nelson, M.W., 2000. Underreactions , overreactions and moderated. Journal of Financial Markets, 3(2), pp.113–137.

Boehme, R.D., Danielsen, B.R. & Sorescu, S.M., 2006. Short-Sale Constraints, Differences of Opinion, and Overvaluation. Journal of Financial and Quantitative Analysis, 41(02), p.455.

Boehmer, E., Jones, C.M. & Zhang, X., 2013. Shackling short sellers: The 2008 shorting ban. Review of Financial Studies, 26(6), pp.1363–1400.

Boehmer, E., Jones, C.M. & Zhang, X., 2008. Which Shorts Are Informed? The Journal of Finance, 63(2), pp.491–527.

Boehmer, E., Masumeci, J. & Poulsen, A., 1991. Event-study methodology under

conditions of event-induced variance. Journal of Financial Economics, 30(2), pp.253–272.
Boehmer, E. & Wu, J.J., 2013. Short selling and the price discovery process. Review of Financial Studies, 26(2), pp.287–322.
De Bondt, W.F.M. & Thaler, R., 1985. Does the Stock Market Overreact? Journal of Finance, 40(3), pp.793–805.
Boulton, T.J. & Braga-Alves, M. V., 2010. The skinny on the 2008 naked short-sale restrictions. Journal of Financial Markets, 13(4), pp.397–421.
Bowman, R.G. & Iverson, D., 1998. Short-run overreaction in the New Zealand stock market. Pacific-Basin Finance Journal, 6(5), pp.475–491.
Bremer, M. et al., 1997. Predictable Patterns after Large Stock Price Changes on the Tokyo Stock Exchange. The Journal of Financial and Quantitative Analysis, 32(3), pp.345–365.
Brent, A., Morse, D. & Stice, E.K., 1990. Short Interest: Explanations and Tests. Journal of Financial and Quantitative Analysis, 25(2), pp.273–289.
Bris, A., Goetzmann, W. & Zhu, N., 2007. Efficiency and the bear: Short sales and markets around the world. The Journal of Finance, 52(3), pp.1029–1079.
Brown, K.C., Harlow, W.V. & Tinic, S.M., 1988. Risk aversion, uncertain information, and market efficiency. Journal of Financial Economics, 22(2), pp.355–385.
Campbell, J., Lo, A. & MacKinlay, A.C., 1997. The Econometrics of Financial. Princeton, New Jersey: Princeton University Press. p.158-163.
Campbell, J.Y., Grossman, S.J. & Wang, J., 1993. Trading volume and serial correlation in stock returns. The Quarterly Journal of Economics, 108(November), p.905.
Chakrabarty, B. & Shkilko, A., 2013. Information transfers and learning in financial markets: Evidence from short selling around insider sales. Journal of Banking & Finance, 37(5), pp.1560–1572.
Chan, W.S., 2003. Stock price reaction to news and no-news: drift and reversal after headlines. Journal of Financial Economics, 70(2), pp.223–260.
Chang, E.C., Cheng, J.W. & Yu, Y., 2007. Short-sales constraints and price discovery: Evidence from the Hong Kong market. The Journal of Finance, 62(5), pp.2097–2122.
Chang, E.C., Luo, Y. & Ren, J., 2013. Short-selling, margin-trading, and price efficiency: Evidence from the Chinese market. Journal of Banking and Finance, 48, pp.411–424.
Chen, C.X. & Rhee, S.G., 2010. Short sales and speed of price adjustment: Evidence from the Hong Kong stock market. Journal of Banking & Finance, 34(2), pp.471–483.
Chen, G.M., Rui, O.M. & Wang, S.S., 2005. The effectiveness of price limits and stock characteristics: Evidence from the Shanghai and Shenzhen stock exchanges. Review of Quantitative Finance and Accounting, 25(2), pp.159–182.
Christophe, S.E., Ferri, M.G. & Angel, J.J., 2004. Short-selling prior to earnings announcements. Journal of Finance, 59(4), pp.1845–1875.

Christophe, S.E., Ferri, M.G. & Hsieh, J., 2010. Informed trading before analyst downgrades: Evidence from short sellers. Journal of Financial Economics, 95(1), pp.85–106.

Cohen, L., Diether, K.B. & Malloy, C.J., 2007. Supply and Demand Shifts in the Securities Lending Market. The Journal of Finance, 62(5), pp.2061–2096.

Corrado, C.J. & Jordan, B.D., 1997. Risk aversion, uncertain information, and market efficiency-Reexamining the Evidence. Review of Quantitative Finance and Accounting,, 8(1), pp.51–68.

Cox, D. & Peterson, D., 1994. Stock Returns following Large One‐Day Declines: Evidence on Short‐Term Reversals and Longer‐Term Performance. The Journal of Finance, 49(1), pp.255–267.

Cuñado Eizaguirre, J., Biscarri, J.G. & Hidalgo, F.P. de G., 2004. Structural changes in volatility and stock market development: Evidence for Spain. Journal of Banking & Finance, 28(7), pp.1745–1773.

Daniel, K., Hirshleifer, D. & Subrahmanyam, A., 1998. Investor Psychology and Security Market Under- and Overreactions. Journal of Finance, 53(6), pp.1839–1885.

Danielsen, B.R. & Sorescu, S.M., 2001. Why Do Option Introductions Depress Stock Prices? A Study of Diminishing Short Sale Constraints. Journal of Financial Quantitative Analysis, 36(4), pp.451–484.

Daske, H., Richardson, S.A. & Tuna, I., 2005. Do Short Sale Transactions Precede Bad News Events? University of Pennsylvania working paper.

Dechow, P.M. et al., 2001. Short-sellers, fundamental analysis, and stock returns. Journal of Financial Economics, 61(1), pp.77–106.

Desai, H. et al., 2002. An Investigation of the Informational Role of Short Interest in the Nasdaq Market. Journal of finance, 57(5), pp.2263–2287.

Diacogiannis, G.P. et al., 2005. Price limits and overreaction in the Athens stock exchange. Applied Financial Economics, 15(1), pp.53–61.

Diamandis, P.F., 2008. Financial liberalization and changes in the dynamic behaviour of emerging market volatility: Evidence from four Latin American equity markets. Research in International Business and Finance, 22(3), pp.362–377.

Diamond, D.W. & Verrecchia, R.E., 1987. Constraints on short-selling and asset price adjustment to private information. Journal of Financial Economics, 18(2), pp.277–311.

Diether, K.B., Lee, K.H. & Werner, I.M., 2009. Short-sale strategies and return predictability. Review of Financial Studies, 22(2), pp.575–607.

Drake, M.S. et al., 2015. Short Selling Around Restatement Announcements: When Do Bears Pounce? Journal of Accounting, Auditing & Finance, 30(2), pp.218–245.

Duffie, D., Gârleanu, N. & Pedersen, L.H., 2002. Securities lending, shorting, and pricing. Journal of Financial Economics, 66(2-3), pp.307–339.

Engelberg, J.E., Reed, A. V. & Ringgenberg, M.C., 2012. How are shorts informed?. Short sellers, news, and information processing. Journal of Financial Economics,

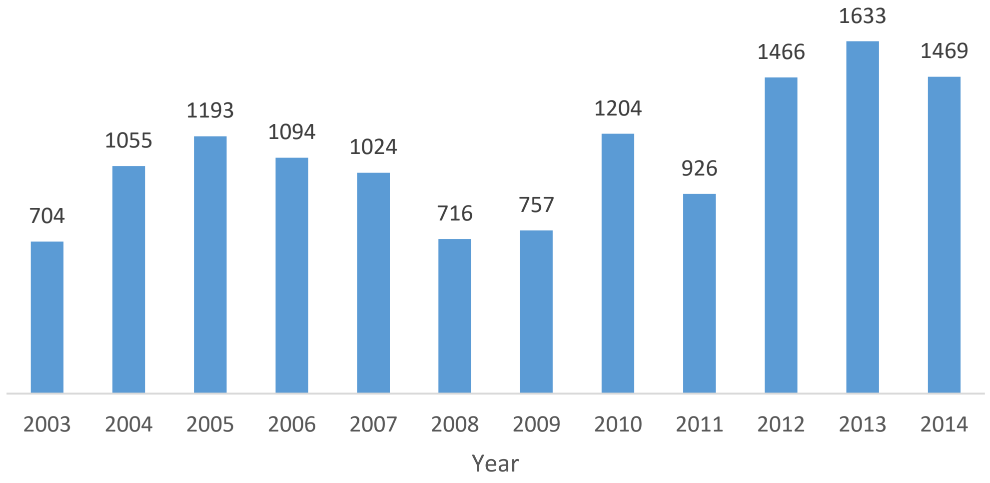
105(2), pp.260–278.
Fama, E., 1998. Market efficiency, long-term returns, and behavioral finance. Journal of financial economics, 49, pp.283–306.
Figlewski, S., 1981. The Informational Effects of Restrictions on Short Sales: Some Empirical Evidence. Journal of Financial and Quantitative Analysis, 16(04), pp.463–476.
Figlewski, S. & Webb, G.P., 1993. Options, Short Sales, and Market Completeness. The Journal of Finance, 48(2), pp.761–777.
Francis, J., Venkatachalam, M. & Zhang, Y., 2005. Do Short Sellers Convey Information About Changes in Fundamentals or Risk? Duke University working paper.
Fung, J. & Draper, P., 1999. Mispricing of index futures contracts and short sales constraints. Journal of Futures Markets, 19(6), pp.695–715.
Grundy, B.D., Lim, B. & Verwijmeren, P., 2012. Do option markets undo restrictions on short sales? Evidence from the 2008 short-sale ban. Journal of Financial Economics, 106(2), pp.331–348.
Hamelink, F., 2003. Systematic patterns before and after large price changes: evidence from high frequency data from the Paris Bourse. Journal of Forecasting, 22(6-7), pp.533–549.
Harris, L., Namvar, E. & Phillips, B., 2013. Price Inflation and Wealth Transfer During the 2008 SEC Short-Sale Ban. Journal of Investment Management, 11, pp.1–23.
Hong, H., Kubik, J.D. & Fishman, T., 2012. Do arbitrageurs amplify economic shocks? Journal of Financial Economics, 103(3), pp.454–470.
Hong, H. & Stein, J.C., 1999. A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. The Journal of Finance, 54(6), pp.2143–2184.
Hong, H. & Stein, J.C., 2003. Differences of Opinion, Short-Sales Constraints, and Market Crashes. Review of Financial Studies, 16(2), pp.487–525.
Howe, J., 1986. Evidence on stock market overreaction. Financial Analysts Journal, 42(4), pp.74–77.
Huang, Y.S., 1998. Stock price reaction to daily limit moves: Evidence from the Taiwan stock exchange. Journal of Business Finance and Accounting, 25(May), pp.469–483.
Jiang, L. & Pang, L., 2015. Does Short Selling Enhance the Allocational Role of Stock Price? Evidence from Hong Kong. Journal of International Financial Management & Accounting, (early view) doi: 10.1111/jifm.12044
Jones, C.M. & Lamont, O. a, 2002. Short-sale constraints and stock returns. Journal of Financial Economics, 66(2-3), pp.207–239.
Karpoff, J.M. & Lou, X., 2010. Short sellers and financial misconduct. Journal of Finance, 65(5), pp.1879–1913.
Larson, S. & Madura, J., 2003. What drives stock price behavior following extreme one-day returns. Journal of Financial Research, 26(1), pp.113–127.
Larson, S. & Madura, J., 2003. What Drives Stock Price Behavior Following Extreme

One-Day Returns. Journal of Financial Research, 26(1), pp.113–127.
Lasfer, M., Melnik, A. & Thomas, D., 2003. Short-term reaction of stock markets in stressful circumstances. Journal of banking & finance, 27(10), pp.1959–1977.
Lasfer, M., Lin, S. X., Muradoglu, G., 2012. Optimism in foreign investors. Review of Behavioral Finance, 4(1) pp.8-27
Lee, C.M.C. & Swaminathan, B., 2000. Price Momentum and Trading Volume. Journal of Finance, 55(5), pp.2017–2069.
Li, J. & Yu, J., 2012. Investor attention, psychological anchors, and stock return predictability. Journal of Financial Economics, 104(2), pp.401–419.
Llorente, G., Saar, G. & Wang, J., 2002. Dynamic Volume-Return Relation of Individual Stocks. , 15(4), pp.1005–1047.
Lo, A. & MacKinlay, A.C., 1990. An econometric analysis of nonsynchronous trading. Journal of Econometrics, 45(1-2), pp.181–211.
Lobe, S. & Rieks, J., 2011. Short-term market overreaction on the Frankfurt stock exchange. The Quarterly Review of Economics and Finance, 51(2), pp.113–123.
Mazouz, K., Alrabadi, D.W.H. & Yin, S., 2012. Systematic liquidity risk and stock price reaction to shocks. Accounting and Finance, 52(2), pp.467–493.
Miller, E.M., 1977. Risk, Uncertainty, and Divergence of Opinion. The Journal of Finance, 32(4), pp.1151–1168.
Ofek, E. & Richardson, M., 2003. DotCom Mania: The Rise and Fall of Internet Stock Prices. Journal of Finance, 58(3), pp.1113–1137.
Otchere, I. & Chan, J., 2003. Short-Term Overreaction in the Hong Kong Stock Market : Can a Contrarian Trading Strategy Beat the Market ? Journal of Behavioral Finance, 4(3), pp.157–171.
Park, J., 1995. A Market Microstructure Explanation for Predictable Variations in Stock Returns following Large Price Changes. The Journal of Financial and Quantitative Analysis, 30(2), p.241.
Pritamani, M. & Singal, V., 2001. Return predictability following large price changes and information releases. Journal of Banking & Finance, 25(4), pp.631–656.
Reed, A.V., 2007. Costly short-selling and stock price adjustment to earnings announcements. The University of North Carolina at Chapel Hill.
Rogers, W.H., 1993. Regression standard errors in clustered samples. Stata Technical Bulletin, 13(July), pp.19–23.
Rosenberg, B., Reid, K. & Lanstein, R., 1985. Persuasive evidence of market inefficiency. The Journal of Portfolio Management, 11(3), pp.9–16.
Saffi, P. a C. & Sigurdsson, K., 2011. Price efficiency and short selling. Review of Financial Studies, 24(3), pp.821–852.
Savor, P. & Gamboa-Cavazos, M., 2011. Holding on to Your Shorts: When Do Short Sellers Retreat ? University of Pennsylvania working paper.
Savor, P.G., 2012. Stock returns after major price shocks: The impact of information. Journal of Financial Economics, 106(3), pp.635–659.
Scheinkman, J.A. & Xiong, W., 2003. Overconfidence and Speculative Bubbles. Journal of Political Economy, 111(6), pp.1183–1220.
Schwert, G.W., 1989. Why Does Stock Market Volatility Change Over Time? The

Journal of Finance, 44(5), pp.1115–1153.
Senchack, A.J. & Starks, L.T., 1993. Short-Sale Restrictions and Market Reaction to Short-Interest Announcements. Journal of Financial and Quantitative Analysis, 28(02), pp.177–194.
Shkilko, A., Ness, B. Van & Ness, R. Van, 2008. Aggressive short selling and price reversals, University of Mississippi working Paper.
Subrahmanyam, A., 2005. Distinguishing Between Rationales for Short-Horizon Predictability of Stock Returns. The Financial Review, 40(1), pp.11–35.
Tetlock, P.C., 2010. Does Public Financial News Resolve Asymmetric Information? Review of Financial Studies, 23(9), pp.3520–3557.
Wang, P. & Theobald, M., 2008. Regime-switching volatility of six East Asian emerging markets. Research in International Business and Finance, 22(3), pp.267–283.
Woolridge, R.J. & Dickinson, A., 1994. Short Selling and Common Stock Prices. Financial Analysts Journal, 50(1), pp.20–28.
Zarowin, P., 1989. Short-run market overreaction: size and seasonality effects. The Journal of Portfolio Management.

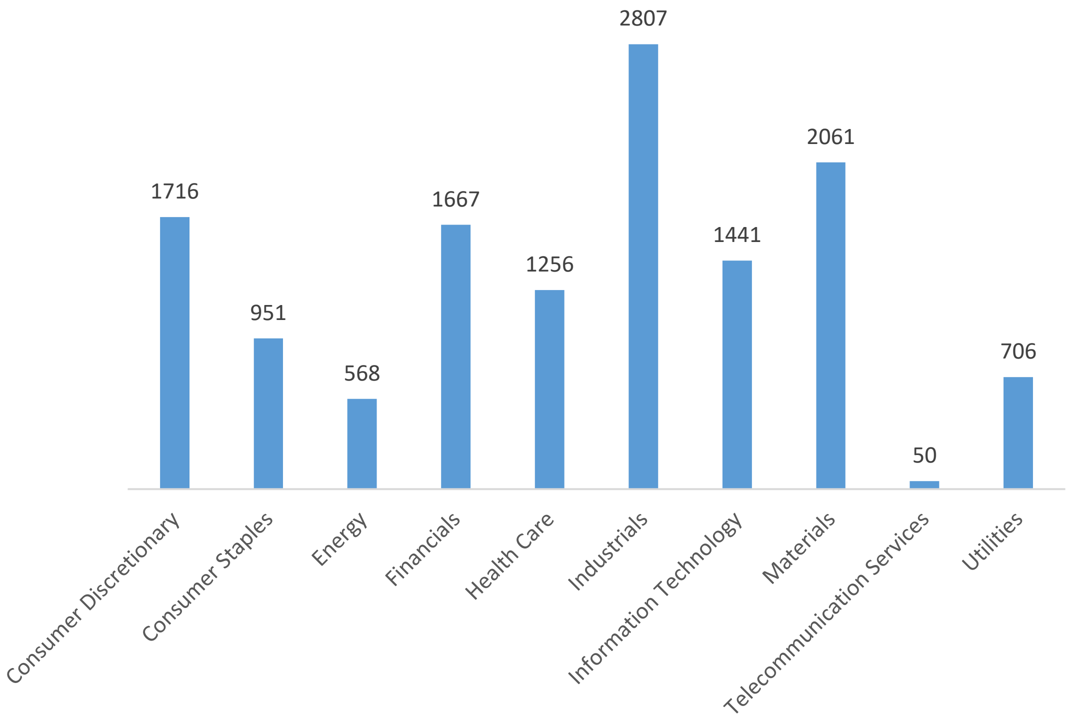
Appendix

Figure 3.1 Distribution of price events by year: 2003 - 2014



Notes: A price event is defined as an extreme daily price change that is larger than three standard deviations of its average based on the 250-day estimation window from day *t-21* to *t-270* prior to the event day *t*.

Figure 3.2 Distribution of price events by industry



Notes: Industry sectors are defined according to the Global Industry Classification Standard as the followings (from left to right): Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Telecommunication Services, and Utilities. A price event is defined as an extreme daily price change that is larger than three standard deviations of its average based on the 250-day estimation window from day *t-21* to *t-270* prior to the event day *t*.

Table 3.1 Summary of sample characteristics

This table reports the statistics of event-day abnormal return (*AR*), post-shock cumulative abnormal returns ($CAR_{a,b}$, subscribes [*a*, *b*] indicate the holding period), and other stock characteristics variables, including Momentum (*Mom*) calculated as the average of daily abnormal returns over the 20-day pre-event window, price-to-book ratio (*PB*), the log value of total market capitalization (*logSize*), and event-day trading volume scaled by the volume of total floating shares.

	Informed (N=3543)			Uninformed (N=9992)		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Panel A: full sample						
AR_0	3.286	7.054	8.045	4.347	7.052	6.971
$CAR_{1,1}$	0.689	0.060	4.415	-0.072	-0.463	3.409
$CAR_{1,5}$	1.559	0.524	9.496	-1.018	-1.259	6.357
$CAR_{1,10}$	2.473	1.424	11.898	-1.460	-1.701	8.105
$CAR_{1,20}$	3.336	2.280	15.450	-1.980	-2.052	11.249
$CAR_{2,5}$	0.929	0.145	7.411	-0.882	-1.073	5.543
$CAR_{2,10}$	1.838	0.854	10.116	-1.325	-1.488	7.695
$CAR_{2,20}$	2.730	1.604	13.934	-1.840	-1.961	10.963
Mom	0.009	-0.004	0.496	0.010	-0.004	0.491
PB	3.736	2.806	4.201	3.971	2.847	9.712
LogSize	9.754	9.724	0.544	9.792	9.750	0.552
Vol	6.175	4.761	5.320	6.913	5.371	5.800
Panel B: positive shocks						
AR_0	8.531	8.680	2.505	8.055	8.274	2.345
$CAR_{1,1}$	1.956	1.155	4.224	0.165	-0.425	3.408
$CAR_{1,5}$	3.887	2.089	9.278	-1.296	-1.594	6.341
$CAR_{1,10}$	5.655	4.144	11.354	-1.925	-2.176	7.853
$CAR_{1,20}$	7.274	5.204	14.895	-2.668	-2.775	10.653
$CAR_{2,5}$	2.054	0.783	7.632	-1.353	-1.503	5.445
$CAR_{2,10}$	3.801	2.495	10.120	-1.984	-2.141	7.401
$CAR_{2,20}$	5.510	3.647	13.947	-2.723	-2.695	10.423
Panel C: negative shocks						
AR_0	-8.003	-8.095	2.100	-7.324	-7.302	2.122
$CAR_{1,1}$	-2.043	-1.622	3.482	-0.820	-0.586	3.304
$CAR_{1,5}$	-3.464	-2.537	7.881	-0.146	-0.010	6.329
$CAR_{1,10}$	-4.395	-3.436	9.997	0.002	0.297	8.693
$CAR_{1,20}$	-5.159	-3.901	13.024	0.183	0.529	12.705
$CAR_{2,5}$	-1.499	-1.005	6.258	0.599	0.408	5.588
$CAR_{2,10}$	-2.397	-1.609	8.716	0.746	0.675	8.220
$CAR_{2,20}$	-3.269	-2.269	11.868	0.933	0.781	12.099

Table 3.2 Summary of sample characteristics (shortable events)

This table reports the statistics of event-day abnormal return (*AR*), post-shock cumulative abnormal returns ($CAR_{a,b}$, subscribes [*a*, *b*] indicate the holding period), and the levels of event-day short-selling (SS_0) and short-covering (SC_0) activities, which are calculated as the volume of short-selling trade scaled by the total volume of lendable shares and the volume of short-covering trades scaled by the total trading volume respectively.

	Informed (N=716)			Uninformed (N=2353)		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Panel A: full sample						
AR_0	2.296	5.770	7.564	4.625	6.627	6.022
$CAR_{1,1}$	0.958	0.142	4.148	0.097	-0.392	3.073
$CAR_{1,5}$	1.939	0.876	8.336	-0.325	-0.850	5.763
$CAR_{1,10}$	2.517	1.241	10.157	-0.781	-1.472	7.484
$CAR_{1,20}$	2.525	1.388	13.053	-1.257	-1.870	10.121
$CAR_{2,5}$	1.253	0.457	6.387	-0.287	-0.813	4.963
$CAR_{2,10}$	1.814	0.674	8.630	-0.747	-1.225	6.899
$CAR_{2,20}$	1.965	0.703	11.921	-1.219	-1.843	9.670
SC_0	1.226	0.681	1.524	1.311	0.746	1.506
SS_0	0.683	0.056	2.815	0.259	0.054	1.325
Panel B: positive shocks						
AR_0	7.322	7.691	2.289	7.099	7.415	3.010
$CAR_{1,1}$	2.383	1.480	4.092	0.147	-0.411	3.066
$CAR_{1,5}$	3.799	1.676	8.768	-0.625	-1.262	5.796
$CAR_{1,10}$	5.184	3.409	10.352	-0.999	-1.818	7.444
$CAR_{1,20}$	5.603	3.342	13.597	-1.560	-2.345	9.841
$CAR_{2,5}$	1.999	0.546	6.962	-0.637	-1.067	4.882
$CAR_{2,10}$	3.278	1.492	9.130	-1.011	-1.614	6.781
$CAR_{2,20}$	4.135	1.992	12.432	-1.572	-2.200	9.383
SC_0	1.245	0.751	1.483	1.357	0.804	1.509
SS_0	0.388	0.058	1.841	0.289	0.066	1.437
Panel C: negative shocks						
AR_0	-6.737	-7.705	4.205	-5.922	-6.527	3.863
$CAR_{1,1}$	-1.603	-1.174	2.912	-0.116	-0.067	3.098
$CAR_{1,5}$	-1.404	-0.484	6.184	0.957	0.753	5.443
$CAR_{1,10}$	-2.274	-1.337	7.926	0.148	0.227	7.589
$CAR_{1,20}$	-3.007	-1.945	10.751	0.038	0.249	11.156
$CAR_{2,5}$	-0.088	0.269	4.933	1.205	0.562	5.033
$CAR_{2,10}$	-0.817	-0.242	6.926	0.378	0.411	7.285
$CAR_{2,20}$	-1.934	-0.989	9.825	0.286	0.157	10.690
SC_0	1.197	0.578	1.586	1.147	0.553	1.485
SS_0	1.127	0.055	3.803	0.155	0.024	0.799

Table 3.3 Regression analysis of post-shock returns: the impact of removing short-selling bans

This table reports the estimation results of the following regression: $CAR_{p,q} = c + \beta_1 AR_0 + \beta_2 (SE \cdot AR_0) + \gamma' X + u.$ $CAR_{p,q}$ is the post-shock abnormal return over the holding period $[t+p, t+q]$. AR_0 is the event-day abnormal returns. Dummy variable *SE* indicates shortable price events. Vector *X* contains a list of controlling variables: price-to-book ratio (*PBR*), momentum (*Mom*), log size (*LS*), and trading volume (*Vol*). Both event-day and post-shock abnormal returns are standardized by the corresponding estimation-period standard deviations adjusted for forecast errors (see Boehmer et al., 1991; Campbell et al., 1997, p.158-163). A price shock is considered informed (uninformed) if it is (not) explained by news articles released on the same or adjacent days. The *t*-test statistics (underlined) are calculated using clustered standard errors (Rogers, 1993). Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

	Panel A: Informed shocks								Panel B: Uninformed shocks							
	AR_0	$SE \cdot AR_0$	*Mom*	*PBR*	*LS*	*Vol*	*Int.*	R^2	AR_0	$SE \cdot AR_0$	*Mom*	*PBR*	*LS*	*Vol*	*Int.*	R^2
$CAR_{1,5}$	0.041	-0.018	0.043	-0.004	-0.007	0.001	0.068	0.050	-0.036	0.014	-0.017	0.000	-0.013	-0.002	0.073	0.036
	8.25***	-2.36**	1.130	-1.430	-0.270	0.240	0.270		-8.81***	1.73*	-0.670	-0.060	-0.490	-0.770	0.300	
$CAR_{1,10}$	0.033	-0.021	0.027	-0.007	-0.011	0.000	0.146	0.063	-0.015	0.007	-0.012	0.000	-0.034	-0.002	0.315	0.016
	9.91***	-3.59***	1.010	-3.17***	-0.600	0.100	0.810		-5.36***	1.68*	-0.730	-0.530	-1.640	-1.550	1.540	
$CAR_{1,20}$	0.023	-0.010	-0.018	-0.005	-0.024	-0.002	0.303	0.065	-0.011	0.001	-0.010	0.000	-0.043	-0.003	0.435	0.030
	9.24***	-2.15**	-0.840	-2.18**	-1.83*	-0.950	2.34**		-5.25***	0.380	-0.840	-0.970	-2.55**	-2.94***	2.65***	
$CAR_{1,30}$	0.018	-0.006	-0.006	-0.004	-0.019	0.000	0.233	0.058	-0.006	0.005	0.012	-0.001	-0.050	-0.003	0.516	0.022
	9.05***	-1.620	-0.310	-2.64***	-1.590	-0.010	1.97**		-3.30***	1.400	1.050	-1.270	-2.62***	-3.66***	2.75***	
$CAR_{2,5}$	0.037	-0.015	0.030	-0.007	-0.053	0.004	0.538	0.039	-0.032	0.018	-0.037	0.000	-0.003	-0.001	0.019	0.026
	6.80***	-1.67*	0.600	-1.94*	-1.82*	1.040	1.87*		-7.46***	2.06**	-1.260	0.110	-0.130	-0.420	0.080	
$CAR_{2,10}$	0.029	-0.016	0.012	-0.009	0.000	0.000	0.079	0.051	-0.012	0.009	-0.022	-0.001	-0.028	-0.002	0.272	0.013
	8.22***	-2.94***	0.420	-3.60***	-0.010	-0.130	0.440		-4.13***	1.94*	-1.300	-0.830	-1.360	-1.500	1.340	
$CAR_{2,20}$	0.021	-0.010	0.000	-0.006	-0.027	-0.003	0.358	0.046	-0.009	0.006	-0.005	-0.001	-0.040	-0.003	0.405	0.013
	8.48***	-1.84*	-0.010	-2.43**	-1.78*	-1.410	2.42**		-4.13***	1.170	-0.330	-1.250	-2.23**	-2.99***	2.34**	
$CAR_{2,30}$	0.014	-0.005	-0.009	-0.004	-0.013	0.000	0.190	0.037	-0.006	0.005	0.006	-0.001	-0.047	-0.003	0.485	0.018
	7.11***	-1.160	-0.490	-2.88***	-0.990	-0.010	1.500		-3.26***	1.630	0.580	-1.090	-2.60***	-3.13***	2.74***	

Table 3.4 Regression analysis of post-shock returns: the impacts of short-sellers' trading activities

This table reports the estimation results of the following regression: $CAR_{p,q} = c + \alpha_1 AS_0 + \alpha_2(UN \cdot AS_0) + \varphi SC_0 + \beta_1 AR_0 + \beta_2(UN \cdot AR_0) + \gamma' X + u$. $CAR_{p,q}$ is the post-shock abnormal return over the holding period $[t+p, t+q]$. AS_0 is the measure of event-day short-selling which is calculated as the volume of short-selling trades scaled by the total volume of lendable shares. SC_0 is the event-day short-covering volume scaled by the total trading volume. AR_0 is the event-day abnormal returns. Dummy variable UN indicates price events which are not explained by the news. Vector X contains a list of controlling variables: price-to-book ratio (*PBR*), momentum (*Mom*), log size (*LS*), and trading volume (*Vol*). Both event-day and post-shock abnormal returns are standardized by the corresponding estimation-period standard deviations adjusted for forecast errors (see Boehmer et al., 1991; Campbell et al., 1997, p.158-163). The *t*-test statistics (underlined) are calculated using clustered standard errors (Rogers, 1993). Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

Table 3 regression analysis of post-shock returns: the impacts of short-sellers' trading activities.

	AS_0	$UN*AS_0$	SC_0	AR_0	$UN*AR_0$	*Mom*	*PBR*	*LS*	*Vol*	*Int.*	R^2
$CAR_{1,1}$	0.043	-0.050	-0.068	0.040	-0.098	0.182	-0.001	-0.041	-0.012	0.505	0.039
	3.83***	-2.50**	-3.68***	3.25***	-5.65***	1.70*	-0.280	-0.610	-1.84*	0.700	
$CAR_{1,5}$	0.023	-0.036	-0.011	0.022	-0.057	0.043	-0.004	-0.047	-0.003	0.559	0.048
	2.99***	-3.54***	-1.090	3.29***	-6.72***	0.890	-1.95*	-1.420	-0.740	1.640	
$CAR_{1,10}$	0.023	-0.031	0.006	0.014	-0.029	0.057	-0.002	-0.037	-0.005	0.412	0.029
	3.33***	-3.52***	0.940	2.81***	-4.98***	1.95*	-1.100	-1.610	-2.65***	1.74*	
$CAR_{1,20}$	0.024	-0.026	0.008	0.015	-0.031	0.015	-0.001	-0.024	-0.005	0.291	0.061
	2.44**	-2.40**	1.77*	3.41***	-6.86***	0.660	-0.880	-1.570	-2.63***	1.78*	
$CAR_{1,30}$	0.012	-0.012	-0.004	0.013	-0.019	0.037	-0.002	-0.017	-0.004	0.215	0.029
	2.26**	-1.87*	-1.160	3.67***	-4.73***	1.70*	-2.11**	-1.190	-2.36**	1.430	
$CAR_{2,5}$	0.021	-0.020	0.020	0.022	-0.045	-0.012	-0.004	-0.088	-0.002	0.939	0.032
	2.06**	-1.550	1.97**	2.57**	-4.86***	-0.170	-1.500	-3.02***	-0.560	3.03***	
$CAR_{2,10}$	0.021	-0.023	0.012	0.015	-0.026	0.038	-0.003	-0.041	-0.005	0.483	0.025
	3.22***	-3.06***	1.75*	3.33***	-4.93***	1.220	-1.87*	-1.78*	-2.72***	2.00**	
$CAR_{2,20}$	0.021	-0.029	0.015	0.013	-0.024	0.045	-0.004	-0.041	-0.005	0.475	0.022
	3.09***	-3.49***	2.03**	2.35**	-3.87***	1.300	-1.83*	-1.650	-2.32**	1.83*	
$CAR_{2,30}$	0.011	-0.010	0.004	0.011	-0.017	0.031	-0.002	-0.025	-0.004	0.307	0.026
	2.09**	-1.340	0.900	2.60**	-3.88***	1.600	-2.32**	-1.69*	-2.48**	1.98*	

Table 3.5 Correlation between short-sellers' trades activities and abnormal price changes during large price shocks

This table provides the statistics of contemporary correlation between short-sellers' trade activities (short covering and short-selling) and event-day abnormal price changes (AR_0). Spearman's rank correlation (Spear.'s rho) test is used to evaluate the statistical significance. The amount of short covering activities is measured by the percentage decrease of short interest for the underlying stock on a price event day; and short-selling activities is measured by the volume of short-selling trades scaled by the total volume of lendable shares. A price event is considered informed (uninformed) if it is (not) explained by the news released on the same or adjacent days.

Trade Activities	Mean	AR_0 Corr.	Spear.'s rho	p-value
	Panel A: Informed Positive Shocks			
Short-covering	52.2340	0.0116	-0.0027	0.9630
Short-selling	0.3996	-0.0189	-0.0771	0.1717
	Panel B: Informed Negative Shocks			
Short Covering	53.3320	-0.0321	-0.0511	0.4624
Short-selling	1.3520	-0.2712	-0.3567	0.0000
	Panel C: Uninformed Positive Shocks			
Short-covering	57.1494	0.1446	0.1594	0.0000
Short-selling	0.3210	0.0700	0.0803	0.0020
	Panel D: Uninformed Negative Shocks			
Short Covering	51.0501	-0.1351	-0.1450	0.0031
Short-selling	0.1772	0.0967	0.0916	0.0697

Table 3.6 Regression analysis of post-shock returns: the impact of removing short-selling bans (a robustness check)

This table reports the estimation results of the following regression: $CAR_{p,q} = c + \beta_1 AR_0 + \beta_2\,(SE \cdot AR_0) + \gamma' X + u.$ $CAR_{p,q}$ is the post-shock abnormal return over the holding period [*t*+*p*, *t*+*q*]. AR_0 is the event-day abnormal returns. Dummy variable *SE* indicates shortable price events. Vector *X* contains a list of controlling variables: price-to-book ratio (*PBR*), momentum (*Mom*), log size (*LS*), and trading volume (*Vol*). The *t*-test statistics (underlined) are calculated using clustered standard errors (Rogers, 1993). Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

	Panel A: Informed shocks								Panel B: Uninformed shocks							
	AR_0	$SE \cdot AR_0$	*Mom*	*PBR*	*LS*	*Vol*	*Int.*	R^2	AR_0	$SE \cdot AR_0$	*Mom*	*PBR*	*LS*	*Vol*	*Int.*	R^2
$CAR_{1,5}$	0.298	-0.126	0.214	-0.065	0.134	0.000	-0.935	0.083	-0.117	0.069	-0.149	0.000	0.041	-0.058	-0.706	0.021
	11.26***	-2.23**	0.490	-1.610	0.550	0.010	-0.380		-5.13***	2.13**	-0.580	0.010	0.250	-2.61***	-0.440	
$CAR_{1,10}$	0.474	-0.214	0.200	-0.174	-0.108	0.041	1.946	0.131	-0.133	0.106	0.013	-0.009	-0.330	-0.100	3.079	0.020
	13.25***	-3.19***	0.330	-3.13***	-0.330	0.750	0.590		-5.14***	2.66***	0.030	-0.660	-1.480	-3.76***	1.380	
$CAR_{1,20}$	0.662	-0.385	-0.624	-0.233	-1.378	-0.062	15.825	0.122	-0.141	0.138	0.314	-0.022	-1.283	-0.266	13.314	0.032
	12.24***	-4.11***	-0.710	-2.16**	-2.94***	-0.880	3.39***		-2.93***	2.36**	0.600	-1.110	-4.37***	-5.99***	4.46***	
$CAR_{1,30}$	0.722	-0.253	-0.651	-0.230	-1.666	0.002	19.018	0.111	-0.251	0.137	0.696	-0.026	-1.696	-0.328	18.380	0.044
	11.49***	-2.26**	-0.580	-2.63***	-2.86***	0.030	3.27***		-4.49***	1.78*	1.020	-0.990	-4.49***	-6.39***	4.77***	
$CAR_{2,5}$	0.169	-0.113	0.165	-0.059	-0.044	0.048	0.825	0.042	-0.106	0.045	-0.286	0.000	0.043	-0.015	-0.519	0.019
	7.53***	-2.34**	0.420	-2.00**	-0.210	1.350	0.400		-5.26***	1.360	-1.080	-0.020	0.290	-0.710	-0.360	
$CAR_{2,10}$	0.345	-0.223	0.183	-0.167	-0.293	0.090	3.774	0.090	-0.123	0.083	-0.118	-0.010	-0.325	-0.058	3.239	0.016
	10.22***	-3.65***	0.310	-3.62***	-0.990	1.85*	1.260		-4.65***	1.92*	-0.290	-0.690	-1.500	-2.18**	1.490	
$CAR_{2,20}$	0.532	-0.312	-0.614	-0.226	-1.535	-0.011	17.397	0.094	-0.131	0.114	0.171	-0.022	-1.284	-0.223	13.539	0.028
	10.43***	-3.51***	-0.720	-2.37**	-3.42***	-0.170	3.88***		-3.33***	2.17**	0.340	-1.070	-4.51***	-5.64***	4.67***	
$CAR_{2,30}$	0.594	-0.253	-0.660	-0.227	-1.880	0.049	21.132	0.084	-0.226	0.102	0.561	-0.028	-1.691	-0.286	18.532	0.038
	9.84***	-2.34**	-0.610	-2.79***	-3.36***	0.620	3.78***		-4.59***	1.470	0.880	-1.010	-4.55***	-6.00***	4.89***	

Table 3.7 Regression analysis of post-shock returns: the impacts of short-sellers' trading activities (a robustness check)

This table reports the estimation results of the following regression: $CAR_{p,q} = c + \alpha_1 AS_0 + \alpha_2(UN \cdot AS_0) + \varphi SC_0 + \beta_1 AR_0 + \beta_2(UN \cdot AR_0) + \gamma' X + u$. $CAR_{p,q}$ is the post-shock abnormal return over the holding period $[t+p, t+q]$. AS_0 is the measure of event-day short-selling which is calculated as the volume of short-selling trades scaled by the total volume of lendable shares. SC_0 is the event-day short-covering volume scaled by the total trading volume. AR_0 is the event-day abnormal returns. Dummy variable UN indicates price events which are not explained by the news. Vector X contains a list of controlling variables: price-to-book ratio (*PBR*), momentum (*Mom*), log size (*LS*), and trading volume (*Vol*). The *t*-test statistics (underlined) are calculated using clustered standard errors (Rogers, 1993). Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *

Table 3 regression analysis of post-shock returns: the impacts of short-sellers' trading activities.

	AS_0	UN*AS_0	SC_0	AR_0	$UN*AR_0$	*Mom*	*PBR*	*LS*	*Vol*	*Int.*	R^2
$CAR_{1,1}$	0.097	-0.069	-0.130	0.202	-0.206	0.290	0.006	-0.075	-0.048	1.147	0.064
	1.93*	-0.890	-3.20***	8.79***	-7.67***	0.820	0.560	-0.500	-2.40**	0.700	
$CAR_{1,5}$	0.258	-0.410	-0.125	0.179	-0.296	0.447	-0.032	-0.668	-0.065	7.775	0.037
	1.350	-2.05**	-1.520	3.22***	-5.52***	0.930	-1.260	-2.58***	-1.66*	2.80***	
$CAR_{1,10}$	0.338	-0.447	-0.011	0.281	-0.376	1.650	-0.039	-0.628	-0.124	7.276	0.041
	2.22**	-2.59***	-0.110	4.74***	-6.16***	2.59***	-1.100	-1.76*	-2.84***	1.91*	
$CAR_{1,20}$	0.551	-0.614	-0.197	0.307	-0.397	2.121	-0.063	-0.766	-0.272	9.526	0.040
	2.76***	-2.17**	-1.450	3.71***	-4.75***	2.37**	-1.470	-1.390	-4.53***	1.610	
$CAR_{1,30}$	0.647	-0.941	-0.314	0.505	-0.699	2.269	-0.067	-1.312	-0.393	16.616	0.059
	2.25**	-2.46**	-1.77*	5.14***	-6.36***	1.76*	-1.410	-2.09**	-4.96***	2.45**	
$CAR_{2,5}$	0.170	-0.305	-0.004	0.063	-0.174	0.152	-0.038	-0.627	-0.020	7.181	0.027
	1.060	-1.85*	-0.050	1.280	-4.00***	0.230	-1.80*	-2.88***	-0.610	2.99***	
$CAR_{2,10}$	0.248	-0.340	0.106	0.143	-0.232	1.388	-0.047	-0.593	-0.081	6.750	0.026
	2.08**	-2.35**	1.040	2.73***	-4.03***	1.69*	-1.340	-1.82*	-2.22**	1.92*	
$CAR_{2,20}$	0.470	-0.517	-0.076	0.251	-0.338	1.890	-0.068	-0.735	-0.226	9.050	0.033
	2.50**	-1.87*	-0.600	3.28***	-4.38***	2.32**	-1.68*	-1.440	-4.07***	1.640	
$CAR_{2,30}$	0.558	-0.834	-0.192	0.376	-0.559	2.000	-0.084	-1.278	-0.350	16.098	0.046
	1.99**	-2.21**	-1.160	3.96***	-5.36***	1.82*	-1.71*	-2.14**	-4.55***	2.52**	

Appendix

Table 3.8 Regression analysis of post-shock returns: the impacts of short-sellers' trading activities (trimmed subsample)

This table reports the estimation results of the following regression: $CAR_{1,1} = c + \alpha_1 AS_0 + \alpha_2(UN \cdot AS_0) + \varphi SC_0 + \beta_1 AR_0 + \beta_2(UN \cdot AR_0) + \gamma' X + u.$ $CAR_{1,1}$ is the post-shock abnormal return over the one-day period following the price event. $CAR_{1,1\ (trimming\ 1\%)}$, $CAR_{1,1\ (trimming\ 5\%)}$, *and* $CAR_{1,1\ (trimming\ 10\%)}$ indicate estimates respectively resulting from trimming 1%, 5%, and 10% of the price events from the top and bottom levels of short-covering trades in the shortable event subsample. AS_0 is the measure of event-day short-selling which is calculated as the volume of short-selling trades scaled by the total volume of lendable shares. SC_0 is the event-day short-covering volume scaled by the total trading volume. AR_0 is the event-day abnormal returns. Dummy variable UN indicates price events which are not explained by the news. Vector X contains a list of controlling variables: price-to-book ratio (*PBR*), momentum (*Mom*), log size (*LS*), and trading volume (*Vol*). Both event-day and post-shock abnormal returns are standardized by the corresponding estimation-period standard deviations adjusted for forecast errors (see Boehmer et al., 1991; Campbell et al., 1997, p.158-163). The *t*-test statistics (underlined) are calculated using clustered standard errors (Rogers, 1993). Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

	AS_0	UN*AS_0	SC_0	AR_0	UN*AR_0	*Mom*	*PBR*	*LS*	*Vol*	*Int.*	R^2
$CAR_{1,1(trimming\ 1\%)}$	0.043	-0.050	-0.071	0.040	-0.097	0.180	-0.001	-0.036	-0.013	0.450	0.038
	<u>3.87***</u>	<u>-2.49**</u>	<u>-3.55***</u>	<u>3.20***</u>	<u>-5.59***</u>	<u>1.70*</u>	<u>-0.240</u>	<u>-0.530</u>	<u>-1.88*</u>	<u>0.630</u>	
$CAR_{1,1(trimming\ 5\%)}$	0.045	-0.051	-0.067	0.043	-0.098	0.174	0.000	-0.022	-0.014	0.312	0.035
	<u>3.93***</u>	<u>-2.57**</u>	<u>-2.87***</u>	<u>3.48***</u>	<u>-5.58***</u>	<u>1.69*</u>	<u>0.020</u>	<u>-0.320</u>	<u>-2.07**</u>	<u>0.420</u>	
$CAR_{1,1(trimming\ 10\%)}$	0.047	-0.051	-0.072	0.047	-0.100	0.169	0.003	-0.013	-0.016	0.218	0.035
	<u>3.93***</u>	<u>-2.52**</u>	<u>-2.58***</u>	<u>3.70***</u>	<u>-5.72***</u>	<u>1.630</u>	<u>0.790</u>	<u>-0.180</u>	<u>-2.21**</u>	<u>0.280</u>	

Chapter 4 Stock Returns Following Rumour Clarification Announcements: Can Investors Distinguish Between Reliable and Unreliable Rumours?

This paper studies investors' reaction to stock market rumours using data from China where listed companies are required to clarify rumours appearing in the media. We adopt Savor's (2012) regression to test whether post-clarification stock returns are predictable from pre-clarification momentum, which reflects investors' initial reaction to rumours. We find that post-clarification abnormal returns exhibit continuation of pre-clarification momentum for rumours that are not denied by the listed companies and reversals for those which are denied. These results suggest that investors are unable to distinguish the reliable rumours from the false ones, as they under-react to rumours containing material information and over-react to those without. Further regression analyses on post-clarification abnormal returns using various subsamples of rumour events show that the under- and over-reaction effects persist across favourable and unfavourable, bull and bear, and other rumour subsamples but become less manifest or insignificant for designated news media, asset restructurings, and large-size stock rumours. This suggests that investors respond more efficiently to rumours when they are more informed about news topics or the rumoured companies. Back-testing results show that investors can make excessive market-adjusted profits by trading on rumour-induced momentum.

KEY WORDS: China, rumour, rumour clarification, over-reaction, under-reaction, predictability of stock returns.

4.1 Introduction

DiFonzo & Bordia (1997) have shown that people tend to trade on rumours as if they are news, suggesting that the information content of rumours is often misjudged. Recent work by Ahern & Sosyura (2015) on takeover rumours, indicates that investors fail to incorporate all public information in processing rumours (see also Chou et al., 2015). Intuitively, if investors are unable to distinguish between reliable and unreliable rumours, they will under-react to rumours containing material information and over-react to those without, resulting in drift and reversals in post-rumour stock prices. While there are numerous studies in the literature on the under- and over-reaction effects, few studies have considered the role of investors' reaction to rumours in shaping those effects. One reason is that stock market rumours are not easy to track, let alone to gauge their accuracy. In this paper, we overcome this difficulty by utilizing the rumour clarification requirement for listed companies in China.

According to the listing regulations of the Chinese stock exchanges (SSE & SZSE), the boards of directors of listed companies are obligated to clarify rumours which have or may have significant impacts on stock prices, in a timely fashion. This requirement allows us to track investors' reactions before and after the rumours are clarified. If investors' initial responses to rumours are unbiased, there should be no systematic adjustments in post-clarification stock returns. We classify each rumour as either denied (unreliable) or undenied (potentially reliable) based on the content of any clarification announcement. Since the rumoured companies are legally accountable for their comments regarding the accuracy of any rumour, denied rumours are considered to be false rumours which contain little information about fundamentals, while the undenied rumours are considered information-based.

We use Savor's (2012) regression, with an indicator for denied rumours, to examine the predictability of post-clarification returns from investors' initial reaction.

Each cross-section represents one stock-rumour event. We measure investors' initial response to rumours using the abnormal changes in stock prices over two alternative horizons preceding the rumour clarification day. Our regression model incorporates various control variables including volume, firm size, price to book ratio, momentum, and percentage of individual investors. Our results show that post-clarification returns are predictable from investors' initial reactions to rumours. Stock prices continue to drift following clarification for undenied rumours and reverse for denied ones. These results suggest that investors under-react to rumours based on material information and over-react to those without such information. This finding corroborates Zivney et al. (1996) and Spiegel et al. (2010) which indicate that stock prices continue to rise after the releases of favourable rumours that turn out to be true, and reverse following the releases of rumours that turn out to be false. Our results are also consistent with prior studies of Pritamani & Singal (2001), Chan (2003), and Savor (2012), which show that the under-reaction effect is associated with information-based price events.

To further investigate investors' reaction to rumours, we divide the full sample of rumour events based on prevailing market sentiment, the source of rumours, the rumour topic, and the size of rumoured stocks. The regularity in post-clarification abnormal returns identified in the full sample is found to persist across the subsamples with the following exceptions. First, the over-reaction effect for favourable rumours is absent in a bull market. Second, investors appear to respond more efficiently to rumours published by the designated news media and to rumours speculating on pending asset restructurings. The designated news media is unlikely to be used by market manipulators for spreading false rumours, while asset restructuring storiesare closely followed by the financial mass media and professional investors in the county so are less susceptible to misinformation. Finally, the under- and over-reaction effects are not significant for rumours associated with large size companies.

Overall, our results suggest that investors are unable to distinguish between reliable and unreliable rumours. It follows that investors may be vulnerable to false rumours spread by market manipulators. Investors are more likely to over- or under-react to rumours associated with topics or companies about which they are not informed. These findings may help to explain why in some cases stock prices under-react/over-react while in other cases they do not. For example, Pound & Zeckhauser (1990) find stock prices react efficiently to takeover rumours appearing on the Wall Street Journal's "Heard on the Street" (HOTS) column, which tends to provide details of investment research. However, Zivney et al. (1996) find stock prices over-reacting to the same type of rumours appearing on the "Abreast of the Market" (AOTM) column, which tends to focus on rumours behind recent price moves, and thus is considered a less reliable source than the HOTS column. More recently, Patel & Michayluk (2016) examine the behaviour of stock returns following large price shocks accompanied by insiders' information disclosures in the Australian stock market and find no significant adjustment in post-shock returns. This result , which appears to contradict the results of Pritamani & Singal (2001) and Savor (2012), is explained by the findings of this paper. First, results from Patel & Michayluk's study are based on large-cap stocks (constituents of the ASX 200 index) while the prior studies broadly include all listed stocks. Moreover, unlike the secondary information sources used in the prior studies, the information-generating environment in Patel & Michayluk’s study is highly organized, and the information disclosure announcements made by the listed companies have explicable pricing implications for stock prices. Therefore, the circumstance under which price events are sampled in Patel & Michayluk’s study matches with the setting of this paper’s subsamples in which the under-reaction effect is insignificant.

Another contribution of our paper is to extend Yang & Luo's (2014) study on stock returns following rumour clarification in the Chinese stock market. This study focuses on favourable rumours that are denied in the follow-up clarification announcements. It shows that post-clarification unconditional abnormal price changes are significantly positive (negative) in bull (bear) market and concludes that under the influence of market sentiment, investors do not response rationally to the clarification announcements. Compared to Yang & Luo's study, the present study is based on a larger and a more comprehensive dataset. Moreover, our study accommodates the effects of investor under- and over-reaction, which have been found in numerous prior studies, by analysing the post-clarification abnormal returns that are conditional on investors’ pre-clarification responses, along with other control variables. Consistent with Yang & Luo's finding, our results indicate that stock prices reversals following clarification announcements are absent for denied favourable rumours occurring in a bull market. This may suggest that Chinese investors either know the false rumours during a bull market or under-react to the clarification announcements denying the good news during the period. The latter explanation is more consistent with the fact that the Chinese stock market is dominated by individual investors (Ng & Wu 2006). In terms of undenied rumours, which are not explored in Yang & Luo's (2014) study, the evidence in the present study indicates that the under-reaction effect is also influenced by the prevailing market sentiment. It is found that the magnitude of the effect for favourable rumours is on average twice as strong in a bull market as it is in a bear market.

The rest of the paper is organized as the follows. The next section provides a review of the relevant literature; section 4.3 gives a brief introduction to rumour clarification requirements in the Chinese stock market; section 4.4 and 4.5 describes the data, definition, and methodology; section 4.6 and 4.7 present the descriptive statistics and empirical results; section 4.8 provides robustness checks using various subsamples, and section 4.9 concludes.

4.2 Literature Review

There has been an on-going debate in the finance literature regarding whether investors can be said to over-react/under-react to information. De Bondt & Thaler (1985) document reversals in monthly stock returns after large price moves and hypothesize that investors tend to over-react to new information. A large collection of empirical studies also find significant post-shock reversals in short-horizon returns that are consistent with the prediction of De Bondt & Thaler’s over-reaction hypothesis (see, Howe, 1986; Zarowin, 1989; Bremer et al., 1997, Bowman & Iverson, 1998; Huang, 1998; Hamelink, 2003; Benou & Richie, 2003; Otchere & Chan, 2003; Wang et al., 2004; Diacogiannis et al., 2005; Zawadowski et al.,2006; Pham et al., 2007; Bharati et al., 2009; Lobe & Rieks, 2011). In contrast, several studies argue against the over-reaction hypothesis by demonstrating that post-shock reversals can be the results of rational, non-behavioural effects. In particular, Brown et al. (1988) argue that post-drop reversals can be explained by investors' aversion to transitory uncertainty associated with the price drops. Lo & MacKinlay (1990) show that periods of non-trading can lead to spurious reversals in stock prices, especially for long-horizon returns. Cox & Peterson (1994) find that short-term (1-3 days) reversals following one-day large declines in stock prices are attributable to the effect of bid-ask bounce. They also document that stock prices continue to fall over a longer horizon after the reversals.

More recently, the literature focuses on the circumstance under which stock prices exhibit the over- and under-reaction anomalies. In particular, Pritamani & Singal (2001) find that large price moves concurrent with news announcements result in continuation in stock prices, and that this regularity is stronger if the large price moves are accompanied by increases in trading volume. Using monthly stock returns, Chan (2003) shows that news-motivated price shocks are followed by drift, while no-news shock are followed by reversals, and the pattern is stronger among small-cap stocks. Larson & Madura (2003) develop a regression model for post-shock abnormal returns using a dummy indicator for uninformed price shocks (not explained by the WSJ announcements) as a predictor in the regression. They find evidence of over-reaction in response to uninformed positive shocks. Savor (2012) uses analyst reports to indicate information-based price events and tests the effect of information in shaping the behaviour of post-shock returns in a predictive regression model. Unlike Larson &

Madura's (2003) regression model, Savor's regression allows the indicator of information to have an interactive effect on the predictive value of investors' initial reaction and thereby highlights the role of information in shaping the behaviour of post-shock returns. Savor's study finds that information-based price events are followed by drift and no-information price events are followed by reversals. These results are interpreted by the author as an evidence of investor under-reaction to news about fundamentals.

One limitation in the prior studies of Pritamani & Singal (2001), Chan (2003), Larson & Madura's (2003), and Savor (2012) is that the information content identified by the authors, either in the forms of newspaper articles or analyst reports, are based on secondary sources, and thus it is unclear whether the information-based price events in these studies are actually motived by material information or rumours. Most recently, Patel & Michayluk (2016) re-examine the role of information in determining the behaviour of stock returns following one-day large moves using price events from the Australian stock market where listed companies are required to promptly disclose new material information to the Australian Securities Exchange. To overcome the shortfall of prior studies based on secondary information sources, they use the information disclosure announcements issued by the listed companies to identity information-based price events. In contrast to the results of prior studies, their findings suggest that price shocks accompanied by new material information are permanent.

Finally, this paper also adds to the collection of studies analysing investors' capacity to process stock market rumours. Pound & Zeckhauser (1990) test the trading strategy of buying on takeover rumours appearing in the Wall Street Journal's "Heard on the Street" (HOTS) column and find insignificant abnormal profits. They conclude that investors' reaction to the takeover rumours is consistent with the semi-strong form of the efficient markets hypothesis. In contrast, using a similar approach but a larger dataset, Zivney et al. (1996) find evidences of over-reaction to takeover rumours appearing in the Wall Street Journal's "Abreast of the Market" (AOTM) column, which provides less research-oriented but more hot-issue rumour stories than the HOTS column. They show that post-rumour abnormal returns exhibit upward adjustment for rumours turning out to be true, suggesting under-reaction in investors' responses to those rumours. Further, for those which turn out to be false, post-rumour stock prices reverse to eliminate most of the prior gains. This suggests an over-reaction component in investors' initial reaction to the rumours.

DiFonzo & Bordia (1997) conduct two control studies in which participants take part in a simulated trading game with different information generating environments for different groups of player. In one of the studies, participants are assigned to three treatment groups which are provided with news, public rumours, and non-public rumours, respectively. The results show that these three groups of participant exhibit a similar anti-regressive (i.e. giving more weight to recent trend) trading behaviour that is different from the control group which are exposed to neither news nor rumours.

Spiegel et al. (2010) focus on abnormal price changes around the releases of web-based rumours that have favourable implications to market prices in the Israeli stock market. They detect significant abnormal returns over the 5-day horizon before rumour release, suggesting that the rumours begin to circulate before they become public. Moreover, they find that post-release abnormal returns continue to rise for realized (true) rumours and decline for unrealized (false) rumours.

Yang & Luo (2014) utilize the rumour clarification requirement for listed companies in the Chinese stock market to investigate the behaviour of stock returns after rumours are denied by the listed companies. They show that investors' reaction to the clarification events are influenced by the prevailing market sentiment in such a way that during bull market periods investors continue to bid up stock prices even after they have been informed that the favourable rumours are not true.

More recently, Ahern & Sosyura (2015) show that the accuracy of merger rumours appearing in newspapers is associated with several characteristics of the articles, such as explicitness, newsworthiness, and journalists background, and that investors are unable to incorporate this public information in their reaction to rumours. Chou et al. (2015) find that the truthfulness of takeover rumours is predictable using pre-publication market prices, but that investors appear to act on rumours irrespective of this prior public information.

4.3 Background Information

4.3.1 Information Disclose and Rumour Clarification Rules in China

The requirement for listed Companies in China to clarify public rumours is written in the Rules Governing the Listing of Stocks on Shanghai (Shenzhen) Stock Exchange (hereafter, the rules) [37], which were enacted in January 1998 and subsequently revised in May 2000, June 2001, February 2002, December 2004, and May 2006.

There are multiple provisions in the rules dictating how listed companies should response to public rumours.[38] First of all, listed companies are required to monitor rumours that circulate in the public news media and have already had (or would have) material impacts on stock prices. Secondly, in case of a rumour event, the rumoured company is obligated to file an ad hoc report (i.e. a non-periodic report) providing the origin and content of the rumour, facts of the matters involved in the rumour, and other information that would help identify the essence of the issue.[39] The report must be approved by the company's board of directors (or in some cases the controlling shareholder) before public release. It is also required that listed companies submit the report to the stock exchange and publish the report through a designated public website (cninfo.com.cn) in a timely manner.

In January 2007, China Securities Regulatory Commission (CSRC), which is the law-making regulatory body for the stock market in China, issued an order restating the information disclosure provisions included in the rules governing the listed companies.[40] As a result of this order, listed companies in China are required not only by the stock exchanges but also by the law to clarify public rumours.

According to the rules for listed companies and CSRC's new order, the board of

[37] An English version of the rules is available on one of the stock exchanges' official web: http://www.szse.cn/main/en/RulesandRegulations/SZSERules/GeneralRules/
[38] While the definition of rumours is still evolving, it is generally accepted in the prior studies that unverified news are rumours (Schindler, 2007).
[39] See articles 11.5.5 and 11.5.6 of the Rules Governing the Listing of Stocks on Shanghai (Shenzhen) Stock Exchange for detail.
[40] An English version of the order is available at: http://www.asianlii.org/cn/legis/cen/laws/mfatidolc709/

directors and senior managers are made accountable for failing to fulfil the rumour clarification requirement. Depending on the severity of the violation, the party at fault may be subject to public criticisms or disciplinary actions (usually fines) sanctioned by the CSRC. Investors may also file civil claims again the company (or its senior managers) alleging failure to disclose material information. As a result, the listed companies in China are responsive to media rumours because a media report on a major event that has not been disclosed would suggest that the rumoured company may have violated the information disclosure requirement. The company impacted by the rumour, therefore, has the incentive to deny the rumour if it is false or to explain why the information has not been disclosed.

Table 4.1 provides a summary of rumour clarification announcements issued by the list companies between 2003 and 2015. The number of the announcement generally increases as more and more companies become public across the years. The average number of announcement per listed company (per year) reflects the tendency of the listed companies to clarify rumour. It is clear that the tendency bounce up to the highest level over the period soon after CSRC's new order for information disclosure but gradually decreases afterward. Overall, listed companies are more inclined to clarify rumours following CSRC's new order.

[Insert Table 4.1]

4.3.2 Overview of Stock Market Rumours in China

The Securities Law of China includes articles prohibiting any dissemination of misleading information through the news media.[41] Violation of the articles may lead to fines and, in some case, criminal investigation. However, due to limited administrative resources and the difficulty of tracing the source of rumours and substantiating evidence of adverse impact, rumour-mongers in China bear little legal risk for spreading rumours - especially the favourable ones.

One of the reasons that stock market rumours can be misleading is that the public media does not always play a responsible role in advising their readers. To illustrate this point, consider a rumour clarification announcement released on January 16th 2007 by China Eastern Airlines. According to the content of the announcement, a news report claiming that the company, together with other two major airlines in China, would receive 10 to 20 billion worth of capital from the government had appeared on the public media. Since the total market value of China Eastern Airlines at the time was just about 17 billion, the stock price of the company continually closed at the daily upper limit (reflecting a 10% increase) for three consecutive days before the rumour was denied in a clarification announcement. The rumour in fact contained little information about fundamentals because it is common knowledge, at least among market professionals, that only the state-controlled parent companies of those airlines could receive such aid from the government. The newspaper which printed the rumours simply failed to provide their readers with this important background information.

4.4 Data & Definitions

4.4.1 Timeline of a Rumour Event

Each rumour clarification announcement corresponds to one rumour event. The announcement day (*t*) is defined as the day in which the rumour clarification announcement is released.[42] The *20*-day horizon preceding the announcement day [*t*-

[41] See article 78 and 79 of the Securities Law of the People's Republic of China (available at: http://www.china.org.cn/english/government/207337.htm)

[42] Clarification announcements are usually posted after market close otherwise they are accompanied by trading halts to give investors enough time to process the information. Clarification announcements that are released on day t+1 before market opening are still considered announcement released on day *t* in this paper.

20, t-1] is defined as the pre-clarification period and the *20*-day horizon after the announcement day [*t+1, t+20*] is defined as the post-clarification period. The extent of the post-clarification period matches with that in Yang & Luo's (2014) study. The estimation period is defined as the *250*-day window preceding the pre-clarification period [*t-270, 2-21*]. The stylized timeline of a rumour event is summarized in Figure 4.1.

A rumour initially appears on the public media during the pre-clarification period,[43] and thus price changes during this period reflect investors' initial reaction to the rumour while price changes following the clarification announcement reflect investors' adjustment to their initial reaction. Prior studies of Pritamani & Singal (2001) and Savor (2012) use the one-day abnormal price change around news publication to measure investors' reaction to the news. This measure however does not account for pre-publication information leakages which may have a significant impact on stock prices (see e.g. Pound & Zeckhauser,1990; Spiegel et al. 2010; Chou et al., 2015). The period between a rumour's first appearance on the public media and the release of the clarification announcement ranges from 1 to 9 trading days across the rumour events in this paper. Therefore, we focus on the 10-day window [*t-10, t-1*] prior to the clarification announcement day for measuring the reaction of stock prices to rumours. Admittedly, the extent of this observation window is arbitrarily defined. To make the results of this paper more robust to the choice of this specification, we also use an

[43] The date of rumour clarification announcement can determined based on the announcement posting date on the designated website (cninfo.com.cn). However, we are unable to precisely determine the date when a stock rumour begin to circulate.

alternative 20-day observation window [*t-20*, *t-1*] in our later analysis even though it may be less precise in capturing investors' initial responses to rumours.

[Insert Figure 4.1]

4.4.2 Clarification Announcements

Listed companies' rumour clarification announcements are posted on a designated website (cninfo.com.cn). We retrieve clarification announcements released during the period from April 2002 to March 2016 on the website, while excluding those issued by companies belonging to any of the following categories: companies (1) under special treatment (ST stocks);[44] (2) which have not completed the split-share structure reform program (S stocks);[45] (3) trading below 2.00 Chinese Yuan or with a daily turnover rate below 0.5%, based on estimation-window averages (4) with less than 300 trading-day data points; (5) in trading suspension for more than one day during the pre- or post-clarification periods. Overnight trading suspensions are often triggered by important information releases. The ST and S stocks are not subjected to the same daily price limits and information disclosure environments as the rest of stocks listed in China. Category (3) is set to reduce the effects of bid-ask bounce and non-trading (MacKinlay, 1990; Cox & Peterson, 1994). At last, to avoid any confounding effects between rumour

[44] According to the rules of listed companies in China, a listed company is under Special Treatment if its listing is likely to be terminated. These listed companies have the prefix "ST" in their short names and thus are referred to as the ST stocks. Listed companies under special treatment are subjected to more stringent information disclosure requirements than the companies in good standing.

[45] The reform program, which was launched by the State Council of the People's Republic of China in 2005, converts non-tradable shares held by the state or domestic corporations into tradable shares. The non-tradable shareholders were often in control of the listed companies before the reform. The rules of exchanges were often not enforceable with the non-tradable shareholders due to their political and institutional backgrounds. Listed companies which have not completed the reform are given the prefix "S" to their short names and thus are referred to as the S stocks.

events, we omit consecutive clarification announcements issued by the same company in a 20 trading-day period.

4.4.3 Rumour Characteristics

Our initial sample contains 2044 rumour announcements.[46] We look into the content of each announcement for the following information: (1) the rumour story; (2) the date when the rumour first appears on the public media; (3) the source of the rumour; (4) comments regarding the truthfulness of the rumour. In particular, we aim to determine whether the rumour is favourable/unfavourable to the rumoured company, and if the position is unclear, the corresponding announcement is removed from our sample. If either information (2) or (3) is missing in the announcement, we search the information on Baidu before omitting the data point.[47] At last, we exclude announcements that clarify multiple rumour articles at the same time.

Following Pritamani & Singal's (2001) definition of an information signal, we characterize a stock market rumour based on the magnitude and accuracy of its information signal. A rumour is considered to be denied if the rumoured company states in its clarification announcement that the rumour is false. Thus by definition denied rumours have zero magnitude (i.e. containing no information) and undenied rumours have non-zero magnitude in their information signals. A rumour is considered accurate if it contains relatively little noise in its information content. In other words, an accurate

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[46] In addition to the summary disclosed in Table 4.1, there are 34 and 20 rumour clarification announcements being made during the periods of April-December 2002 and January-March 2016.
[47] Established in 2000, Baidu is the most popular Chinese search engine for websites. It ranked 4th overall in the Alexa Internet rankings

rumour has a clear implication for the stock price, while an inaccurate rumour delivers an imprecise information signal that is subject to ambiguous interpretation. Prior studies have indicated that the information content of rumours may derive from insider information leakages (e.g. see Keown & Pinkerton, Meulbroek, 1992). Furthermore, it is argued by rational expectations that informed investors may spread imprecise rumours to maximize profits (Van Bommel, 2003; Brunnermeier, 2005). Therefore, it is assumed that undenied rumours are information-based.

4.4.4 Full Sample of Rumour Events

Our final (full) sample contains 1786 complete data points of rumour events, which are categorized into four types of rumours as described in Table 4.2. Recall that Yang & Luo (2014) only examine denied "favourable" rumour events in their study.

[Insert Table 4.2]

4.4.5 Abnormal Returns

Stock market data are collected from Wind Data Terminal.[48] The daily return is calculated as the percentage change in closing prices (adjusted for dividends and stock splits), and the corresponding daily abnormal return (AR) is defined as the daily return minus the market model estimated return. The coefficients of the market model are

[48] Wind (Wind Information Co., Ltd.) is the most popular financial data provider in China. According to the company's webpage, it serves "more than 90% of financial institutions including hedge funds, asset management firms, securities companies, insurance companies, banks, research institutions, and regulatory bodies"; overseas, it serves "75% of Qualified Foreign Institutional Investors (QFII)". The company's data and research are "frequently quoted by Chinese and international media, in research reports, and in academic papers" (http://www.wind.com.cn/En/).

estimated using data from the estimation window. Cumulative abnormal returns ($CAR_{m,n}$) are calculated as the sum of daily abnormal returns over the cumulative horizon [$t+m$, $t+n$].

4.5 Methodology

According to De Bondt & Thaler's (1985) over-reaction hypothesis, the behaviour of stock returns following a price event is predictable from investors' initial reaction to the event. In particular, they argue that post-shock reversals indicate investor over-reaction. Savor (2012) develops a regression model on abnormal returns following one-day large price changes using the event-day abnormal return as the main predictor for the over-reaction effect. The study adds an interaction term between the main predictor and a dummy indicator for no-information event to accommodate the impact of information in shaping the behaviour of post-shock returns. Unlike the prior studies based on unconditional post-shock abnormal returns, Savor's regression approach incorporates not only investors' initial reactions but also the role of information, and thus it is better positioned for testing De Bondt & Thaler's (1985) hypothesis. Following Savor's regression approach, we define the following regression model for post-clarification stock returns.

$$CAR_{1,n} = c + \alpha_1 PCAR_{-m,-1} + \alpha_2 \left(DR \cdot PCAR_{-m,-1} \right) + b_1 IncVol_{-m,-1} + b_2 LogSize + b_3 LogPtB + b_4 Mom + b_5 PH + u \quad (1)$$

The dependent variance $CAR_{1,n}$ is the cumulative abnormal return over the horizon [$t+1,t+n$] following the announcement clarification day t. The main predictor

$PCAR_{-m,-1}$ is the cumulative abnormal return over the pre-clarification horizon [*t-m*, *t-1*]. Two alternative settings (*m*=10 and *m*=20) for the pre-clarification horizon are used in this paper. *DR* is a dummy variable set equal to one for a denied rumour. Coefficients α_1 and α_2 model the predictive role of investors' initial reaction to rumours on post-announcement returns. In particular, coefficient α_1 reflects investors' reaction to information-based (undenied) rumours and coefficient α_2 is associated with investors' reaction to false (denied) rumours. A positive (negative) α_1 suggests that investors under-react (over-react) to the information content of rumours, and any significance of α_2 indicates the presence of an interaction effect associated with false rumours.

The remainder of the explanatory variables are introduced to control for stock- and rumour-specific characteristics. $IncVol_{-m,-1}$ is the increase in trading volume and measured over the pre-clarification period, and is calculated as the average daily trading volume(scaled by the total amount of floating shares) over this period divided by the average calculated over the estimation window. *LogSize* and *LogPtB* are the log values of the rumoured company's total market capitalization and price to book ratio. *Mom* is the momentum of stock returns, calculated as the buy-and-hold returns over the 250-day estimation window. *PH* is the per capita holdings expressed as a percentage of the company's total floating shares and is calculated as the inverse of the total number of shareholders. Companies with a high percentage of holdings per shareholder are expected to have more institutional investors. All control variables, except for $IncVol_{-m,-1}$, are measured on day *t-21* of the estimation window to isolate the effect of rumour spread. The prior study of Pritamani & Singal (2001) indicates that the under-reaction effect is stronger when it is accompanied by a volume increase. Studies such as Harris and Raviv (1993) and Blume et al. (1994) suggest that trade volume is associated with the precision of information signal. In other words, the level of pre-clarification trade volume may reflect another dimension of rumour characteristics that is not captured by price change. The explanatory variables *LogSize*, *LogPtB*, and *Mom* are used in Savor's (2012) regression to control for the effects of stock-level characteristics. . Zivney et al. (1996) show that investor over-reaction to rumours is associated with the level of institutional ownership of the rumoured company. Yang & Luo (2014) find post-announcement stock returns exhibit stronger regularity when the percentage of institutional investors in the rumoured company is small.

4.6 Results

4.6.1 Summary Statistics

Table 4.3 presents the summary statistics of cumulative abnormal returns over the pre- and post-clarification horizons for the full sample and various subsamples. It indicates that the magnitude of any pre-clarification abnormal price change is considerably larger for favourable rumours than it is for unfavourable rumours. Denied rumours that have favourable implications on stock prices experience a larger pre-clarification run-up but smaller post-clarification abnormal normal returns than rumours based on fundamentals. This result is consistent with Yang & Luo's (2014) finding, which suggests Chinese investors cannot distinguish between rumours that can credibly predict favourable events from those that cannot. On the other hand, undenied rumours, irrespective of whether the content is favourable or unfavourable, are associated with momentum in post-announcement abnormal returns, which suggests that investors under-react to information-based rumours.

[Insert Table 4.3]

Table 4.4 presents the summary statistics for the explanatory variables in this paper. It indicates that daily trading volumes over the 10- and 20-day pre-clarification horizons are on average 1.57 and 1.41 times higher than their (estimation-window) baseline averages respectively. This is consistent with prior studies of Tumarkin & Whitelaw (2001), Clarkson et al., (2006), and Schmidt (2015) which demonstrate that stock market rumours are associated with more trading.

[Insert Table 4.4]

4.6.2 Estimation Results

Table 4.5 presents the estimation results for the regression model on post-clarification abnormal returns for the full sample and subsamples of favourable/unfavourable rumours and clarification announcements made before/after CSRC's new order in January 2007. *t*-Statistics are calculated using clustered standard errors (Rogers, 1993), where rumour clarification announcements made on the same date are place in one cluster. The estimates for coefficients α_1 and α_2 will be focus of our discussion.

It is shown that the estimates for α_1 are positive and significant across the three post-clarification horizons in both the full sample and the subsamples. On the other hand, the estimates for α_2 are also significant but exhibit the opposite sign to the estimates for α_1. In sum, the estimates for the full and favourable/unfavourable rumours subsample suggest that post-clarification stock returns exhibit continuation (of the pre-clarification price moves) for rumours that are not denied in the clarification announcements and reversals for those which are denied. The magnitudes of the under- and over-reaction effects are stronger for unfavourable rumours, which is consistent with the fact that short-selling is either restricted or constrained in China over the course of the observation period of this paper.[49] Diamond & Verrecchia (1987) hypothesis that short-restriction reduces the adjustment speed of stock prices to new information, especially bad news. The post-clarification continuation and reversals suggest that investors tend to under-react to rumours containing material information and over-react to those without any such information. The under- and over-reaction effects are both statistically and economically significant. For example, post-clarification abnormal returns are expected to continue to increase by 23.9% of the pre-clarification return run-up over the 20-day post-clarification window for favourable rumours that are not denied in the clarification announcements and reverse 4% of the pre-clarification price moves for rumours which are subsequently denied.

The estimates for the subsamples of rumour events based on CSRC's new order in

[49] Short-selling had not been allowed in the Chinese stock market until March 2010 when China SEC launched a pilot program lifting the short-selling bans for a list of elite stocks in terms of market capitalization and liquidity. Even after that, short-selling activates only account for less than 1% of the daily market volume due to lack of lendable shares and high borrowing costs for short sellers.

January 2007 show that the post-clarification continuation associated with undenied rumours persists across the two periods but reversals for denied rumours only prevail over the period following the new order. One explanation for this result is that before CSRC's new order rumour clarification announcements are less informative and thus have smaller impacts on stock prices because listed companies were not required to provide details in their responses. One evidence for backing up this explanation is that the text length (i.e. number of characters) of the rumour clarification announcement is on average 39% shorter before CSRC's new order.

[Insert Table 4.5]

Our evidence of post-clarification stock price reversals, which are associated with the false rumours, supports DiFonzo & Bordia's (1997) experimental finding that investors trade rumours as if they are news. The behaviour of post-rumour returns are consistent with those found in prior studies of Zivney et al. (1996) and Spiegel et al. (2010). Yang & Luo (2014) compare the unconditional post-clarification abnormal returns for denied rumours which turn out to be true by the end of their study period against those associated with the other denied rumours in their sample. They find no significant difference in post-clarification abnormal returns between the two types of rumours, and conclude that investors are unable to distinguish between the false and true rumours. This conclusion is supported by the under- and over-reaction effects identified in this section. If investors trade on a true rumour as if it is false, their price response to the rumour will fall short of the rational level; on the other hand, if investors trade on a false rumour as if it is news, their price response will overshoot.

Finally, our results are consistent with Savor's (2012) in a way that both studies find evidences of investor under-reaction to information-based events. The over-reaction effect identified in this section is not associated with information-based rumours and therefore the results do not support investor over-reaction to information.

4.7 Robustness Check with Subsamples of Rumour Events

4.7.1 Bull and Bear Market Periods

Yang & Luo (2014) show that post-clarification abnormal returns associated with denied favourable rumours are significantly positive during a bull market. They argue that the prevailing market sentiment influences investors' responses to the clarification announcements in such a way that during a bull market, Chinese investors continue to believe rumoured events will occur even after they have been denied by the rumoured companies. To revisit this issue, we classify each rumour event as either a bull market or a bear market event based on the prevailing market cycle covering the rumour clarification date. The bull and bear periods are determined according to Yan et al.'s (2007) algorithm using a 120-day moving average of the SSE Composite Index. Our bull market period covers Yang & Luo's (2014) bull market and our bear market period also contains the bear and neutral markets in their study. Table 4.6 provides a summary of the bull and bear market periods defined in this study.

[Insert Table 4.6]

Table 4.7 presents the regression results for the bull and bear market rumour subsamples. It is shown that the under-reaction effect associated with undenied rumours persists across the bull and bear market periods, but the effect is less significant for favourable rumours during a bear market. One explanation for this result is that during the bear market period where overall market sentiment is likely to be low, investors are less sensitive to favourable rumours and the resulting clarification announcements that verify the rumours (Mian & Sankaraguruswamy, 2012). Moreover, the over-reaction effect persists across both the bull and bear market periods except that post-clarification reversals in stock prices are absent for denied favourable rumours during the bull market period. This finding is consistent with Yang & Luo's (2014) conjecture that Chinese investors tend to ignore bad news when prevailing market sentiment is high.

[Insert Table 4.7]

4.7.2 Source of Rumour

Stock market rumours in this paper appeared on the news media before they were clarified by the rumoured companies. We classify the news media into three groups: Internet, common news, and designated news media. The Internet news media includes all the web-based news media and news websites that do not operate as paper-based newspapers. The designated news media refers to the four major financial newspapers designated by the two stock exchanges and the CSRC for information disclosure of public companies in China,[50] and the remaining paper-based newspapers are defined as common news media. Table 4.8 provides a summary of the accuracy of rumours associated with the three types of news media. As expected, the designated news media

[50] The four designated financial newspapers are: China Securities Journal, Securities Daily, Securities Times, and Shanghai Securities News.

has the highest rank in accuracy (lowest false rate) and the common and Internet news media have a similar accuracy rate in their rumour stories. A hypothesis test for the difference in false rates shows that the chance of being denied by the rumoured company is significantly lower (z-statistics = -5.32) for the designated news media rumours than for those associated with other news media sources.

[Insert Table 4.8]

Table 4.9 presents the regression results for the Internet news media, common news media, and designated news media subsamples. It indicates that the underreaction effect identified in the previous sub-sections persists across the subsamples of Internet and common news media rumours but remains insignificant for the designated news media rumours. The estimated coefficient measuring the effect is larger among Internet media rumours than it is among common media rumours, which is consistent with the fact that Internet rumours are generally less precious than common media news. The over-reaction effect is found to be significant for non-designated media rumours expect for the favourable Internet media rumour events in which stock prices continue to drift after the rumours are denied.

[Insert Table 4.9]

In summary, Chinese investors respond efficiently to designated news media rumours but are unable to fully appreciate the information content of information-based rumours appeared on the Internet and common news media. They are also misled by false rumours circulated on the Internet in a way that they either overreact to false news or continue to trade on denied rumours. One potential explanation for this result is that market manipulators in China prefer to use the Internet and common news media to spread false rumours among the individual investors.[51] This class of investor constitutes more than 99% of investor brokerage accounts in China and perceive public news, especially that printed in newspapers, as a reliable source of information (Ng & Wu, 2006). On the other hand, the designated news media newspapers are either founded or managed by agents of the securities regulatory body in China. As such, they are widely read by financial professionals, and we believe the designated news media is less likely to be used as a mechanism for spreading rumours designed to manipulate prices.

4.7.3 Asset Restructurings Rumours

Asset restructurings (hereafter, ARes) rumours constitute the largest subsample (29.8%) in terms of rumour topic. ARes rumours frequently appear in the financial news media in China. We conjecture that this is because ARes events often bring substantial changes to the rumoured companies' business perspectives and hence realign fundamental corporate values. In China, ARes typically occur among state-controlled enterprises being reformed for future privatization. These enterprises seek to transfer their assets to their listed subsidiaries or associated companies through mergers, acquisitions, or direct capital injections, during which time the market value of the listed counterparts moves up (or down) to reflect the changes in investors' expectation toward the events. These type of events are anticipated, as they are results of government

[51] For example, rumor-mongers in China may purchase so-called "soft-article promoting" service, which facilitate publication of unverified articles as news via on-line and/or paper-based media outlet, over the most popular on-trading trading platform Taobao (www.taobao.com).

policies which are reported before the asset restructurings are announced. As a result, listed companies with pending asset restructuring projects are closely followed by the financial news media and the investor community.

Table 4.10 presents the estimates based on ARes and non-ARes rumours. It is shown that the under- and over-reaction effects are statistically significant for non-ARes rumours across all post-clarification horizons. In contrast, the under-reaction is not significant across all post-clarification horizons for ARes rumours and the over-reaction effect is only significant for favourable ARes rumours over the 10-day post-clarification horizon. These results suggest that investors exhibit a greater tendency to make mistakes, in the sense they are unable to correctly identify credible rumour as opposed to false ones, when processing non-ARes rumours. In regard to investors' reaction to ARes rumours, there is some evidence indicating that investors' over-react to favourable ARes rumours that turn out to be false, but the evidence is insufficient to suggest that investors are in general unable to identify false ARes rumours, especially the favourable ones.

[Insert Table 4.10]

4.7.4 Size of the Rumoured Company

Chan (2003) studies monthly stock returns following large price moves concurrent with public news and finds the under-reaction effect is mostly confined to small-size stocks. In contrast, Larson & Madura (2003) examine the behaviour of daily stock returns following large price shocks and find large-size stocks experience stronger over-reaction effect in post-shock returns. More recently, Patel & Michayluk (2016) re-examine the behaviour of stock returns following one-day large price moves among the constituent stocks of the Australian ASX 200 index, which is dominated by large-size companies, and find the under-reaction effect insignificant.

In this subsection, we examine whether the under- and over-reaction effects identified in previous subsections are conditional on firm size. Intuitively, investors are more likely to be informed about large-size firms than they are about small-size firms, and thus it is expected that investors have a better capacity to process rumours associated with large-size firms. We rank the full sample of rumour events in term of market size of the rumoured companies (measured on day *t*-21) and then use the top and bottom 25% rumour events to construct the large- and small-size stock subsamples, respectively. The large-size stock rumours are associated with firms operating under a more effective information-generating environment than that associated with small-size stock rumours. For example, 301 out of 447 large-size stock rumours are related to constituent stocks of the CSI300 index. This index represents the most sizeable and liquid stocks in China. Moreover, 42 out of 447 large-size stock rumours are related to companies that are cross-listed (H shares) in Hong Kong[52]. By way of comparison, none of the small-size stock rumours fit into either of these categories.

Table 4.11 provides the regression results for the large-size and small-size stock subsamples. It shows that the under-reaction effect is significant across all the post-

[52] Chinese companies dual-listed in Hong Kong are required to make additional information disclosure according to the local securities regulations.

clarification horizons in the small-size stock subsample but not in the large-size stock subsample. Moreover, the over-reaction effect is statistically significant over all post-clarification horizons for small-size stock rumours but is only significant at 10% level over the 5- and 10-day horizons for unfavourable large-size stock rumours. This evidence supports our conjecture that investors respond more efficiently to rumours about companies with which investors are likely to be familiar. In this sense the findings are consistent with those of Chan (2003) and Patel & Michayluk (2016) .

[Insert Table 4.11]

4.8 Rumour-induced Momentum Trading Strategies

Rumour-induced momentum refers to the change in stock prices associated with the dissemination of rumours. So far, the results of this paper indicate that stock prices tend to extend their pre-clarification momentum for information-based rumours. It follows that one simple trading strategy based on this rumour-induced momentum is to bet on the trend as soon as the rumour is clarified without denial. Since short-selling has been either prohibited or constrained in the Chinese stock market for much of our sample period and composition, only trading strategies based on positive momentum are examined in this section.

Table 4.12 presents a summary of trading profits for two rumour-induced momentum trading strategies. A trading cost of 0.5% is applied to each round of trades. Raw returns are calculated as the percentage changes in stock prices from the opening price of day t+1 to the close of day t+20 following the clarification announcement day t. The opening price is used because clarification announcements are usually released after market close on the announcement day and it is assumed that momentum traders take positions as soon as the next day's market opens. Market-adjusted returns are calculated by subtracting the contemporaneous CSI300 index return from the raw return. The first trading strategy we consider gives equal weight to each trade. The second strategy adjusts the size of each trade in proportion to the magnitude of pre-clarification momentum, which is measured by the abnormal return over the *10*-day pre-clarification horizon. Since the results to date have shown that the magnitude of post-clarification momentum is positively related to the magnitude of pre-clarification momentum, traders may set a minimum level of pre-clarification momentum as a filter for a more advantageous bet. Results using two filters requiring a 5% and 10% minimum pre-clarification abnormal return, respectively, are provided in Table 4.12.

The results indicate that both trading strategies result in positive returns per trade. The equal-weighted strategy results in 3.3%, 3.87%, and 3.46% (2.12%, 2.5%, and 1.99% after adjusting for market returns) profit per trade under the settings of 0, 5%, and 10% pre-clarification abnormal return filter respectively while the momentum-weighted strategy results in 4.9%, 5.1%, and 5.5% (3.45%, 3.58%, and 3.83% after adjusting for market returns) profit per trade under the same filter settings. The momentum-weighted strategy yields a higher average profit per trade but is more risky in terms of the resulting variation in returns. Setting a higher filter only seems to improve the performance of the momentum-weighted strategy, and the trade-off between expected return and risk lies is in favour of the momentum-weighted strategy which outperforms its equal-weight counterpart in terms of standard Sharpe ratio comparisons. Finally, z-test results reveal that it appears possible for traders to make excessive market-adjusted returns by following the momentum-weighted strategy, notwithstanding the fact that such trade opportunities are rare (on average 11.7 trades per year) and that reasonably sophisticated trading skills may be required for determining the appropriate trade size.

[Insert Table 4.12]

4.9 Conclusion

This paper examines investors' reaction to stock market rumours by using data from China where listed companies are required to clarify rumours appearing in the media. Rumours that are denied by the listed companies are considered to be false rumours, which contain little information about fundamentals, and rumours that are not denied are considered to be information-based. Investors' responses to rumours are measured by the abnormal price changes over a pre-clarification period. Savor's (2012) regression formulation is applied to test whether investors' responses have predictive value on post-clarification stock returns. Our results indicate that post-clarification abnormal returns exhibit continuation of pre-clarification abnormal returns for undenied rumours and reversals for denied ones. These results suggest that investors are unable to distinguish between reliable and unreliable rumours, as they appear to under-react to rumours containing material information and over-react to those without. Further regression analyses on post-clarification abnormal returns using various subsamples of rumour events show that the under- and over-reaction effects persist across favourable and unfavourable, bull and bear, and other rumour subsamples.

However, abnormal returns are less manifest or insignificant for rumours associated with the designated news media, asset restructurings, and large firms. The latter finding suggests that investors respond more efficiently to rumours when they are more informed about news topics or the rumoured companies. This paper contributes to two distinct branches of the current literature. Prior studies on the predictability of stock returns following large price changes have not considered investors' capacity in processing rumours, while prior studies on stock market rumours have not used the under- and over-reaction effects to examine investors' reaction to rumours. Results of this paper are consistent with the previous analyses conducted by Pritamani & Singal (2001), Chan (2003), and Savor (2012), which show that investors tend to under-react to information-based events. The results also provide an empirical support for DiFonzo & Bordia's (1997) experimental finding which shows that investors trade rumours as if they are news. This paper also extent the prior study of Yang & Luo (2014) on stock price adjustment to rumour clarification announcements during the bull and bear market periods in China by showing that the post-clarification regularity is predicted by investors' initial reaction to rumours. Finally, this paper offers an explanation for the contrasting results found in Patel & Michayluk (2016), which claims that the over-reaction effect is absent among large-size companies listed in ASX, and the prior studies of Pritamani & Singal (2001), Chan (2003), and Savor (2012).

The results of this paper present evidence of biases in information processing that challenges the efficient market hypothesis. The results also have important implications for both financial professionals and stock market regulators in China. They demonstrate that traders may improve their momentum trading strategies by following information-based rumours and by adjusting the sizes of their trades according to investors' initial reaction to rumours. They suggest stock market regulators in China should consider imposing more controls on Internet and common news media, as investors appear vulnerable to false rumours emanating from these sources.

One limitation of this paper, however, is that only binary indicators are used to characterize rumours. In practice, each rumour characteristic can be categorized into multiple levels, and each may have particular implications on investors' reaction to the rumour. Further study is required to look into the details of these rumour characteristics for further patterns that may reveal the precise circumstances in which investors make mistakes in processing the pricing implications of stock market rumours.

References

Ahern, K.R. & Sosyura, D., 2015. Rumor Has it: Sensationalism in Financial Media. Rev. Financ. Stud., 28(7), pp.2050–2093.

Benou, G. & Richie, N., 2003. The reversal of large stock price declines: The case of large firms. Journal of Economics and Finance, 27(1), pp.19–38.

Bharati, R., Crain, S. & Nanisetty, P., 2009. Evaluating stock price behavior after events: an application of the self-exciting threshold autoregressive model. Quarterly Journal of Finance and Accounting, 48(2), pp.23–43.

De Bondt, W.F.M. & Thaler, R., 1985. Does the Stock Market Overreact? Journal of Finance, 40(3), pp.793–805.

Blume, L., Easley, D., & O'hara, M., 1994. Market statistics and technical analysis: The role of volume. The Journal of Finance, 49(1), 153-181.

Bowman, R.G. & Iverson, D., 1998. Short-run overreaction in the New Zealand stock market. Pacific-Basin Finance Journal, 6(5), pp.475–491.

Bremer, M. et al., 1997. Predictable Patterns after Large Stock Price Changes on the Tokyo Stock Exchange. The Journal of Financial and Quantitative Analysis, 32(3), pp.345–365.

Brown, K.C., Harlow, W.V. & Tinic, S.M., 1988. Risk aversion, uncertain information, and market efficiency. Journal of Financial Economics, 22(2), pp.355–385.

Chan, W.S., 2003. Stock price reaction to news and no-news: drift and reversal after headlines. Journal of Financial Economics, 70(2), pp.223–260.

Chou, H.I., Tian, G.Y. & Yin, X., 2015. Takeover rumors: Returns and pricing of rumored targets. International Review of Financial Analysis, 41, pp.13–27.

Clarkson, P.M., Joyce, D. & Tutticci, I., 2006. Market reaction to takeover rumour in Internet Discussion Sites. Accounting and Finance, 46(1), pp.31–52.

Cox, D. & Peterson, D., 1994. Stock Returns following Large One - Day Declines: Evidence on Short - Term Reversals and Longer - Term Performance. The Journal of Finance, 49(1), pp.255–267.

Diacogiannis, G.P. et al., 2005. Price limits and overreaction in the Athens stock exchange. Applied Financial Economics, 15(1), pp.53–61.

Diamond, D.W. & Verrecchia, R.E., 1987. Constraints on short-selling and asset price adjustment to private information. Journal of Financial Economics, 18(2), pp.277–311.

DiFonzo, N. & Bordia, P., 1997. Rumor and Prediction: Making Sense (but Losing Dollars) in the Stock Market. Organizational Behavior and Human Decision Processes, 71(3), pp.329–353.

Hamelink, F., 2003. Systematic patterns before and after large price changes: evidence from high frequency data from the Paris Bourse. Journal of Forecasting, 22(6-7), pp.533–549.

Harris, M., & Raviv, A., 1993. Differences of opinion make a horse race. Review of Financial studies, 6(3), pp. 473-506.

Howe, J., 1986. Evidence on stock market overreaction. Financial Analysts Journal, 42(4), pp.74–77.

Huang, Y.S., 1998. Stock price reaction to daily limit moves: Evidence from the Taiwan stock exchange. Journal of Business Finance and Accounting, 25(May), pp.469–483.

Larson, S. & Madura, J., 2003. What drives stock price behavior following extreme one-day returns. Journal of Financial Research, 26(1), pp.113–127.

Lo, A. & MacKinlay, A.C., 1990. An econometric analysis of nonsynchronous trading. Journal of Econometrics, 45(1-2), pp.181–211.

Lobe, S. & Rieks, J., 2011. Short-term market overreaction on the Frankfurt stock exchange. The Quarterly Review of Economics and Finance, 51(2), pp.113–123.

Mian, G.M. & Sankaraguruswamy, S., 2012. Investor sentiment and stock market response to earnings news. Accounting Review, 87(4), pp.1357–1384.

Ng, L. & Wu, F., 2006. Revealed stock preferences of individual investors: Evidence from Chinese equity markets. Pacific-Basin Finance Journal, 14(2), pp.175–192.

Otchere, I. & Chan, J., 2003. Short-Term Overreaction in the Hong Kong Stock Market : Can a Contrarian Trading Strategy Beat the Market ? Journal of Behavioral Finance, 4(3), pp.157–171.

Park, J., 1995. A Market Microstructure Explanation for Predictable Variations in Stock Returns following Large Price Changes. The Journal of Financial and Quantitative Analysis, 30(2), p.241.

Patel, V. & Michayluk, D., 2016. Return predictability following different drivers of large price changes. International Review of Financial Analysis, 45, pp.202–214.

Pham, V.T.L., Nguyen, D.Q.T. & Tô, T.-D., 2007. Abnormal Returns after Large Stock Price Changes: Evidence from Asia-Pacific Markets. International Financial Review, 8, pp.205–227.

Pound, J. & Zeckhauser, R., 1990. Clearly Heard on the Street : The Effect of Takeover Rumors on Stock Prices. The Journal of Business, 63(3), pp.291–308.

Pritamani, M. & Singal, V., 2001. Return predictability following large price changes and information releases. Journal of Banking & Finance, 25(4), pp.631–656.

Rogers, W.H., 1993. Regression standard errors in clustered samples. Stata Technical Bulletin, 13(July), pp.19–23.

Savor, P.G., 2012. Stock returns after major price shocks: The impact of information. Journal of Financial Economics, 106(3), pp.635–659.

Schmidt, D., 2015. Stock market rumors and credibility, HEC School of Management Working Paper.

Schindler, M., 2007. Rumors in financial markets: Insights into behavioral finance.

Hoboken, NJ: Wiley Finance Series

Spiegel, U., Tavor, T. & Templeman, J., 2010. The effects of rumours on financial market efficiency. Applied Economics Letters, 17(15), pp.1461–1464.

Tumarkin, R. & Whitelaw, R.F., 2001. News or Noise? Internet Postings and Stock Prices. Financial Analysts Journal, 57(3), pp.41–51.

van Bommel, Jos (2003). Rumors. The Journal of Finance, 58(4), 1499-1520.

Wang, J., Burton, B.M. & Power, D.M., 2004. Analysis of the overreaction effect in the Chinese stock market. Applied Economics Letters, 11(7), pp.437–442.

Yan, W. et al., 2007. Chinese stock market cyclical regimes: 1991-2006. Economics Letters, 97(3), pp.235–239.

Yang, X. & Luo, Y., 2014. Rumor Clarification and Stock Returns: Do Bull Markets Behave Differently from Bear Markets? Emerging Markets Finance and Trade, 50(1), pp.197–209.

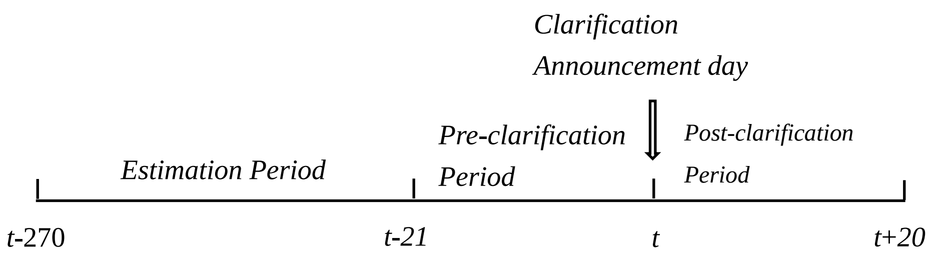
Zarowin, P., 1989. Short-run market overreaction: size and seasonality effects. The Journal of Portfolio Management.

Zawadowski, Á.G., Andor, G. & Kertész, J., 2006. Short-term market reaction after extreme price changes of liquid stocks. Quantitative Finance, 6(4), pp.283–295.

Zivney, T.L., Bertin, W.J. & Torabzadeh, K.M., 1996. Overreaction to takeover speculation. Quarterly Review of Economics and Finance, 36(1), pp.89–115.

Appendix

Figure 4.1 Stylized timeline of a rumour event



Notes: the announcement day (*t*) is defined as the day in which the rumour clarification announcement is released.

Table 4.1 Summary of rumour clarification announcements between 2003 and 2015

Year	Number of rumour clarification announcements	Number of listed companies	Average number of announcements per listed company
2003	45	1125	0.040
2004	54	1192	0.045
2005	56	1291	0.043
2006	117	1305	0.090
2007	261	1371	0.190
2008	159	1497	0.106
2009	230	1574	0.146
2010	137	1672	0.082
2011	155	2020	0.077
2012	187	2301	0.081
2013	248	2456	0.101
2014	210	2458	0.085
2015	129	2583	0.050

Notes: Listed companies in China are required to clarify public rumours that have had (or would have) significant impacts on stock prices. The numbers of rumour clarification announcements are based on the postings found on the designated website cninfo.com.cn.

Table 4.2 Description of rumour events

This table categorizes the full sample of rumour events according to the content of clarification announcements released by the company which is the subject of the rumour.

Content	Unfavourable	Favourable
Denied	528 Rumours: have unfavourable implications for the rumoured companies' market prices but are denied in the clarification announcements.	766 Rumours: have favourable implications for the rumoured companies' market prices but are denied in the clarification announcements.
Undenied	249 Rumours: have unfavourable implications for the rumoured companies' market prices and are not denied in the clarification announcements.	243 Rumours: have favourable implications for the rumoured companies' market prices and are not denied in the clarification announcements.

Table 4.3 Summary of abnormal price changes around rumour clarification

This table presents the statistics of cumulative abnormal returns over six horizons [*t+m, t+n*] around the rumour clarification announcement day (*t*). Rumour events are classified into four subsamples according to the content of rumours (unfavourable vs. favourable) and clarification announcements (undenied vs. denied). Cumulative abnormal returns ($CAR_{m,n}$) are calculated as the sum of daily abnormal returns over the cumulative horizon [*t+m, t+n*], and daily abnormal return is defined as the daily return minus the market model estimated return. Returns are expressed in percentages.

	Pre-clarification horizons			Post-clarification horizons		
$CAR_{m,n}$	[*t-20, t-1*]	[*t-10, t-1*]	[*t-5, t-1*]	[*t+1, t+5*]	[*t+1, t+10*]	[*t+1, t+20*]
	Full Samples (n = 1786)					
Mean	4.617	3.563	2.793	-0.655	-0.918	-1.267
Median	2.916	2.265	1.490	-1.005	-1.467	-1.774
Std. Dev.	16.238	12.713	9.845	7.680	10.067	13.690
	Subsample 1: unfavourable denied rumours (n = 528)					
Mean	0.491	-0.533	-0.919	-0.436	-0.670	-1.037
Median	-0.138	-0.488	-0.949	-1.079	-1.710	-1.246
Std. Dev.	15.603	12.250	8.754	6.386	9.061	12.813
	Subsample 2: unfavourable undenied rumours (n = 249)					
Mean	-1.651	-1.912	-2.054	-1.562	-1.993	-2.092
Median	-1.178	-0.846	-1.281	-0.965	-1.465	-1.563
Std. Dev.	16.616	11.805	8.715	8.677	11.348	14.387
	Subsample 3: favourable denied Rumours (n = 766)					
Mean	8.724	7.418	6.004	-0.877	-1.330	-1.710
Median	7.279	6.121	4.747	-1.019	-1.553	-2.339
Std. Dev.	15.331	12.038	9.280	6.900	9.168	13.061
	Subsample 4: favourable undenied rumours (n = 243)					
Mean	6.896	5.923	5.703	0.498	0.944	0.473
Median	5.411	4.229	4.205	-0.431	-0.610	-0.914
Std. Dev.	15.587	12.015	10.128	10.774	12.873	16.404

Table 4.4 Summary statistics of explanatory variables

$IncVol_{-m,-1}$ is the increase in trading volume(normalized by the amount of floating shares) measured over the period [*t-m, t-1*] preceding the rumour clarification day *t* and is calculated as the average daily trading volume over the period divided by the average calculated over the estimation window [*t-270,t-21*]. *LogSize and LogPtB* are the log values of the rumoured company's total market capitalization and price to book ratio. *Mom* is the momentum of stock returns, calculated as the buy-and-hold return over the estimation window (expressed in personages). *PH* is the per capita holdings expressed in percentage of the company's total floating shares and calculated as the inverse of the total number of shareholders (expressed in hundreds).

	Mean	Std. Dev.	Minimum	Maximum
Panel A: Full Sample (n = 1786)				
$IncVol_{-10,-1}$	1.5625	1.3870	0.0683	20.8040
$IncVol_{-20,-1}$	1.4191	1.1145	0.0504	14.7616
LogSize	22.2696	1.1707	19.4440	27.9950
LogPtB	1.2629	0.6997	-0.6513	5.6553
Mom(%)	56.0705	124.0232	-91.7851	1025.1500
PH(%)	0.4322	0.4423	0.0085	4.8473
Panel B: Favourable Rumours (n = 1009)				
$IncVol_{-10,-1}$	1.6695	1.3941	0.0683	20.8040
$IncVol_{-20,-1}$	1.4987	1.1364	0.0504	14.7616
LogSize	22.1878	1.1848	19.4440	27.3690
LogPtB	1.2275	0.6705	-0.5186	3.9227
Mom(%)	62.3440	130.2058	-83.7421	990.5830
PH(%)	0.4011	0.4209	0.0093	4.0128
Panel A: Unfavourable Rumours (n = 777)				
$IncVol_{-10,-1}$	1.4236	1.3663	0.1665	18.1048
$IncVol_{-20,-1}$	1.3156	1.0774	0.1864	10.2205
LogSize	22.3760	1.1443	19.9890	27.9950
LogPtB	1.3089	0.7338	-0.6513	5.6553
Mom(%)	47.9238	115.0748	-91.7851	1025.1500
PH(%)	0.4725	0.4658	0.0085	4.8473

Table 4.5 Regression analysis of post-clarification abnormal returns

	$PCAR_{-10,-1}$	$DR{*}PCAR_{-10,-1}$	$IncVol_{-10,-1}$	*LogSize*	*LogPtB*	*Mom (%)*	*PH (%)*	*Int.*	R^2
Panel A: Full Sample (n=1786)									
$CAR_{1,5}$	0.160	-0.199	-0.205	-0.155	-0.420	-0.002	0.122	3.709	0.029
	3.52***	-4.19***	-1.60	-0.93	-1.18	-0.78	0.26	1.00	
$CAR_{1,10}$	0.220	-0.255	-0.342	-0.130	-0.806	-0.006	-0.220	3.941	0.041
	3.80***	-4.17***	-2.09**	-0.63	-1.88*	-2.14**	-0.36	0.85	
$CAR_{1,20}$	0.243	-0.297	-0.845	-0.395	-0.830	-0.012	-0.776	10.956	0.048
	2.94***	-3.46***	-3.97***	-1.37	-1.46	-3.29***	-0.94	1.68*	
Panel B: Unfavourable Rumours (n=777)									
$CAR_{1,5}$	0.189	-0.249	-0.421	-0.263	-0.429	0.002	0.544	5.986	0.045
	2.90***	-3.60***	-2.38**	-1.02	-0.80	0.58	0.87	1.05	
$CAR_{1,10}$	0.256	-0.328	-0.696	-0.159	-0.897	-0.003	-0.131	4.964	0.057
	3.32***	-4.09***	-3.07***	-0.51	-1.43	-0.77	-0.14	0.71	
$CAR_{1,20}$	0.242	-0.341	-0.935	-0.569	-0.674	-0.016	-0.488	14.698	0.066
	2.06**	-2.78***	-3.28***	-1.42	-0.78	-2.81***	-0.42	1.63	
Panel C: Favourable Rumours (n=1009)									
$CAR_{1,5}$	0.142	-0.176	-0.093	-0.085	-0.421	-0.004	-0.194	2.300	0.045
	2.29**	-2.76***	-0.49	-0.39	-0.91	-1.54	-0.28	0.47	
$CAR_{1,10}$	0.193	-0.216	-0.127	-0.130	-0.683	-0.008	-0.217	3.578	0.035
	2.32**	-2.47**	-0.52	-0.47	-1.20	-2.12**	-0.27	0.57	
$CAR_{1,20}$	0.239	-0.274	-0.830	-0.314	-0.850	-0.010	-1.002	9.109	0.037
	2.05**	-2.27**	-2.53**	-0.77	-1.17	-2.26**	-0.88	0.99	

	$PCAR_{-20,-1}$	$DR{*}PCAR_{-20,-1}$	$IncVol_{-20,-1}$	*LogSize*	*LogPtB*	*Mom (%)*	*PH (%)*	*Int.*	R^2
Panel A: Full Sample (n=1786)									
$CAR_{1,5}$	0.107	-0.142	-0.243	-0.161	-0.378	-0.002	0.071	3.871	0.026
	2.80***	-3.56***	-1.45	-0.99	-1.08	-0.85	0.15	1.06	
$CAR_{1,10}$	0.110	-0.152	-0.297	-0.169	-0.788	-0.006	-0.327	4.846	0.031
	2.12**	-2.81***	-1.33	-0.81	-1.85*	-2.26**	-0.52	1.03	
$CAR_{1,20}$	0.187	-0.228	-1.042	-0.372	-0.756	-0.012	-0.828	10.519	0.048
	2.66***	-3.11***	-3.60***	-1.31	-1.33	-3.31***	-0.99	1.62	
Panel B: Unfavourable Rumours (n=777)									
$CAR_{1,5}$	0.086	-0.133	-0.496	-0.248	-0.416	0.001	0.387	5.774	0.029
	1.74*	-2.59***	-2.36**	-0.98	-0.80	0.41	0.60	1.02	
$CAR_{1,10}$	0.066	-0.120	-0.739	-0.141	-0.934	-0.004	-0.406	4.710	0.032
	0.96	-1.68*	-2.54**	-0.45	-1.53	-1.10	-0.43	0.66	
$CAR_{1,20}$	0.101	-0.200	-0.974	-0.576	-0.708	-0.017	-0.685	14.976	0.060
	1.41	-2.54**	-2.43**	-1.43	-0.85	-3.07***	-0.56	1.64	
Panel C: Favourable Rumours (n=1009)									
$CAR_{1,5}$	0.134	-0.162	-0.141	-0.065	-0.362	-0.004	-0.196	1.831	0.031
	2.36**	-2.80***	-0.59	-0.30	-0.78	-1.60	-0.28	0.37	
$CAR_{1,10}$	0.151	-0.190	-0.037	-0.137	-0.615	-0.008	-0.209	3.649	0.037
	2.02**	-2.49**	-0.12	-0.49	-1.06	-2.17**	-0.26	0.57	
$CAR_{1,20}$	0.274	-0.273	-1.203	-0.221	-0.702	-0.010	-1.081	6.986	0.048
	2.33**	-2.33**	-2.93***	-0.55	-0.96	-2.23**	-0.96	0.76	

These tables present the estimation results for the following regression:

$$CAR_{1,n} = c + \alpha_1 PCAR_{-m,-1} + \alpha_2\left(UN \cdot PCAR_{-m,-1}\right) + b_1 IncVol_{-m,-1} + b_2 LogSize + b_3 LogPtB + b_4 Mom + b_5 PH + u$$

$CAR_{1,n}$ and $PCAR_{-m,-1}$are the post- and pre-clarification cumulative abnormal returns over the holding periods [*t+1, t+n*] and [*t-m, t-1*] following and preceding the rumour clarification day *t* respectively. *DR* is a dummy variable set to one for denied rumour. $IncVol_{-m,-1}$ is the average daily trading volume over the pre-clarification period [*t-m, t-1*] expressed in multiples of the daily average calculated over the estimation window [*t-270, t-21*]. *LogSize and LogPtB* are the log values of the rumoured company's total market capitalization and price to book ratio. *Mom* is the momentum of stock returns, calculated as the buy-and-hold return over the estimation window. *PH* is the per capita holdings expressed in percentage of the company's total floating shares (in hundred units). All returns are expressed in percentages. Results for m=10 and 20 are provide in the left and right tables respectively. *t*-Statistics (underlined) are calculated using clustered standard errors (Rogers, 1993). Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

Table 4.5 (Continued)

	$PCAR_{-10,-1}$	$DR*PCAR_{-10,-1}$	$IncVol_{-10,-1}$	*LogSize*	*LogPtB*	*Mom (%)*	*PH (%)*	*Int.*	R^2
Panel D: Rumours before January 2007 (n=261)									
$CAR_{1,5}$	0.345	-0.357	-0.160	0.018	0.964	-0.019	-2.043	-0.634	0.142
	2.71***	-2.74***	-1.09	0.05	0.96	-2.44**	-2.16**	-0.09	
$CAR_{1,10}$	0.473	-0.456	-0.075	0.689	-0.650	-0.025	-1.628	-14.172	0.165
	3.14***	-2.90***	-0.34	1.61	-0.56	-2.75***	-1.30	-1.51	
$CAR_{1,20}$	0.552	-0.470	-0.408	0.784	-1.055	-0.024	-0.333	-16.505	0.116
	2.66***	-2.21**	-1.43	1.11	-0.65	-2.05**	-0.15	-1.08	
Panel E: Rumours After January 2007 (n=1525)									
$CAR_{1,5}$	0.130	-0.178	-0.281	-0.246	-0.617	0.000	0.526	5.979	0.026
	2.87***	-3.64***	-1.64	-1.27	-1.63	-0.19	1.04	1.36	
$CAR_{1,10}$	0.178	-0.229	-0.496	-0.372	-0.891	-0.005	0.138	9.640	0.037
	2.98***	-3.56***	-2.26**	-1.58	-1.95*	-1.65*	0.21	1.80*	
$CAR_{1,20}$	0.187	-0.279	-1.013	-0.827	-0.960	-0.011	-0.853	21.369	0.051
	2.18**	-3.08***	-3.52***	-2.51**	-1.58	-2.95***	-0.97	2.82***	

	$PCAR_{-20,-1}$	$DR*PCAR_{-20,-1}$	$IncVol_{-20,-1}$	*LogSize*	*LogPtB*	*Mom (%)*	*PH (%)*	*Int.*	R^2
Panel D: Rumours before January 2007 (n=261)									
$CAR_{1,5}$	0.340	-0.353	-0.274	-0.053	1.212	-0.017	-2.313	0.819	0.166
	3.13***	-3.17***	-1.34	-0.16	1.21	-2.46**	-2.39**	0.12	
$CAR_{1,10}$	0.406	-0.401	-0.123	0.596	-0.447	-0.023	-2.000	-12.257	0.161
	2.98***	-2.82***	-0.42	1.42	-0.38	-2.72***	-1.57	-1.32	
$CAR_{1,20}$	0.516	-0.447	-0.694	0.635	-0.738	-0.020	-0.789	-13.189	0.124
	2.96***	-2.49**	-1.79*	0.92	-0.45	-1.80*	-0.35	-0.88	
Panel E: Rumours After January 2007 (n=1525)									
$CAR_{1,5}$	0.080	-0.121	-0.321	-0.261	-0.596	-0.001	0.494	6.376	0.024
	2.05**	-2.92***	-1.47	-1.38	-1.58	-0.30	0.98	1.48	
$CAR_{1,10}$	0.073	-0.128	-0.441	-0.438	-0.904	-0.005	0.046	11.194	0.030
	1.35	-2.25**	-1.54	-1.85*	-1.98**	-1.82*	0.07	2.07**	
$CAR_{1,20}$	0.144	-0.210	-1.232	-0.791	-0.909	-0.011	-0.847	20.652	0.050
	1.91*	-2.66***	-3.17***	-2.41**	-1.49	-3.01***	-0.96	2.73***	

Table 4.6 Bull and bear market periods in the Chinese Stock Market: April 2002 to March 2016

Periods		Cycle	Rumour Events
Apr-02	Jun-02	Bull	11
Jun-02	Oct-03	Bear	56
Oct-03	Mar-04	Bull	21
Mar-04	May-05	Bear	58
May-05	Jan-08	Bull	358
Jan-08	Feb-09	Bear	138
Feb-09	Feb-10	Bull	205
Feb-10	Aug-10	Bear	70
Aug-10	Apr-11	bull	76
Apr-11	Aug-14	bear	601
Aug-14	Aug-15	bull	128
Aug-15	Mar-16	Bear	64
		Total:	1786

Notes: the bull and bear market periods are determined based on Yan et al.'s (2007) algorithm using a 120-day moving average of the SSE Composite Index.

Table 4.7 Regression analysis of post-clarification abnormal returns: bull and bear market rumour subsamples.

	$PCAR_{-10,-1}$	$DR{*}PCAR_{-10,-1}$	$IncVol_{-10,-1}$	*LogSize*	*LogPtB*	*Mom (%)*	*PH (%)*	*Int.*	R^2
Panel A: Bear Market Unfavourable Rumours (n=527)									
$CAR_{1,5}$	0.197	-0.241	-0.482	-0.104	-0.516	0.007	0.641	2.681	0.054
	2.57**	-3.05***	-2.21**	-0.34	-0.81	1.57	0.93	0.39	
$CAR_{1,10}$	0.226	-0.289	-0.793	-0.023	-1.028	0.001	0.127	2.223	0.053
	2.51**	-3.10***	-3.05***	-0.06	-1.40	0.26	0.12	0.25	
$CAR_{1,20}$	0.192	-0.300	-1.065	-0.398	-0.960	-0.007	-0.387	11.353	0.042
	1.39	-2.07**	-3.30***	-0.83	-0.93	-0.62	-0.32	1.04	
Panel B: Bull Market Unfavourable Rumours (n=250)									
$CAR_{1,5}$	0.194	-0.284	-0.010	-0.796	-0.177	0.000	0.116	16.878	0.050
	1.63	-2.14**	-0.03	-1.75*	-0.20	-0.10	0.07	1.70*	
$CAR_{1,10}$	0.379	-0.472	-0.205	-0.733	-0.370	-0.004	-1.939	16.552	0.078
	2.32**	-2.81***	-0.39	-1.38	-0.30	-0.71	-0.81	1.43	
$CAR_{1,20}$	0.449	-0.530	-0.441	-1.233	-0.307	-0.022	-0.907	28.372	0.125
	2.55**	-2.91***	-0.67	-1.65*	-0.20	-3.35***	-0.24	1.70*	
Panel C: Bear Market Favourable Rumours (n=454)									
$CAR_{1,5}$	0.081	-0.173	-0.136	0.071	-0.215	-0.010	-0.705	-0.841	0.038
	1.37	-2.69***	-0.39	0.18	-0.28	-1.80*	-0.86	-0.10	
$CAR_{1,10}$	0.136	-0.220	0.115	0.095	-0.578	-0.012	-0.629	-1.601	0.038
	1.95*	-2.67***	0.28	0.21	-0.63	-1.92*	-0.68	-0.16	
$CAR_{1,20}$	0.059	-0.208	-0.229	0.145	-0.607	-0.029	-0.687	-2.106	0.058
	0.70	-2.10**	-0.41	0.24	-0.56	-2.32**	-0.49	-0.15	
Panel D: Bull Market Favourable Rumours (n=555)									
$CAR_{1,5}$	0.190	-0.182	-0.106	-0.063	-0.573	-0.003	1.391	1.206	0.033
	1.80*	-1.73*	-0.47	-0.22	-0.94	-1.08	1.11	0.19	
$CAR_{1,10}$	0.239	-0.218	-0.338	-0.087	-0.759	-0.008	1.351	2.573	0.044
	1.65*	-1.50	-1.14	-0.24	-1.02	-1.88*	0.90	0.31	
$CAR_{1,20}$	0.386	-0.332	-1.405	-0.357	-0.374	-0.011	-0.761	10.430	0.050
	1.92*	-1.66*	-3.08***	-0.65	-0.36	-1.93*	-0.34	0.84	

	$PCAR_{-20,-1}$	$DR{*}PCAR_{-20,-1}$	$IncVol_{-20,-1}$	*LogSize*	*LogPtB*	*Mom (%)*	*PH (%)*	*Int.*	R^2
Panel A: Bear Market Unfavourable Rumours (n=527)									
$CAR_{1,5}$	0.126	-0.169	-0.686	-0.107	-0.445	0.005	0.519	2.914	0.045
	2.01**	-2.67***	-2.59***	-0.35	-0.73	1.31	0.74	0.43	
$CAR_{1,10}$	0.123	-0.175	-0.875	0.009	-1.013	0.000	-0.017	1.595	0.038
	1.58	-2.15**	-2.48**	0.02	-1.44	-0.01	-0.02	0.17	
$CAR_{1,20}$	0.083	-0.178	-1.058	-0.376	-0.995	-0.008	-0.502	10.878	0.035
	0.76	-1.51	-2.23**	-0.77	-0.99	-0.79	-0.39	0.98	
Panel B: Bull Market Unfavourable Rumours (n=250)									
$CAR_{1,5}$	0.038	-0.092	0.116	-0.734	-0.274	-0.001	-0.037	15.476	0.026
	0.53	-1.18	0.27	-1.63	-0.31	-0.20	-0.02	1.57	
$CAR_{1,10}$	0.001	-0.056	-0.270	-0.700	-0.625	-0.006	-2.291	16.448	0.032
	0.01	-0.49	-0.46	-1.28	-0.50	-1.07	-0.90	1.39	
$CAR_{1,20}$	0.126	-0.225	-0.582	-1.277	-0.322	-0.022	-1.279	29.683	0.107
	1.54	-2.42**	-0.78	-1.69*	-0.21	-3.39***	-0.33	1.75*	
Panel C: Bear Market Favourable Rumours (n=454)									
$CAR_{1,5}$	0.113	-0.189	-0.163	0.141	-0.180	-0.010	-0.586	-2.519	0.046
	1.96**	-2.94***	-0.45	0.37	-0.23	-1.86*	-0.72	-0.29	
$CAR_{1,10}$	0.129	-0.223	0.284	0.108	-0.534	-0.013	-0.529	-2.039	0.047
	1.59	-2.51**	0.69	0.25	-0.56	-2.08**	-0.58	-0.21	
$CAR_{1,20}$	0.139	-0.237	-0.383	0.305	-0.584	-0.029	-0.483	-5.881	0.060
	1.45	-2.30**	-0.67	0.52	-0.54	-2.33**	-0.35	-0.43	
Panel D: Bull Market Favourable Rumours (n=555)									
$CAR_{1,5}$	0.140	-0.141	-0.092	-0.073	-0.498	-0.003	1.352	1.384	0.035
	1.71*	-1.71*	-0.28	-0.25	-0.82	-1.02	1.08	0.22	
$CAR_{1,10}$	0.158	-0.165	-0.283	-0.119	-0.689	-0.008	1.338	3.282	0.042
	1.47	-1.53	-0.64	-0.32	-0.91	-1.83*	0.87	0.39	
$CAR_{1,20}$	0.340	-0.281	-1.931	-0.343	-0.154	-0.010	-1.117	10.424	0.064
	1.98**	-1.65*	-3.11***	-0.63	-0.15	-1.83*	-0.51	0.84	

These tables present the estimation results for the following regression:

$$CAR_{1,n} = c + \alpha_1 PCAR_{-m,-1} + \alpha_2\left(UN \cdot PCAR_{-m,-1}\right) + b_1 IncVol_{-m,-1} + b_2 LogSize + b_3 LogPtB + b_4 Mom + b_5 PH + u$$

$CAR_{1,n}$ and $PCAR_{-m,-1}$ are the post- and pre-clarification cumulative abnormal returns over the holding periods $[t+1, t+n]$ and $[t-m, t-1]$ following and preceding the rumour clarification day t respectively. *DR* is a dummy variable set to one for denied rumour. $IncVol_{-m,-1}$ is the average daily trading volume over the pre-clarification period $[t-m, t-1]$ expressed in multiples of the daily average calculated over the estimation window $[t-270, t-21]$. *LogSize and LogPtB* are the log values of the rumoured company's total market capitalization and price to book ratio. *Mom* is the momentum of stock returns, calculated as the buy-and-hold return over the estimation window. *PH* is the per capita holdings expressed in percentage of the company's total floating shares (in hundred units). All returns are expressed in percentages. Bull and bear market periods are determined based on Yan et al.'s (2007) algorithm. Results for m=10 and 20 are provide in the left and right tables respectively. *t*-Statistics (underlined) are calculated using clustered standard errors (Rogers, 1993). Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

Table 4.8 Accuracy of news media sources

Media Sources	Denied	Undenied	Total	False Rate
Internet News Media	428	160	588	0.728
Common News Media	639	202	841	0.760
Designated News Media	227	130	357	0.636

Notes: This table reports the total numbers of denied and undenied rumours for each media source. The Internet news media includes all the web-based news media and websites that do not operate as paper-based newspapers. The designated news media refers to the four major financial newspapers designated by the two stock exchanges and the CSRC for information disclosure of public companies in China, and the remaining the paper-based newspapers are defined as the common news media.

Table 4.9 Regression analysis of post-clarification abnormal returns: Internet, common, and designated news media rumour subsamples

	$PCAR_{-10,-1}$	$DR*PCAR_{-10,-1}$	$IncVol_{-10,-1}$	*LogSize*	*LogPtB*	*Mom (%)*	*PH (%)*	*Int.*	R^2
Panel A: Internet News Media Unfavourable Rumours (n=247)									
$CAR_{1,5}$	0.209	-0.275	-0.444	-0.378	-0.810	0.002	2.826	8.980	0.102
	2.72***	-2.89***	-1.15	-0.98	-1.24	0.33	2.38**	0.99	
$CAR_{1,10}$	0.173	-0.296	-0.589	0.105	-1.717	-0.005	1.260	0.295	0.093
	1.75*	-2.62***	-1.36	0.22	-1.89*	-0.80	0.94	0.03	
$CAR_{1,20}$	0.084	-0.232	-0.765	0.306	-0.790	-0.018	1.053	-3.728	0.063
	0.63	-1.52	-1.38	0.43	-0.62	-1.63	0.42	-0.22	
Panel B: Common News Media Unfavourable Rumours (n=408)									
$CAR_{1,5}$	0.150	-0.084	-0.355	1.021	-0.980	-0.001	-1.099	-21.848	0.036
	0.63	-0.36	-0.63	1.14	-0.68	-0.28	-0.57	-1.11	
$CAR_{1,10}$	0.254	-0.319	-0.870	-0.521	-0.338	-0.005	-0.691	12.529	0.055
	2.39**	-2.78***	-2.92***	-1.21	-0.38	-1.15	-0.56	1.32	
$CAR_{1,20}$	0.309	-0.436	-1.156	-1.200	-0.761	-0.017	-0.614	28.615	0.089
	2.47**	-3.16***	-3.37***	-2.14**	-0.60	-2.41**	-0.42	2.29**	
Panel C: Designated News Media Unfavourable Rumours (n=122)									
$CAR_{1,5}$	0.150	-0.084	-0.355	1.021	-0.980	-0.001	-1.099	-21.848	0.054
	0.63	-0.36	-0.63	1.14	-0.68	-0.28	-0.57	-1.11	
$CAR_{1,10}$	0.317	-0.373	0.044	1.171	-1.285	0.003	0.006	-25.289	0.066
	1.22	-1.42	0.04	1.07	-0.66	0.28	0.00	-1.04	
$CAR_{1,20}$	0.458	-0.391	-0.980	0.288	-0.106	-0.023	-1.125	-5.462	0.089
	1.27	-1.08	-0.77	0.26	-0.05	-1.70*	-0.36	-0.22	

	$PCAR_{-20,-1}$	$DR*PCAR_{-20,-1}$	$IncVol_{-20,-1}$	*LogSize*	*LogPtB*	*Mom (%)*	*PH (%)*	*Int.*	R^2
Panel A: Internet News Media Unfavourable Rumours (n=247)									
$CAR_{1,5}$	0.116	-0.191	-0.502	-0.334	-0.772	0.002	2.935	7.945	0.091
	2.04**	-2.78	-1.27	-0.86	-1.14	0.27	2.38	0.87	
$CAR_{1,10}$	0.036	-0.135	-0.720	0.169	-1.785	-0.007	1.549	-0.984	0.078
	0.59	-1.79*	-1.70*	0.35	-1.96*	-1.08	1.15	-0.09	
$CAR_{1,20}$	0.037	-0.225	-0.333	0.262	-0.809	-0.019	1.175	-3.264	0.073
	0.41	-1.96*	-0.54	0.38	-0.64	-1.81*	0.47	-0.20	
Panel B: Common News Media Unfavourable Rumours (n=408)									
$CAR_{1,5}$	0.010	-0.065	-0.463	-0.504	-0.023	0.000	-0.596	11.104	0.024
	0.15	-0.94	-1.66*	-1.46	-0.03	0.08	-0.81	1.48	
$CAR_{1,10}$	-0.018	-0.054	-0.859	-0.592	-0.326	-0.008	-1.299	14.257	0.036
	-0.14	-0.42	-2.23**	-1.38	-0.38	-1.59	-1.11	1.50	
$CAR_{1,20}$	0.115	-0.236	-1.362	-1.198	-0.687	-0.020	-1.105	28.871	0.083
	1.29	-2.39**	-2.60***	-2.20**	-0.58	-2.72***	-0.78	2.36**	
Panel C: Designated News Media Unfavourable Rumours (n=122)									
$CAR_{1,5}$	0.105	-0.059	-0.462	0.951	-1.023	-0.001	-1.301	-20.167	0.051
	0.63	-0.37	-0.80	1.07	-0.76	-0.18	-0.61	-1.03	
$CAR_{1,10}$	0.230	-0.186	-0.275	1.075	-1.299	0.002	-0.716	-22.741	0.057
	1.24	-0.94	-0.25	0.93	-0.72	0.24	-0.24	-0.89	
$CAR_{1,20}$	0.198	-0.129	-0.841	0.271	-0.569	-0.021	-2.100	-4.745	0.060
	0.67	-0.42	-0.68	0.23	-0.27	-1.56	-0.56	-0.18	

These tables present the estimation results for the following regression:

$$CAR_{1,n} = c + \alpha_1 PCAR_{-m,-1} + \alpha_2 (UN \cdot PCAR_{-m,-1}) + b_1 IncVol_{-m,-1} + b_2 LogSize + b_3 LogPtB + b_4 Mom + b_5 PH + u$$

$CAR_{1,n}$ and $PCAR_{-m,-1}$ are the post- and pre-clarification cumulative abnormal returns over the holding periods [*t+1*, *t+n*] and [*t-m*, *t-1*] following and preceding the rumour clarification day *t* respectively. *DR* is a dummy variable set to one for denied rumour. $IncVol_{-m,-1}$ is the average daily trading volume over the pre-clarification period [*t-m*, *t-1*] expressed in multiples of the daily average calculated over the estimation window [*t-270*, *t-21*]. *LogSize and LogPtB* are the log values of the rumoured company's total market capitalization and price to book ratio. *Mom* is the momentum of stock returns, calculated as the buy-and-hold return over the estimation window. *PH* is the per capita holdings expressed in percentage of the company's total floating shares (in hundred units). All returns are expressed in percentages. The Internet news media includes all the web-based news media and news websites that do not operate as paper-based newspapers. The designated news media refers to the four major financial newspapers designated by the two stock exchanges and the CSRC for information disclosure of public companies in China, and the rest of the paper-based newspapers are defined as the common news media. Results for m=10 and 20 are provide in the left and right tables respectively. *t*-Statistics (underlined) are calculated using clustered standard errors (Rogers, 1993). Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

Table 4.9 (Continued)

	$PCAR_{-10,-1}$	$DR*PCAR_{-10,-1}$	$IncVol_{-10,-1}$	*LogSize*	*LogPtB*	*Mom (%)*	*PH (%)*	*Int.*	R^2
Panel D: Internet News Media Favourable Rumours (n=341)									
$CAR_{1,5}$	0.295	-0.268	-0.234	0.334	-0.253	-0.007	-0.175	-7.603	0.063
	3.07***	-2.68***	-0.98	0.85	-0.31	-1.31	-0.14	-0.83	
$CAR_{1,10}$	0.346	-0.322	-0.366	-0.185	-0.666	-0.007	-0.453	4.290	0.071
	2.98***	-2.69***	-1.46	-0.42	-0.76	-1.10	-0.34	0.42	
$CAR_{1,20}$	0.472	-0.408	-1.080	-0.422	-1.144	-0.017	-1.418	10.979	0.090
	2.11**	-1.87*	-2.51**	-0.61	-0.95	-2.10**	-0.78	0.69	
Panel E: Common News Media Favourable Rumours (n=433)									
$CAR_{1,5}$	0.106	-0.146	0.078	-0.020	-0.582	-0.004	0.063	1.134	0.024
	1.50	-1.99**	0.24	-0.06	-0.79	-1.35	0.07	0.15	
$CAR_{1,10}$	0.228	-0.287	0.332	0.368	-1.398	-0.011	0.600	-7.002	0.067
	2.71***	-3.09***	0.84	0.86	-1.38	-2.08**	0.53	-0.73	
$CAR_{1,20}$	0.179	-0.236	-0.522	0.098	-0.604	-0.014	0.608	-0.680	0.037
	1.73*	-2.06**	-0.95	0.16	-0.51	-2.26**	0.40	-0.05	
Panel F: Designated News Media Favourable Rumours (n=235)									
$CAR_{1,5}$	0.012	-0.120	-0.329	-1.029	0.353	0.000	-2.546	23.241	0.033
	0.09	-0.80	-0.56	-1.79*	0.40	0.09	-1.60	1.80*	
$CAR_{1,10}$	-0.037	0.025	-0.444	-1.061	1.177	-0.002	-3.851	23.439	0.015
	-0.19	0.12	-0.50	-1.29	1.11	-0.43	-1.63	1.26	
$CAR_{1,20}$	-0.015	-0.109	-0.816	-1.072	0.142	0.002	-7.156	26.953	0.032
	-0.06	-0.43	-0.73	-1.02	0.10	0.21	-2.25**	1.14	

	$PCAR_{-20,-1}$	$DR*PCAR_{-20,-1}$	$IncVol_{-20,-1}$	*LogSize*	*LogPtB*	*Mom (%)*	*PH (%)*	*Int.*	R^2
Panel D: Internet News Media Favourable Rumours (n=341)									
$CAR_{1,5}$	0.291	-0.290	-0.365	0.325	-0.209	-0.006	-0.427	-7.064	0.102
	3.87***	-3.80	-0.95	0.87	-0.26	-1.20	-0.34	-0.82	
$CAR_{1,10}$	0.281	-0.327	-0.281	-0.273	-0.667	-0.007	-0.650	6.727	0.091
	2.58***	-3.09	-0.69	-0.61	-0.74	-1.14	-0.50	0.66	
$CAR_{1,20}$	0.503	-0.443	-1.833	-0.394	-1.051	-0.014	-1.941	11.188	0.134
	2.54**	-2.34	-2.71	-0.58	-0.86	-1.83	-1.10	0.71	
Panel E: Common News Media Favourable Rumours (n=433)									
$CAR_{1,5}$	0.088	-0.119	0.142	-0.005	-0.553	-0.005	0.135	0.655	0.024
	1.51	-1.89*	0.45	-0.01	-0.75	-1.50	0.15	0.09	
$CAR_{1,10}$	0.192	-0.234	0.506	0.407	-1.337	-0.012	0.717	-8.214	0.067
	2.94***	-3.16***	1.18	0.94	-1.31	-2.20**	0.62	-0.85	
$CAR_{1,20}$	0.185	-0.184	-0.678	0.192	-0.438	-0.015	0.631	-3.191	0.036
	2.17**	-1.87*	-1.20	0.32	-0.37	-2.35**	0.42	-0.24	
Panel F: Designated News Media Favourable Rumours (n=235)									
$CAR_{1,5}$	-0.017	-0.060	-0.456	-1.039	0.384	0.000	-2.764	23.621	0.029
	-0.16	-0.53	-0.63	-1.81*	0.43	0.00	-1.69*	1.83*	
$CAR_{1,10}$	-0.050	0.019	-0.478	-1.112	1.170	-0.003	-3.956	24.761	0.017
	-0.35	0.13	-0.44	-1.38	1.10	-0.45	-1.69*	1.35	
$CAR_{1,20}$	0.042	-0.152	-1.038	-1.011	0.227	0.001	-7.100	25.631	0.032
	0.21	-0.73	-0.75	-0.98	0.17	0.13	-2.24**	1.10	

Table 4.10 Regression analysis of post-clarification abnormal returns: ARes and Non-ARes rumour subsamples

	PCAR $_{-10,-1}$	***DR*PCAR*** $_{-10,-1}$	***IncVol*** $_{-10,-1}$	***LogSize***	***LogPtB***	***Mom (%)***	***PH (%)***	***Int.***	R^2
Panel A: Unfavourable ARes Rumours (n=116)									
$CAR_{1,5}$	-0.066	-0.032	0.347	0.026	-1.163	0.002	0.356	-0.826	0.024
	-0.22	-0.10	0.57	0.03	-1.19	0.26	0.22	-0.04	
$CAR_{1,10}$	0.166	-0.252	0.046	1.731	-1.963	-0.013	2.498	-38.628	0.084
	0.58	-0.90	0.06	2.08**	-1.92*	-1.86*	1.24	-2.07**	
$CAR_{1,20}$	0.294	-0.324	-1.285	1.333	-3.588	-0.029	2.678	-23.805	0.109
	0.66	-0.73	-1.27	0.98	-1.68*	-2.24**	0.75	-0.77	
Panel B: Unfavourable Non-ARes Rumours (n=661)									
$CAR_{1,5}$	0.223	-0.274	-0.485	-0.322	-0.361	0.003	0.473	7.396	0.062
	3.63***	-4.10***	-2.58***	-1.20	-0.60	0.80	0.68	1.25	
$CAR_{1,10}$	0.280	-0.341	-0.754	-0.507	-0.638	-0.001	-0.757	12.966	0.064
	3.56***	-4.07***	-3.21***	-1.54	-0.92	-0.18	-0.79	1.75*	
$CAR_{1,20}$	0.249	-0.348	-0.878	-0.898	-0.185	-0.015	-1.068	21.595	0.067
	2.10**	-2.76***	-2.89***	-2.13**	-0.20	-2.25**	-0.90	2.28**	
Panel C: Favourable ARes Rumours (n=418)									
$CAR_{1,5}$	0.144	-0.111	0.324	-0.117	-0.476	-0.002	0.743	1.622	0.030
	1.47	-1.07	0.96	-0.35	-0.65	-0.46	0.49	0.21	
$CAR_{1,10}$	0.166	-0.225	-0.388	-0.136	0.030	-0.012	-1.028	4.239	0.052
	1.64	-2.13**	-1.48	-0.33	0.04	-2.42**	-1.16	0.46	
$CAR_{1,20}$	0.312	-0.272	-0.920	-0.356	-1.587	-0.009	2.064	9.269	0.046
	1.42	-1.19	-1.19	-0.59	-1.43	-1.35	0.73	0.66	
Panel D: Favourable Non-ARes Rumours (n=591)									
$CAR_{1,5}$	0.141	-0.222	-0.248	-0.017	-0.378	-0.006	-0.485	1.439	0.041
	1.81*	-2.87***	-1.05	-0.05	-0.63	-1.86*	-0.61	0.20	
$CAR_{1,10}$	0.166	-0.225	-0.388	-0.136	0.030	-0.012	-1.028	4.239	0.044
	1.64	-2.13**	-1.48	-0.33	0.04	-2.42**	-1.16	0.46	
$CAR_{1,20}$	0.181	-0.267	-0.735	-0.121	-0.635	-0.011	-1.865	5.299	0.040
	1.67*	-2.34**	-2.18**	-0.21	-0.63	-1.86*	-1.42	0.41	

	PCAR $_{-20,-1}$	***DR*PCAR*** $_{-20,-1}$	***IncVol*** $_{-20,-1}$	***LogSize***	***LogPtB***	***Mom (%)***	***PH (%)***	***Int.***	R^2
Panel A: Unfavourable ARes Rumours (n=116)									
$CAR_{1,5}$	-0.126	0.068	0.900	0.113	-1.551	0.002	0.199	-2.801	0.032
	-0.81	0.43	1.23	0.13	-1.54	0.23	0.15	-0.15	
$CAR_{1,10}$	0.032	-0.046	-0.093	1.820	-2.283	-0.012	1.913	-39.955	0.069
	0.21	-0.31	-0.10	2.08**	-2.07**	-1.55	1.00	-2.05**	
$CAR_{1,20}$	-0.064	0.038	-1.070	1.295	-4.359	-0.026	1.707	-22.226	0.099
	-0.25	0.15	-0.79	0.92	-1.96*	-1.85*	0.43	-0.70	
Panel B: Unfavourable Non-ARes Rumours (n=661)									
$CAR_{1,5}$	0.114	-0.158	-0.631	-0.316	-0.320	0.002	0.332	7.389	0.044
	2.15**	-2.86***	-3.04***	-1.22	-0.56	0.65	0.46	1.29	
$CAR_{1,10}$	0.078	-0.133	-0.817	-0.509	-0.633	-0.003	-1.004	13.123	0.035
	1.00	-1.64	-2.77***	-1.55	-0.95	-0.58	-1.01	1.77*	
$CAR_{1,20}$	0.135	-0.244	-0.902	-0.914	-0.198	-0.015	-1.213	21.986	0.066
	1.88*	-2.99***	-2.16**	-2.18**	-0.23	-2.40**	-0.99	2.32**	
Panel C: Favourable ARes Rumours (n=418)									
$CAR_{1,5}$	0.125	-0.111	0.268	-0.129	-0.406	-0.001	0.685	2.035	0.034
	1.41	-1.23	0.59	-0.40	-0.55	-0.42	0.46	0.27	
$CAR_{1,10}$	0.175	-0.188	0.381	-0.185	-1.516	-0.002	2.093	3.514	0.053
	1.50	-1.56	0.60	-0.45	-1.63	-0.52	1.13	0.37	
$CAR_{1,20}$	0.309	-0.269	-1.441	-0.304	-1.448	-0.009	1.788	8.473	0.064
	1.55	-1.34	-1.48	-0.51	-1.29	-1.29	0.65	0.61	
Panel D: Favourable Non-ARes Rumours (n=591)									
$CAR_{1,5}$	0.142	-0.205	-0.306	-0.006	-0.291	-0.006	-0.430	1.062	0.044
	2.11**	-3.01***	-1.06	-0.02	-0.49	-1.91*	-0.55	0.15	
$CAR_{1,10}$	0.121	-0.186	-0.212	-0.143	0.089	-0.012	-0.976	4.093	0.042
	1.46	-2.17**	-0.60	-0.35	0.12	-2.43**	-1.09	0.45	
$CAR_{1,20}$	0.233	-0.262	-1.042	-0.037	-0.462	-0.011	-1.832	3.124	0.042
	2.53**	-2.69***	-2.49**	-0.06	-0.45	-1.82*	-1.40	0.24	

These tables present the estimation results for the following regression:

$$CAR_{1,n} = c + \alpha_1 PCAR_{-m,-1} + \alpha_2(UN \cdot PCAR_{-m,-1}) + b_1 IncVol_{-m,-1} + b_2 LogSize + b_3 LogPtB + b_4 Mom + b_5 PH + u$$

$CAR_{1,n}$ and $PCAR_{-m,-1}$ are the post- and pre-clarification cumulative abnormal returns over the holding periods [*t+1, t+n*] and [*t-m, t-1*] following and preceding the rumour clarification day *t* respectively. *DR* is a dummy variable set to one for denied rumour. $IncVol_{-m,-1}$ is the average daily trading volume over the pre-clarification period [*t-m, t-1*] expressed in multiples of the daily average calculated over the estimation window [*t-270, t-21*]. *LogSize and LogPtB* are the log values of the rumoured company's total market capitalization and price to book ratio. *Mom* is the momentum of stock returns, calculated as the buy-and-hold return over the estimation window. *PH* is the per capita holdings expressed in percentage of the company's total floating shares (in hundred units). All returns are expressed in percentages. ARes rumours refer to stock market rumours which speculates on pending asset restructurings. Results for m=10 and 20 are provide in the left and right tables respectively. *t*-Statistics (underlined) are calculated using clustered standard errors (Rogers, 1993). Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

Table 4.11 Regression analysis of post-clarification abnormal returns: large-size and small-size rumour subsamples

	$PCAR_{-10,-1}$	$DR*PCAR_{-10,-1}$	$IncVol_{-10,-1}$	LogSize	LogPtB	Mom (%)	PH (%)	Int.	R^2
Panel A: Unfavourable Small-Cap Rumours (n=169)									
$CAR_{1,5}$	0.334	-0.383	-0.520	-2.983	0.261	0.021	0.408	63.059	0.089
	1.66*	-1.76*	-1.02	-1.05	0.17	1.18	0.26	1.05	
$CAR_{1,10}$	0.430	-0.517	-0.964	-1.674	-0.872	0.016	0.111	36.937	0.093
	2.03**	-2.31**	-1.70*	-0.48	-0.57	0.95	0.05	0.51	
$CAR_{1,20}$	0.622	-0.643	-1.733	-1.018	-0.952	0.007	1.139	24.841	0.095
	2.10**	-2.00**	-2.19**	-0.28	-0.44	0.36	0.45	0.33	
Panel B: Unfavourable Large-Cap Rumours (n=207)									
$CAR_{1,5}$	0.007	-0.120	-0.541	-0.596	-0.530	-0.002	0.394	14.700	0.066
	0.13	-1.65*	-1.71*	-1.35	-0.89	-0.59	0.39	1.35	
$CAR_{1,10}$	0.120	-0.171	-0.652	-1.569	-0.010	-0.009	-3.055	39.121	0.109
	1.49	-1.74*	-1.60	-2.43**	-0.01	-1.66*	-1.68*	2.47**	
$CAR_{1,20}$	-0.150	-0.053	-0.583	-1.689	0.394	-0.035	-1.860	40.883	0.164
	-0.77	-0.26	-0.88	-1.84*	0.25	-3.61***	-0.77	1.81*	
Panel C: Favourable Small-Cap Rumours (n=278)									
$CAR_{1,5}$	0.200	-0.248	-0.033	-0.405	-1.011	0.009	-2.302	10.491	0.060
	2.26**	-2.80***	-0.09	-0.30	-0.89	1.05	-1.86*	0.37	
$CAR_{1,10}$	0.333	-0.378	0.233	-0.921	-1.592	0.013	-2.120	20.612	0.083
	4.04***	-4.20***	0.54	-0.55	-1.14	1.22	-1.68*	0.59	
$CAR_{1,20}$	0.255	-0.314	-0.605	-0.736	-2.410	0.016	-1.602	19.520	0.043
	1.93*	-2.38**	-1.05	-0.27	-1.45	1.14	-0.76	0.35	
Panel D: Favourable Large-Cap Rumours (n=240)									
$CAR_{1,5}$	0.197	-0.167	-0.330	-0.410	-0.744	-0.006	2.418	10.655	0.065
	1.34	-1.05	-1.43	-0.75	-1.15	-2.18**	2.04**	0.79	
$CAR_{1,10}$	0.359	-0.376	-0.489	0.214	-0.645	-0.015	1.973	-3.943	0.111
	1.19	-1.18	-1.38	0.32	-0.70	-3.08***	1.34	-0.24	
$CAR_{1,20}$	0.337	-0.377	-0.759	0.213	0.715	-0.024	-0.817	-4.102	0.106
	0.87	-0.93	-1.74*	0.21	0.61	-3.45***	-0.36	-0.17	

	$PCAR_{-20,-1}$	$DR*PCAR_{-20,-1}$	$IncVol_{-20,-1}$	LogSize	LogPtB	Mom (%)	PH (%)	Int.	R^2
Panel A: Unfavourable Small-Cap Rumours (n=165)									
$CAR_{1,5}$	0.325	-0.338	-1.023	-3.177	0.398	0.016	0.239	67.397	0.114
	2.30**	-2.30**	-1.74*	-1.18	0.29	1.05	0.16	1.19	
$CAR_{1,10}$	0.410	-0.451	-1.843	-2.040	-0.700	0.010	-0.175	45.358	0.121
	2.61***	-2.83***	-2.68***	-0.62	-0.52	0.71	-0.09	0.65	
$CAR_{1,20}$	0.536	-0.584	-2.572	-1.455	-0.913	0.001	0.805	34.772	0.110
	2.36**	-2.42**	-2.67***	-0.42	-0.48	0.04	0.34	0.47	
Panel B: Unfavourable Large-Cap Rumours (n=210)									
$CAR_{1,5}$	-0.003	-0.096	-0.277	-0.613	-0.583	-0.003	0.274	14.957	0.065
	-0.06	-1.58	-0.63	-1.38	-0.97	-0.91	0.27	1.36	
$CAR_{1,10}$	-0.021	-0.085	-0.560	-1.661	-0.080	-0.013	-3.161	41.283	0.115
	-0.24	-0.90	-1.03	-2.59***	-0.09	-2.47**	-1.76*	2.62***	
$CAR_{1,20}$	-0.125	-0.077	-0.332	-1.720	0.096	-0.036	-1.904	41.780	0.174
	-0.95	-0.51	-0.35	-1.90*	0.07	-3.76***	-0.80	1.88*	
Panel C: Favourable Small-Cap Rumours (n=282)									
$CAR_{1,5}$	0.243	-0.249	-0.293	-0.205	-0.796	0.008	-2.428	6.058	0.082
	3.13***	-3.03***	-0.73	-0.15	-0.70	0.92	-1.97**	0.21	
$CAR_{1,10}$	0.296	-0.335	0.103	-0.811	-1.273	0.010	-2.135	18.196	0.088
	4.00***	-4.42***	0.22	-0.49	-0.89	1.01	-1.67*	0.53	
$CAR_{1,20}$	0.350	-0.309	-1.214	-0.377	-2.162	0.015	-1.907	11.635	0.065
	3.15***	-2.81***	-2.26**	-0.14	-1.32	1.17	-0.91	0.21	
Panel D: Favourable Large-Cap Rumours (n=237)									
$CAR_{1,5}$	0.045	-0.061	-0.328	-0.631	-0.748	-0.006	2.077	16.202	0.055
	0.47	-0.56	-0.94	-1.11	-1.10	-2.16**	1.74*	1.16	
$CAR_{1,10}$	0.168	-0.207	-0.378	-0.003	-0.648	-0.015	1.575	1.353	0.099
	1.22	-1.30	-0.64	0.00	-0.71	-3.03***	1.11	0.08	
$CAR_{1,20}$	0.173	-0.130	-1.000	0.355	0.798	-0.024	-1.220	-7.586	0.097
	0.88	-0.59	-1.40	0.35	0.68	-3.54***	-0.58	-0.31	

These tables present the estimation results for the following regression:

$$CAR_{1,n} = c + \alpha_1 PCAR_{-m,-1} + \alpha_2\left(UN \cdot PCAR_{-m,-1}\right) + b_1 IncVol_{-m,-1} + b_2 LogSize + b_3 LogPtB + b_4 Mom + b_5 PH + u \backslash$$

$CAR_{1,n}$ and $PCAR_{-m,-1}$are the post- and pre-clarification cumulative abnormal returns over the holding periods [*t+1, t+n*] and [*t-m, t-1*] following and preceding the rumour clarification day *t* respectively. *DR* is a dummy variable set to one for denied rumour. $IncVol_{-m,-1}$ is the average daily trading volume over the pre-clarification period [*t-m, t-1*] expressed in multiples of the daily average calculated over the estimation window [*t-270, t-21*]. *LogSize and LogPtB* are the log values of the rumoured company's total market capitalization and price to book ratio. *Mom* is the momentum of stock returns, calculated as the buy-and-hold return over the estimation window. *PH* is the per capita holdings expressed in percentage of the company's total floating shares (in hundred units). All returns are expressed in percentages. The large- and small-size subsamples are constituted by taking the top and bottom 25% rumour events in terms of market capitalization of the rumoured companies. Results for m=10 and 20 are provide in the left and right tables respectively. *t*-Statistics (underlined) are calculated using clustered standard errors (Rogers, 1993). Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

Table 4.12 Returns of rumour-induced momentum trading strategies

This table provides the summary statistics for returns generated by two rumour-induced momentum trading strategies. Equal-weighted strategy assigns each trade an equal amount of investment while momentum-weighted strategy assign an amount in proportion to the pre-clarification momentum, calculated as the abnormal price changes over the 10-day pre-clarification horizon. PCAR Filters set the minimum levels (5% & 10%) of pre-clarification abnormal returns required for applying the strategies. Raw returns are calculated as the percentage changes in stock prices from the open of day t+1 to the close of day t +20 following the clarification announcement day t. Market-adjusted returns are calculated by subtracting the contemporaneous CSI300 index returns from the raw returns. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *.

Momentum Strategies	Trades	Mean	Std. Dev.	Sharpe Ratio	*z*-test
Panel A: Equal-weighted Raw Returns					
No Filter	165	0.0330	0.1896		
5% PCAR Filter	121	0.0387	0.1969		
10% PCAR Filter	78	0.0346	0.1792		
Panel B: Equal-weighted Market-adjusted Returns					
No Filter	165	0.0212	0.1688	0.1255	1.613
5% PCAR Filter	121	0.0250	0.1799	0.1390	1.529
10% PCAR Filter	78	0.0199	0.1530	0.1302	1.150
Panel C: Momentum-weighted Raw Returns					
No Filter	165	0.049	0.260		
5% PCAR Filter	121	0.051	0.236		
10% PCAR Filter	78	0.055	0.218		
Panel B: Momentum-weighted Market-adjusted Returns					
No Filter	165	0.0345	0.2198	0.1571	2.016**
5% PCAR Filter	121	0.0358	0.1994	0.1798	1.977**
10% PCAR Filter	78	0.0383	0.1826	0.2100	1.855*

Chapter 5

Summary and Suggestions for Future Research

In this thesis, I investigate three documented market anomalies in which returns exhibit predictable patterns following reports of large future traders' positions (Chapter 2), extreme price moves (Chapter 3), and announcements of rumour clarification (Chapter 4). In general, results of this thesis present new evidences and explanations that contribute to the current understanding these market anomalies.

In Chapter 2, I find the commercial (hedger) net positioning level appears to be a short-run significant predictor of future index returns whereas the non-commercial (speculator) net positioning level appears inversely related to future index returns. However, the presence of the dotcom and subprime crises in our sample significantly impacts on the nature of this predictability, suggesting that the state of the market strongly conditions the results. Specifically, I find that during the dotcom crisis, the link between commercial net positioning level and future (1- and 2-week ahead) returns is strengthened whereas, during the subprime crisis, this link is strongly reversed and thus turns (significantly) negative. This can explain the instability of any attempted prediction from one period to another and therefore the lack of reliability of a COT-based sentiment in practical pursuit. The result is also consistent with the recent studies of Chung et al. (2012) and Wolff (2013) which find the predictive power of their investor sentiment measures to be conditioned by the state of the market. The two crises also affect the nature of the relationship between large traders' net positioning changes – represented here by the unexpected level component – and next-day index returns.

Although the direction is reversed, the two crises have, once more, opposing effect on this relationship. Whereas the norm suggests that commercial traders may receive price concessions perhaps in exchange for short-term liquidity, this norm is reversed during the dotcom episode. Once more, I therefore call into question the current use of traditional COT measures in forecasting.

In addition, my evidence does not support Keynes' (1930) hedging pressure hypothesis or speculators' superior market timing ability documented by Wang (2003). On the other hand, my findings are consistent with Fishe and Smith (2012) in suggesting that commercial traders often provide market liquidity at the demand of their noncommercial counterparties whilst being relatively less informed. Furthermore, results from a contemporaneous correlation analysis between specialist traders' net positioning changes and index returns highlight asset managers and dealers' role as commercial hedgers who position their trades in response to market returns. As for hedge funds, the lack of significant correlation between hedge funds' net positioning changes and contemporaneous weekly returns appears to undermine the idea that they are chasing returns and may suggest a relative information advantage at intraday frequency. This is further corroborated by the fact that hedge funds' unexpected net positioning levels are positively correlated with reporting-day returns. These findings are in line with Fishe and Smith (2012) but the issue of which class of specialist traders is more informed, over precisely what horizon and, more importantly, what is the source of their comparative advantage and its stability through time is far from being settled. As more COT data on specialist trades becomes available, more research is needed in order to answer these questions. Last but not least, I show that trading signals based on a popular position-based sentiment index fail to deliver significant average returns over our period of study.

In Chapter 3, I provide empirical evidence highlighting the impact of short-sellers' trading activities on the behaviour of post-shock returns using Savor's (2012) regression framework. Consistent with the Diamond & Verrecchia (1987)'s model, I find shortable price events exhibit less price drift/reversals in post-shock returns than non-shortable ones, indicating that there is an increase in price efficiency when short-selling bans are removed. Among the shortable price events, more aggressive short-selling during informed large price drops is associated with less post-shock downward price drift; moreover, extreme levels of short-covering volume are associated with negative reversals on day one immediately following the price event days. Further analysis of the contemporaneous correlation between short-sellers' trading activities and abnormal price changes on the actual event days, reveals that short sellers seek to increase their short exposure as the magnitudes of informed price drops expand and reduce their short exposure as the magnitudes of uninformed price shocks become more extreme.

Overall, my results suggest that short sellers are successful and active in trading informed price events in which they exploit short-term underreaction in stock prices to new information. They are less successful in trading uninformed ones in which they bear the risk of suffering losses when overshooting in stock prices becomes extreme. This finding adds to the current understanding of the impacts of short sales on stock returns by highlighting the importance of information content in dictating short sellers' trading. It also contributes to the growing literature on investor over- and underreaction by showing the roles short-constraints and short sales might have in shaping these anomalies. For financial market regulators in mainland China, this study provides empirical evidences to support the on-going efforts of reducing short-sale constraints.

In Chapter 4, I examine investors' reaction to stock market rumours by using data from China where listed companies are required to clarify rumours appearing in the media. Rumours that are denied by the listed companies are considered to be false rumours, which contain little information about fundamentals, and rumours that are not denied are considered to be information-based. Investors' responses to rumours are measured by the abnormal price changes over a pre-clarification period. Savor's (2012) regression formulation is applied to test whether investors' responses have predictive value on post-clarification stock returns. My results indicate that post-clarification abnormal returns exhibit continuation of pre-clarification abnormal returns for undenied rumours and reversals for denied ones. These results suggest that investors are unable to distinguish between reliable and unreliable rumours, as they appear to under-react to rumours containing material information and over-react to those without. Further regression analyses on post-clarification abnormal returns using various subsamples of rumour events show that the under- and over-reaction effects persist across favourable and unfavourable, bull and bear, and other rumour subsamples. However, abnormal returns are less manifest or insignificant for rumours associated with the designated news media, asset restructurings, and large firms. The latter finding suggests that investors respond more efficiently to rumours when they are more informed about news topics or the rumoured companies.

In addition, Charter 4 contributes to two distinct branches of the current literature. Prior studies on the predictability of stock returns following large price changes have not considered investors' capacity in processing rumours, while prior studies on stock market rumours have not used the under- and over-reaction effects to examine investors' reaction to rumours. Results of my study are consistent with the previous analyses conducted by Pritamani & Singal (2001) and Savor (2012), which show that investors tend to under-react to information-based events, but are at odds with De Bondt & Thaler's (1985) over-reaction hypothesis. The results also provide an empirical support for DiFonzo & Bordia's (1997) experimental finding which shows that investors trade rumours as if they are news. My study also extents the prior study of Yang & Luo (2014) on stock price adjustment to rumour clarification announcements during the bull and bear market periods in China by showing that the post-clarification regularity is predicted by investors' initial reaction to rumours. Finally, my study offers an explanation for the contrasting results found in Patel & Michayluk (2016), which claims that the over-reaction effect is absent among large-size companies listed in ASX, and the prior studies of Pritamani & Singal (2001), Chan (2003), and Savor (2012).

At last, the results of Chapter 4 have important implications for both financial professionals and stock market regulators in China. They demonstrate that traders may improve their momentum trading strategies by following information-based rumours and by adjusting the sizes of their trades according to investors' initial reaction to rumours. They suggest stock market regulators in China should consider imposing more controls on Internet and common news media, as investors appear vulnerable to false rumours emanating from these sources.

One limitation of the study in Chapter 4, however, is that only binary indicators are used to characterize rumours. In practice, each rumour characteristic can be categorized into multiple levels, and each may have particular implications on investors' reaction to the rumour. Further study is required to look into the details of these rumour characteristics for further patterns that may reveal the precise circumstances in which investors make mistakes in processing the pricing implications of stock market rumours.

References

De Bondt, W.F.M. & Thaler, R., 1985. Does the Stock Market Overreact? Journal of Finance, 40(3), pp.793–805.

Chan, W.S., 2003. Stock price reaction to news and no-news: drift and reversal after headlines. Journal of Financial Economics, 70(2), pp.223–260.

Chung, S.-L., Hung, C.-H. & Yeh, C.-Y., 2012. When does investor sentiment predict stock returns? Journal of Empirical Finance, 19(2), pp.217–240.

Diamond, D.W. & Verrecchia, R.E., 1987. Constraints on short-selling and asset price adjustment to private information. Journal of Financial Economics, 18(2), pp.277–311.

DiFonzo, N. & Bordia, P., 1997. Rumor and Prediction: Making Sense (but Losing Dollars) in the Stock Market. Organizational Behavior and Human Decision Processes, 71(3), pp.329–353.

Fishe, R.P.H. & Smith, A.D., 2012. Identifying informed traders in futures markets. Journal of Financial Markets, 15(3), pp.329–359.

Patel, V. & Michayluk, D., 2016. Return predictability following different drivers of large price changes. International Review of Financial Analysis, 45, pp.202–214.

Pritamani, M. & Singal, V., 2001. Return predictability following large price changes and information releases. Journal of Banking & Finance, 25(4), pp.631–656.

Savor, P.G., 2012. Stock returns after major price shocks: The impact of information. Journal of Financial Economics, 106(3), pp.635–659.

Wang, C., 2003. Investor sentiment, market timing, and futures returns. Applied Financial Economics, 13(12), pp.891–898.

Wolff, A.F., 2013. Investor sentiment and stock prices in the subprime mortgage crisis. Applied Financial Economics, 23(16), pp.1301–1309.

Yang, X. & Luo, Y., 2014. Rumor Clarification and Stock Returns: Do Bull Markets Behave Differently from Bear Markets? Emerging Markets Finance and Trade, 50(1), pp.197–209.