Macrothink Institute™

Asian Journal of Finance & Accounting
ISSN 1946-052X
2009, Vol. 1, No. 2: E2

Price–Performance and Liquidity Effects of Index Additions and Deletions: Evidence from Chinese Equity Markets

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Abstract

We investigate the impacts of index revisions on the return and liquidity of Chinese equities, using a sample of 69 stocks added to or deleted from the S&P/CITIC 300 index over the period October 2004–August 2007. Our findings show that stock prices respond positively to index additions, and negatively to index deletions. Furthermore, our study provides evidence in support of a long-term improvement in liquidity for both stock additions and stock deletions. Overall, the results are largely consistent with prior empirical findings, and also appear to be in line with the predictions of some behavioral finance models.

Keywords: Chinese equity market, Index additions and deletions, Abnormal returns, Liquidity changes

JEL Classifications: G14, G15

1. Introduction

Modern portfolio theory has demonstrated the importance of international diversification in selecting an optimal portfolio. Emerging markets are attractive alternatives for international diversification, offering substantial potential rewards in added return, and the opportunity to reduce diversifiable risk. Previous studies from emerging economies suggest that stock returns are homogeneous within each market, as the stocks move closely together, and heterogeneous externally because of the low correlation that they have with returns in developed markets. As a result, investing in funds that mimic emerging market equity indices is a viable diversification choice for fund managers in developed countries.

China is the world's biggest emerging economy and its exceptional economic growth rate over the past two decades has been largely boosted by foreign investments. Most of these investments are in direct form (FDI)[1]. China began to open its market to indirect (portfolio) investment in 1990s. Concerned that capital flows might "destabilize" markets, China initially restricted access by foreign investors, establishing separate classes of shares for domestic investors (A shares) and for foreigners (B shares). Other than proprietorship, these shares are legally identical, with the same voting rights and dividends. The rule changed in March 2001 when domestic investors were allowed to trade B shares as well. Apart from investing in B shares, foreigners may also now invest in H shares—the shares listed on the Hong Kong stock market. In 2003, the Chinese government also introduced the Qualified Foreign Institutional Investors scheme[2] that allowed for the entry of foreign investors into the domestic A-share market. In the light of these developments, more and more foreign investors have become interested in investing in the Chinese markets.

[1] China is now the world's second largest host for foreign direct investment, after the United States.

[2] Financial Times reported on July 1, 2003 (p. 19) that qualified foreign institutional investors (QFII) include UBS Investment Bank, Morgan Stanley, Nomura Securities, Goldman Sachs, and Citigroup, which all began to invest in Chinese A-shares.

Investors seeking international diversification by investing in China may consider “indexing” as a cost-effective and logical step toward achieving their goals. According to indexing rules, a fund manager attempts to replicate in his portfolio the result of the investment target by holding all, or in the case of very large indices, a representative sample of stocks. Although indexing is generally considered a passive investment strategy, index fund managers must actively minimize the tracking errors[3] of their portfolio as a result of changes in the composition of the indices that they follow[4].

In response to the accelerating trend to create index funds, or to have benchmarks by which the performance of fund managers can be evaluated, several equity indexes have been developed for China. These include the FTSE/XINHUA 400 index covering both China’s A share and B shares and the S&P/CITIC 300 index, which gauges the broad market performance of China’s A-shares universe, comprising over 1200 stocks traded on the Shenzhen and Shanghai exchanges.

Conventional finance theory based on the efficient market hypothesis (EMH) considers shares with identical risk and return as perfect substitutes for each other. This makes market demand for securities elastic and horizontal, implying that changes in the composition of equity indices, which may cause an increase or decrease in demand for shares, would have no impact on share prices. Empirical evidence, however, documents that index changes can put upward or downward pressure on share prices and abnormal returns are found when stocks are added to or deleted from an index. Positive abnormal returns are usually associated with index additions: increases in demand by index fund managers, who must adjust their portfolio

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[3] Tracking error is defined as the annualized standard deviation of the difference in returns between an index fund and its target index.

[4] The composition of an index can change due to various factors such as mergers or acquisitions, bankruptcy, restructuring and lack of representation. Changes can also occur when firms are dropped from an index due to poor performance and loss of status in the industry. Alternatively, they may be added to an index due to their superior performance and elevated status in their industry.

weights, push stock prices up. On the other hand, index deletion usually leads to negative price reaction, due to a decrease in demand by index managers for the stocks. Index additions and deletions have attracted considerable interest from academics and practitioners because of their implications for the EMH. When a market is efficient, prices move randomly, implying that index revision events reduce the ability of investors to profit from the anomalies.

There are two theoretical perspectives on the effects of stock addition and deletion: (i) a demand-based explanation; and (ii) an information-based explanation. The demand-based explanation sees index changes as information-free events. For example, Shleifer (1986), employing the downward-sloping demand curve hypothesis, showed that the price effects following the index changes are due to the demand from index tracking. These effects can be temporary or permanent. The temporary effect is explained by the price pressure hypothesis, predicting a reversal of initial price increases in the long run (Harris and Gurel, 1986). The permanent effect is explained by the imperfect substitute hypothesis, which assumes that there would be no price reversal, as the new price reflects changes in the distribution of security holdings in equilibrium[5].

Information-based explanations include the information hypothesis and the liquidity hypothesis. Unlike the demand-based explanations, information-based explanations assume that index changes are not information-free events. Some studies, such those by Dhillon and Johnson (1991) and Jain (1987), support the information hypothesis: they show that the addition of a stock to the index conveys favorable news about the firm's prospects and a permanent price increase can result following the stock addition. Amihud and Mendelson (1986), Beneish and Whaley (1996), and Hegde and McDermott (2003) contend that the price reactions can be explained by changes in market liquidity. According to the liquidity

[5] Refer to Beneish and Whaley (1996), Lynch and Mendenhall (1997), Kaul et al. (2000), and Wurgler and Zhuravskaya (2002) for more details.

hypothesis, the price increase at index inclusion is from the increased liquidity due to the greater visibility of the stock when it is added to the index, greater interest from institutional investors, higher trading volume, and lower bid–ask spreads. Amihud and Mendelson (1986) suggest that the increase in stock liquidity is positively related to the firm's value through the reduction in the cost of capital (Becker-Blease and Donna, 2006). Previous studies, such as Harris and Gurel (1986), and Hegde and McDermott (2003) report liquidity increases following S&P500 index additions, while deletions appear to reduce liquidity.

The above theories largely explain the impacts of S&P index additions and deletions in the context of symmetric excess returns. However, price responses to index revisions are not always symmetric. According to Merton (1987), index inclusion can increase the recognition of a firm, leading to increases in its value as investors use it to construct their optimal portfolios. However, index deletions are not necessarily accompanied by reduced recognition, causing asymmetric price effects. Chen et al. (2004) studied the S&P 500 index and revealed a permanent increase in the price of added firms and a temporary decline in the price of deleted firms. They explained this asymmetric effect by the investor awareness hypothesis, suggesting that an index addition can potentially lead to investor awareness due to enhanced monitoring and reduction in the information asymmetry component of the bid–ask spread. However, index deletion does not necessarily lead to a reduction in investors' awareness to prompt negative abnormal returns. Elliot et al. (2006) found more evidence in support of the investor awareness hypothesis. From an analytical survey of all existing theories on index additions to the S&P 500 index, they found that increased investor awareness is the primary factor behind the cross-section of abnormal announcement returns. Hacibedel (2007) also found a permanent long-term price impact for index additions, but not for deletions. This is consistent with the findings of Chen et al. (2004). However, Hacibedel attributed this asymmetry to the mild segmentation of emerging markets. According to this hypothesis, the inclusion of stocks in a global benchmark index intensifies the process of companies' integration in the world markets, enhancing their stocks' returns, while, this does not happen when stocks are deleted from an index[6].

The objective of this study is to examine the efficiency of the Chinese equity market in reaction to index additions and deletions. More specifically, the focus of our research is to:

i. Investigate the effects on the price, performance and liquidity of the Chinese equity market resulting from the addition of stocks to and deletion from the S&P/CITIC 300.

ii. Discuss which explanations raised by previous research best explain the effects on the Chinese market of stock additions and deletions.

Since our findings are not entirely consistent with previous studies, we have also attempted to provide other possible explanations for price and liquidity changes caused by index revisions in the Chinese equity market.

Several factors motivated our research. First, existing research from developed markets interprets results inconsistently and offers competing explanations. For instance, Shleifer (1986) suggested that the positive stock reaction to index addition is consistent with the imperfect substitute hypothesis, in which the effect persists in the long term, while Harris and Gurel's (1986) study supports the price pressure hypothesis, predicting a reverse in the price increase effect. Jain's (1987) results support neither the imperfect substitute hypothesis nor the price pressure hypothesis, showing that the index changes are not information free. Furthermore, evidence from Dhillon and Johnson's (1991) research is consistent with the imperfect substitute hypothesis and the information hypothesis, but not with the price pressure hypothesis. Thus, there is a need for further research to find more compelling evidence on the impacts of index additions and deletions on share prices.

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[6] Mild segmentation refers to markets which fall in between segmentation and integration. Errunza and Losq (1985) conducted a theoretical and empirical investigation of the implications of investment under mild segmentation. We plan to examine whether Chinese markets are mildly segmented in a separate study.

Second, studies of index additions and deletions on emerging markets are rare. Noticeable exceptions are the papers by Hacibedel and Bommel (2006), and Hacibedel (2007) who investigated the performance of stock additions to the Morgan Stanley Capital International Emerging Market Index (MSCI EM) for 24 countries[7]. However, they explained the overall response of emerging markets to the index changes. Our study examines the specific characteristics of a single emerging market, the Chinese stock market.

Third, previous studies indicate that there are significant differences in the character of price processes in emerging countries as compared with those seen in developed markets. Emerging markets are generally considered to have higher volatility, higher long-term returns, higher transaction costs, and greater predictability (Bekaert and Harvey, 1997). Chan et al. (2007) also portrayed Chinese financial markets as imperfect and incomplete markets, with high transaction costs and information asymmetry. These differences can have pronounced impacts on the magnitude of excess returns due to index additions and deletions. As a result, it would be interesting to see how findings of such event studies on emerging markets differed from those presented in the studies that are based on mature markets.

Fourth, S&P/CITIC inclusions are expected to attract more foreign investment into China. Since foreign investment in emerging economies is much more important than in developed economies, stock inclusion in the internationally recognized S&P/CITIC 300 index can have more profound price and liquidity impact than stock inclusion in a mature market. This study provides an opportunity to test how price and liquidity effects of index inclusion in China are different from those in mature markets.

Fifth, the Chinese equity market was very volatile during our study period, even compared with other emerging markets, and when global capital markets were exhibiting extremely low volatility. Friedmann and Sanddorf-Köhle (2002), who analyzed volatility dynamics in the Chinese stock market, found that good news increases volatility in B-share indices more than bad news does. If the market interprets stock additions as good news and stock deletion as

[7] They found evidence of positive (negative) permanent price impacts upon index inclusion (exclusion).

bad news, then stock additions can increase the volatility of returns more than stock deletions can[8]. The asymmetry in volatility is translated into the degree of statistical significance of cumulative abnormal returns coefficients. By conducting this study, we should be able find out how the statistical significance of these coefficients varies across index additions and deletions in the Chinese equity market.

Finally, this research is motivated by the importance, the scale of growth, and the increased public attention to the development of Chinese economy. This has made investors increasingly look towards the Chinese equity market as a source of higher returns and further diversification. As a result, studies like ours are expected to add to the stock of information investors require to help them to make a better investment decision.

The rest of this study is organized as follows: Section II outlines our methodology, data and hypothesis development. Empirical findings are discussed in Section III. Section IV articulates our conclusions, and describes the limits of our study.

2. Data and Methodology

2.1 Data

The data used in the present study were sourced from S&P/CITIC Index Information Services Co., Ltd. and DataStream. Data series consisting of daily stock prices, bid and ask prices, and volume of trade were collected from DataStream. The rest of the data, such as the announcement dates of the additions and deletions, and daily index time series, were collected from S&P/CITIC Index Information Services Co., Ltd.

[8]According to Kyle (1985) and several other studies, much of the information is revealed in the volatility of stock prices, rather than the prices themselves.

Our sample consists of 69 (69) S&P/CITIC listed firms that were added to (deleted from) the S&P/CITIC 300 index from October 2003 to August 2007[9]. Based on prior research, we used the following criteria to select our samples.

i. The firms were not involved in a merger or an acquisition event that led to their addition to or deletion from the S&P/CITIC 300 index.

ii. The firms' stocks did not split in the period during the study period.

iii. The firms had historical data available for a period commencing 150 trading days before and ending 150 trading days after the announcement dates.

We applied criteria (i) and (ii) to minimize the effects of confounding events. According to the information provided by S&P, the deleted firms in our sample were all removed for financial reasons such as unstable income and low profitability, and no company was involved in a merger or acquisition[10]. Criterion (iii) was used to make sure that there were sufficient pre-event and post-event data to determine the estimation periods.

It is interesting to note that criterion (iii) can introduce survivorship bias for the deletion samples because it excludes companies that collapsed following stock deletion and they are more likely to experience significant negative returns. Consequently, it is possible that estimated abnormal returns for the deletion samples in our study have become upwardly biased. However, this issue was unavoidable, because our tests required a certain number of post-event observations and we had to exclude companies with insufficient data.

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[9] There is also a smaller index called S&P/CITIC 50 whose constituents are the largest companies from the S&P/CITIC 300. From a portfolio diversification perspective, Seddik Meziani (2008) found that US investors seeking exposure to China stand to gain the most from funds tracking the S&P/CITIC 50 index than from those tracking the FTSE/Xinhua China 25 Index or the Halter USX China Index. However, the number of additions and deletions for this index was very small compared to S&P CITIC 300, so we could not use it in our study.

[10] One exception was the removal of SH600207, not because of financial problems this company had, but to provide space for ICBC SH601398 as a newly appointed public company.

The S&P/CITIC 300 index examined in this paper is one of several S&P/CITIC indices [11]codeveloped by Standard & Poor and CITIC Securities Company Ltd. (S&P/CITIC Index Information Services Co., Ltd.) for the China and the Chinese offshore markets. Its constituents consist of the 300 enterprises with the largest float-adjusted market capitalization and liquidity, drawn from the entire universe of listed A-share companies in China. The S&P/CITIC indices, in general, are weighted by market capitalization and provide a complete product for exposure to Chinese companies and the Chinese markets. They are calculated according to Standard & Poor's global index methodology, providing consistency, transparency and liquidity services for both Chinese and global investors. S&P/CITIC indices serve as investment benchmarks for the entire Chinese stock market and a variety of sub-markets. According to S&P policy, a stock addition is generally made only if a vacancy is created by a stock deletion. The selection criteria for the addition of a new constituent stock are consistent with those of other constituents, namely size, liquidity, profitability and sector representation. For deletion, a guiding principle of index management is the minimization of turnover among index constituents. The possible reasons for deleting a stock from the S&P/CITIC index include acquisition by another company, bankruptcy, and reorganization. A company may also lose eligibility criteria for stock inclusion due to size or liquidity requirements. S&P/CITIC indices only cover the Chinese A share market.

2.2 Methodology

2.2.1 Price Effect

To estimate abnormal share price returns, an event study methodology was applied. The estimated abnormal return is the difference between the realized return observed from the

[11] S&P/CITIC indices only cover the Chinese A share market. We also examined FTSE/XINHUA indices, because they cover both China's A shares and B shares. However, we did not obtain enough observations (only four) for B shares and they were too limited to warrant a meaningful outcome.

market and the benchmark return. The return to the market portfolio is estimated via both ordinary least square (OLS) and Scholes and William (1997) procedures. The latter method is usually used when stocks do not trade at the same level of frequency as the market index and OLS may produce biased beta estimates. This problem is exacerbated for infrequently or thinly traded stocks as the sampling interval is reduced[12]. The advantages of these models are that they control for the effect of market movements through the market portfolio, and also allow for an individual security's responsiveness as measured by beta. Return on the S&P/CITIC 300 index was used as a proxy for the market rate of return.

Defining an event date is an important issue in event studies. We defined the event date as the day that a stock is added or deleted from the S&P/CITIC 300 index. S&P/CITIC Index Information Services Co., Ltd. announces the stock addition and deletion after the close of trading, so the trading day following the day on which the index announcement is made is regarded as the event day. For each event, the return time series data are divided into an estimation period and an event window. The estimation time series data are used to calculate the benchmark parameters, and the event window period is used for computing prediction errors based on the estimated parameters. The abnormal returns are represented by the prediction errors. The abnormal returns over the event windows can be interpreted as a measure of the effect of the event on the value of the firms, which is reflected in their share price.

The length of the event window varies across prior studies. Dhillon and Johnson (1991) estimated the event window over the period starting 10 days before the event and ending 20 days after the event. Harris and Gurel (1986) extended the post event window by 10 days (–10, 30). Shleifer (1986) has symmetric pre-event and post-event windows, which are 20 days before to 20 days after the event. Since the Chinese market is relatively less efficient and the impact of events can last longer, we extended the event window from 30 days before to 45 days after the event. The asymmetric event window was chosen to examine the

[12] The frequency of trading declines with the reduction in the sampling interval.

longer-term effect of excess returns on post-event periods. However, it is likely that the analysis based on a long event window becomes biased by noise from other events, especially in such a large market in China. As a result, we repeated the tests based on shorter windows of (–5, 5), (–10, 10), (–20, 20) to make sure that our estimates are robust.

The normal returns of stocks are the expected returns if there are no events. The normal returns are estimated over a period of time outside the event window (Peterson, 1989). For applications in which the determinants of the normal return are expected to change due to the event, the estimation period can fall on both sides of the event window. In this study, the estimation period commences 150 trading days before and ends 150 trading days after the announcement dates, excluding the event period of day –30 to Day 45. As a result, the estimation period consists of Day –150 to Day –31 and Day 46 to Day 150. To avoid biasing the parameter estimates in the direction of the event effect, we did not allow the event period to overlap with the estimation period.

The following section describes the event study methodology that we used in our study. MacKinlay (1997), and Kothari and Warner (2004) have provided a survey of event study models, and we closely follow their papers to describe the models here.

We define the market model we used in our study according to the following equation:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \,, \qquad (1)$$

where:

- R_{it} is the return on firm i at time t.
- R_{mt} is the corresponding return on the S&P CITIC 300 Index at time t.
- α_i is the intercept term.
- β_i is a parameter that measures the sensitivity of R_{it} to the market index.

Asian Journal of Finance & Accounting
ISSN 1946-052X
2009, Vol. 1, No. 2: E2

- ε_{it} is a random variable that by construction has an expected value of zero, and is assumed to be uncorrelated with R_{mt}.

Beta for the Scholes and Williams (1977) model was estimated as follows:

$$\hat{\beta}_j^* = \frac{\hat{\beta}_j^- + \hat{\beta}_j + \hat{\beta}_j^+}{1 + 2\hat{p}_m} \tag{2}$$

where:

- $\hat{\beta}_j^-$ is the OLS slope estimate from the simple linear regression of Rjt on Rmt–1.
- $\hat{\beta}_j^+$ is the OLS estimate from the regression of R_{it} on R_{mt+1}.
- $\hat{p}_m$ is the estimated first-order autocorrelation of R_m.

As in OLS, the intercept estimator forces the estimated regression line through the sample mean:

$$\hat{\alpha}_j^* = \overline{R_{jEst}} - \hat{\beta}_j^* \overline{R_{mEst}}. \tag{3}$$

where:

- $\overline{R_j}$ is the mean return of stock j over the estimation period,
- $\overline{R_{mEst}}$. is the mean market return over the estimation period.

Using the estimates from equation (1), the abnormal returns of each security over a test period were estimated according to the following relationship:

$$AR_{it} = R_{it} - \left(\hat{\alpha}_i + \hat{\beta}_i R_{mt}\right) \tag{4}$$

where the coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$ are ordinary least squares estimates of α_i and β_i.

In addition, the average abnormal return (or average prediction error) AAR_t was calculated.

The daily abnormal returns were averaged using the below formula:

$$AAR_T = \frac{\sum_{j=1}^{N} A_{jt}}{N} \tag{5}$$

where T is defined as the trading days before the event date.

Over an interval of two or more trading days beginning with day T_1, and ending with day T_2, the cumulative average abnormal return is as follows:

$$CAAR_{T_1,T_2} = \frac{1}{N} \sum_{j=1}^{N} \sum_{t=T_1}^{T_2} A_{jt} \tag{6}$$

For each day in the event period, the cross-sectional variance of the standardized abnormal return is then calculated as follows:

$$S^2_{SAR_T} = \frac{1}{N-1} \sum_{i=1}^{N} \left(SAR_{it} - \frac{1}{N} \sum_{j=1}^{N} SAR_{jt} \right)^2 \tag{7}$$

The standardized cross-sectional test statistic is thus:

$$Z_T = \frac{TSAR_t}{N^{\frac{1}{2}} \left(S_{SAR_t} \right)} \tag{8}$$

The individual standardized cross-sectional test for market model abnormal returns is reported to perform well even if there is an increase in the variance within the event period, and the sample contains small and thinly traded companies (Boehmer et al., 1991)[13].

2.2.2 Liquidity Effect

Two proxies were used in our study to measure market liquidity, the bid–ask spread and the volume of transactions. The bid–ask spread represents the difference between prices quoted by a liquidity supplier to the buyer and seller of a security. An increase in the volume of trade and a drop in spread signal improvement in market liquidity. A problem with using the bid–ask spread for this purpose is that if events reveal important information and cause higher information asymmetry in the market, the bid–ask spread widens in the short term, making the long-term impacts of liquidity changes harder to measure[14]. An increase in bid–ask spread in a quote-driven market arises from the reaction of designated market makers as the adverse selection costs increase[15]. In order-driven markets (such as Chinese equity market), public limit traders raise their bid–ask spread in reaction to a higher adverse selection cost[16]. The

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[13] Index changes may result in an increase in the volume of trade, leading to an increase in return volatility.

[14] Many researchers discuss how asymmetric information and adverse selection costs affect the bid–ask spread in the market. Interested readers may refer to Aharoney and Swary (1980), Easley and O’Hara (1987), Glosten and Milgrom (1985), Glosten and Harris (1988), Rendleman et al. (1982), and Venkatesh and Chiang (1986), for previous empirical evidence.

[15] Of three components of the bid–ask spread, i.e., adverse selection cost, inventory cost, and order-processing cost, the first one is more directly affected by information asymmetry. According to Stoll (1989), as much as 43% of the bid–ask spread is due to adverse selection cost.

[16] The inverse relationship between adverse selection cost and liquidity is a central hypothesis in the theory of limit-order book markets. Earlier studies, such as one by Frey and Grammig (2006) provided empirical support for this theory. A direct relationship between adverse selection costs and bid–ask spreads was also established by Glosten (1994) Proposition 3. This author presented a theoretical model of price revisions due to the information conveyed by trading throughout the limit order book mechanism.

impacts of adverse selection costs on the bid–ask spread as the price of immediacy is similar in both trading systems (Chung, 1999)[17].

In the methodology of liquidity analysis, we closely follow Hegde and McDermott (2003), computing the percentage change in percentage bid–ask spread, and the percentage change in trading volume. We define the quoted percentage spread as the difference between the ask price and the bid price for each firm, divided by the midpoint of the spread. The midpoint spread is the mean of the ask price and the bid price for each firm. The ratio of the daily average percentage spreads (i.e., percentage change in percentage bid–ask spread) were constructed over various event intervals to their counterparts in the pre-addition/deletion period over trading days (–150, –16). If either the bid or the ask prices were less than zero, the quotes were omitted. We use a one-tail *t*-test to measure the statistical significance of this coefficient.

The volume of trade was computed as the daily average of the transaction size. We examined the mean of the daily trading volume ratios. The trading volume ratio (i.e., percentage change in trading volume) for a stock is defined as the ratio of average trading volume over the indicated event time interval to average trading volume in the preaddition or predeletion period. These volume ratios are more robust than examining trading volumes in levels as they control for the effects of large-volume stocks in each of our addition and deletion samples. The event intervals were the same as those for measuring the daily average percentage spread, i.e., (–150, –16). The statistical significance of the percentage change in the volume is also estimated according to the 1-tail *t*-test.

3. Results

In light of the insights we developed in the previous sections, we applied a number of tests for the evidence of abnormal returns and changes in liquidity due to S&P/CITIC 300 index

[17] According to Chung (1999) study, the cost of adverse selection in an order-driven market is between 30 to 34% of the bid–ask spread.

additions and deletions. Three of these tests are relevant to abnormal returns, two to the change in bid–ask spread, and two to the change in the volume of trade. Our findings have certain implications for the EMH, which predicts that stock prices reflect all publicly available information and market prices represent the fair value of the shares. If this hypothesis holds, any large-scale trade on shares because of index inclusion or exclusion will have no significant impact on their return and liquidity.

3.1 Price Effects

Table 1 and Table 2 present mean cumulative abnormal returns (CARs) for the added and the deleted firms, respectively. To test the robustness of our findings, we have used both the OLS market model and the Scholes–Williams market model as the benchmarks for estimating normal return. Our results show that the magnitudes of CARs and the level of their statistical significance from the application of two methods are similar. Nevertheless, we discuss the results from the Scholes–Williams model to avoid nonsynchronous trading bias, as shares in emerging equity markets are likely to trade less frequently.

Table 1 presents the estimated CARs for various intervals in the pre- and post-event periods. The coefficient for CARs, accumulated over the interval Day –30 to Day 0, is –5.93% and statistically significant at the 5% level. The CARs coefficient estimated over the shorter interval of Day –5 to Day 0, increases to –1.88% and remains statistically significant at the 5% level. CARs increase to the highest level of –0.83% on the event day (Day 0) and become marginally significant at the 10% level, then start to decline. This coefficient remains negative, although statistically insignificant, over the interval Day 0 to Day 30, then decreases to –3.24% over the interval Day 0 to Day 45 and becomes marginally significant at the 10% level. Figure 1 illustrates the continuous change in CARs over the event window, providing further support for the findings in Table 1. According to this figure, CARs show an upward trend starting on Day –14, reach their peak level on Day 13 and decline thereafter. Based on this evidence, we can conclude that the Chinese stock market response to index additions is positive, even though the estimated coefficients for CARs remain negative throughout the event period. A possible cause of negative CARs throughout the event period is market manipulation by informed traders.

Table 1. Cumulative abnormal return and relevant statistics for stock addition to the S&P/CITIC 300 index

	OLS market model		Scholes–Williams market model	
Intervals	**Cumulative abnormal return**	***t*-statistic**	**Cumulative abnormal return**	***t*-statistic**
(–30, 0)	–6.22%	–2.40**	–5.93%	–2.31*
(–5, 0)	–1.97%	–2.03*	–1.88%	–1.95*
0	–0.90%	–1.58$	–0.83%	–1.45$
(0, +5)	–1.54%	–1.65*	–1.32%	–1.37$
(0, +30)	–2.55%	–1.23	–2.59%	–1.25
(0, +45)	–3.56%	–1.59$	–3.24%	–1.41$

Symbols $,*, **, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a 1-tail test.

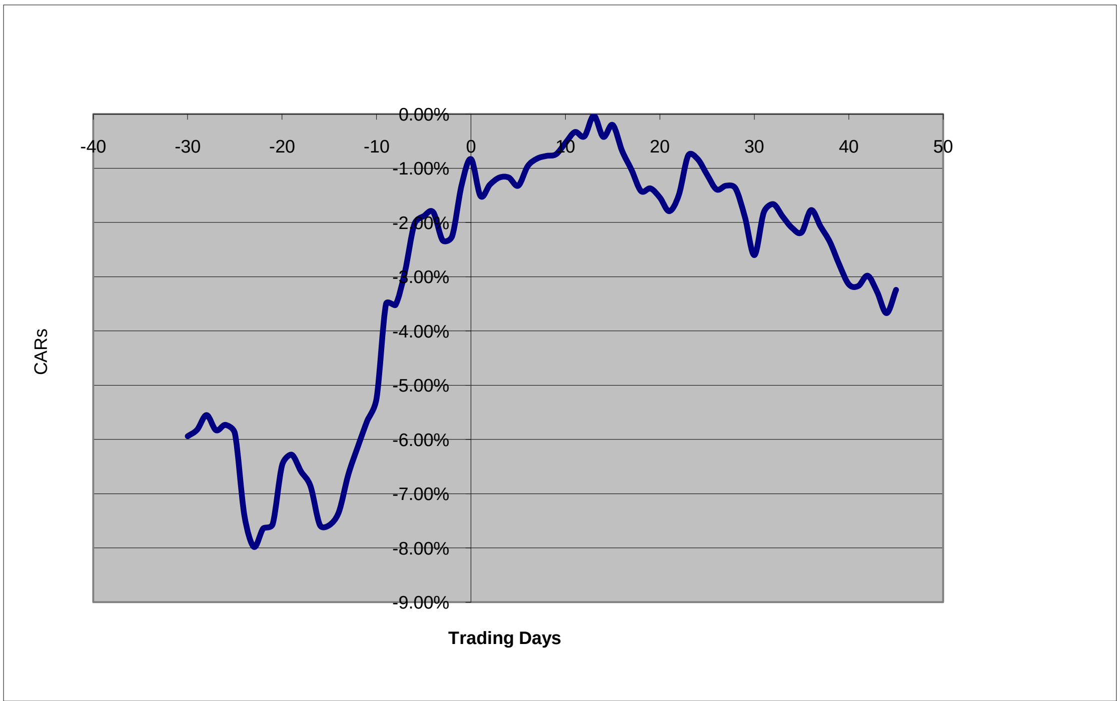

Figure 1. Cumulative Abnormal Return for Stock Addition to S&P/CITIC 300 Index During Event Period

Since the Chinese A share market is dominated by investors who possess little knowledge of stock investment, they can be easily manipulated by informed syndicate speculators (Kang et al., 2002), who send false signals to encourage sales of shares prior to an inclusion announcement and pose as buyers in the market. This can put downward pressure on prices, making excess returns temporarily negative. However, the announcement of the addition as good news leads other uninformed investors to buy the added firms back, causing stock prices to increase and provide syndicate speculators with some windfall profits. As reflected in Table 1 and Figure 1, negative CARs are less significant after the event, since the informed traders and the uninformed investors take opposite positions in the shares of the added firms. Buying the added firms partially offsets the negative effects of earlier selling behavior, making post-event CARs still negative, but statistically insignificant.

Table 2 - Cumulative abnormal return and relevant statistics for stock deletion from the S&P/CITIC 300 index

	OLS market model		Scholes–Williams market model	
Intervals	**Cumulative abnormal return**	***t*-statistic**	**Cumulative abnormal return**	***t*-statistic**
(–30, 0)	1.40%	–0.762	–0.70%	–0.37
(–5, 0)	0.84%	1.07	0.93%	1.14
0	–0.56%	–1.83*	–0.56%	–1.79*
(0, +5)	–1.26%	–2.18*	–1.27%	–2.09*
(0, +30)	–6.26%	–3.31***	–6.47%	–3.38***
(0, +45)	–4.35%	–2.27*	–4.74%	–2.47**

Symbols $,*, **, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a 1-tail test.

Table 2 documents the results for stock deletion from the S&P/CITIC 300 index. The estimated coefficient for CARs over the interval Day –30 to Day 0 is –0.70% and statistically insignificant. This coefficient becomes positive and remains insignificant over the interval Day –5 to Day 0. The abnormal return on the event day is –0.56% and significant at the 5% level. The estimated CARs decline continuously during the post-event period, reaching the minimum level of –6.47% over the interval Day 0 to Day 30, and become highly significant at the 0.1% level. The increase in the statistical significance of negative CARs during this period can be attributed to an increase in selling activities of informed traders in reaction to the stock deletions, and a corresponding decline in the volatility of returns. According to

Hellwig (1980) and Wang (1994), informed trading leads to a decline in the volatility of stock returns. However, as the dissemination of deletion information and selling activities decline over a longer period, this coefficient increases to –4.74% over the interval Day 0 to Day 45 and becomes statistically less significant at the 5% level.

Figure 2 shows the change in CARs due to index deletion and provides further evidence of the impact of such events on share prices. According to this figure, the decline in CARs starts on Day –17 and reaches the minimum level of –6.76% on Day 29, before rising to –5.00% on Day 45. Similar to stock addition arguments, positive coefficients for CARs in the

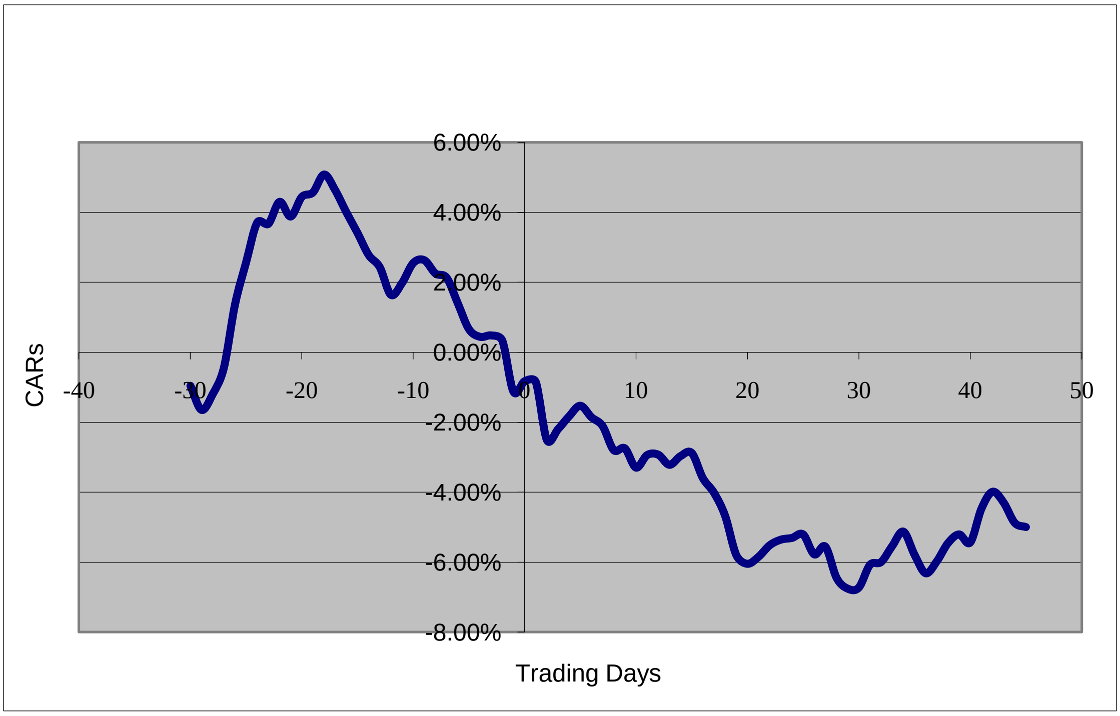

Figure 2. Change in Cumulative Abnormal Return For Stock Deletion from S&P/CITIC 300 Index During Event Period

pre-deletion period might have been caused by the spread of false information by syndicate speculators, encouraging uninformed investors to buy underperforming firms, pushing prices up. Once the deletion is announced, the overall market view about deleted firms is revised, leading to post-event negative effects. The evidence provided in Table 2 and Figure 2 is generally consistent with previous findings, suggesting that the Chinese market response to index deletion is negative.

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Table 3 – Cumulative abnormal return difference between stock addition to and deletion from S&P CITIC 300 index

Intervals	Cumulative abnormal return difference	*t*-statistic
(–30, 0)	–04.98%	–2.93***
(–5, 0)	–2.54%	–1.37$
0	0.00%	0.00
(0, +5)	0.21%	0.19
(0, +30)	4.14%	2.16**
(0, +45)	1.77%	0.98

Symbols $,*, **, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a 1-tail test.

If pre-addition negative and pre-deletion positive CARs are actually caused by the activities of syndicate speculators, then differencing this variable for the added and the deleted firms should partially neutralize the noise from these activities (canceling each other out as random errors), and reveal the impact of the index revisions more clearly. Table 3 shows the estimated coefficients for the CAR differences between the added and deleted firms during the event period. The estimated coefficient for this variable over the interval Day –30 to Day 0 is –4.98% and is statistically significant at the 1% level. It then rises and reaches 0.00 on the event day, then becomes positive during intervals after the event day. This coefficient reaches 4.14% over the interval Day 0 to Day 30 and becomes highly significant at the 1% level.

Figure 3 provides further evidence for the findings in Table 3. According to this figure, the estimated coefficient for CARs starts to rise from Day –15 and reaches its maximum level of 5.08% on Day 28 during the post-event interval, becoming highly significant at the 0.1% level. Based on the evidence in Table 3 and Figure 3, we can conclude that the estimated CAR differences between index addition and index deletion reduces noise and reveals the net impacts of these events more clearly.

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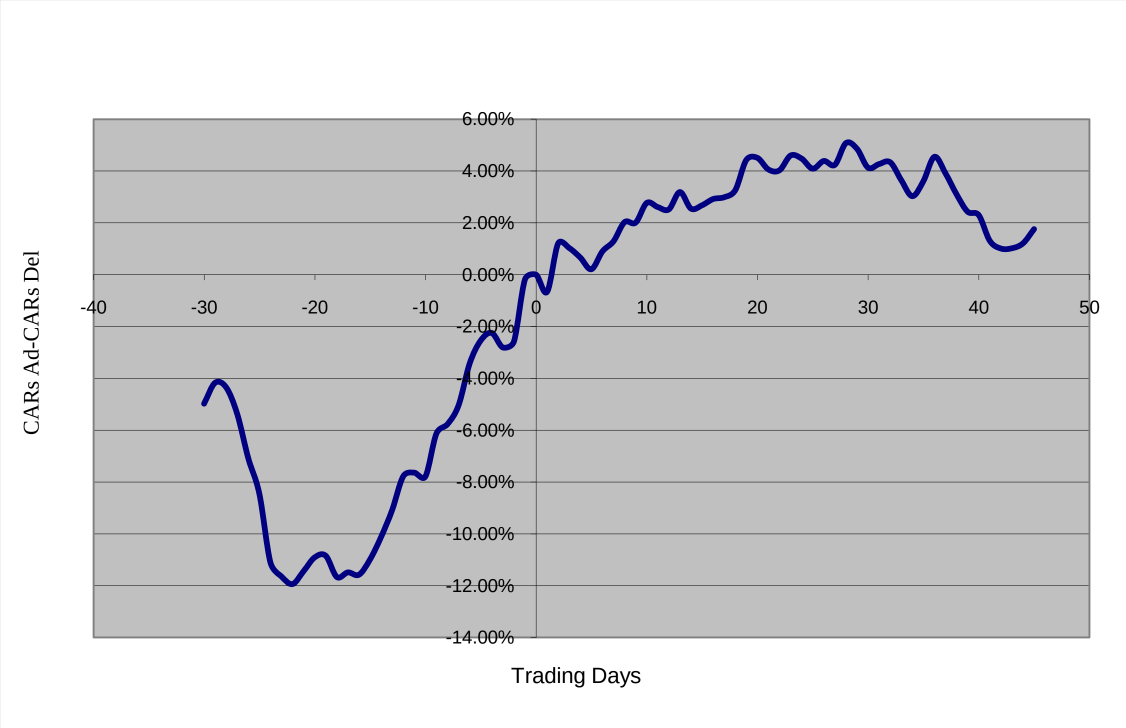

Figure 3. Cumulative Abnormal Return Difference Between Added Firms to and Deleted Firms from S&P/CITIC 300 Index During the Event Period

The prolonged effects of the index addition and deletion on CARs indicate that these events are likely to contain information, thus sending signals about the health of the added and deleted firms to the market. To test this hypothesis, we compared the cumulative returns for the added and deleted firms with cumulative return for the market over the period from Day –150 to Day 150[18]. Figure 4 shows the cumulative return for the added firms return and market return. The general trend shows that they both slope upwards; however, the added firms' performance is far better than the market, suggesting that these firms may have been added to the index due to their superior performance prior to the event. To the extent that their performance has led to their inclusion in the index, the stock addition cannot be considered an information-free event.

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[18] We believe that if index inclusion and exclusion contain information, this information must have been reflected in share prices earlier than the beginning of the event window and should extends for some time afterwards. As a result, we have used a sample of data that extends from 150 days before to 150 days after the event.

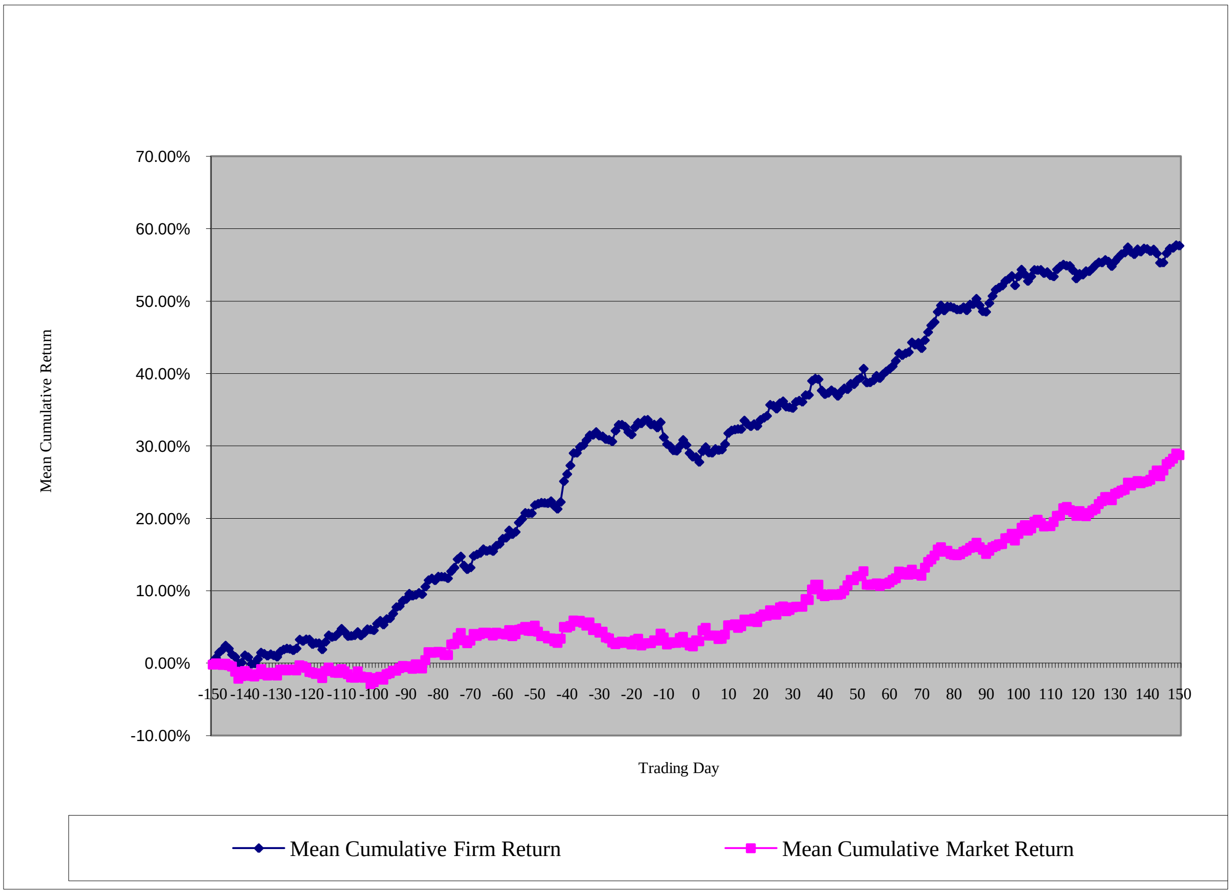

Figure 4. Cumulative Firm Return and Market Return for Stock Addition to S&P/CITIC 300 Index

The cumulative returns for the deleted firms compared with the market are shown in Figure 5. They show a positive upward trend for the market, whereas the returns for the deleted firms are largely negative and below the market return. This suggests that poor performance may have been the main reason for exclusion of deleted firms, and this event is not an information-free event. The evidence in Figure 4 and in Figure 5 largely rules out the demand-based explanations in our findings, as both the price-pressure hypothesis, and the imperfect-substitute hypothesis assume that index additions and deletions are information-free events[19].

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[19] Our interpretation of information effects in Figures 4 and 5 is based on the cumulative returns only. We have also estimated firms' and market performance risk-adjusted cumulative returns (cumulative return adjusted by standard deviation). For index additions, the risk-adjusted cumulative return for the firms is 10.742, compared

3.2 Diagnostic Tests

To diagnose any potential problems in our findings we examined the parameters of the applied models and the return distribution. We deemed this investigation necessary because the OLS market model applied in this study was developed under the EMH, with the assumption that the distribution of returns is normal. This assumption is more relevant to developed markets. However, the Chinese equity market is a newly developed market and thus less efficient than developed markets. As a result, the distribution of returns on shares might not be normal.

The normality of the distribution of returns on stocks was tested by investigating estimated skewness and kurtosis coefficients over the estimation period. Ignoring these elements will cause the model to understate the risk of the variables with high skewness or kurtosis. If the returns are not normally distributed because of the degree of skewness, or because the tails are too “fat”, *t*-statistics may not be valid. From our estimates, the skewness coefficient for addition is 0.04 and for deletion is –0.18. The kurtosis coefficient for addition is 0.31 and slightly higher than that of deletion (–0.01). These coefficients are all low and negligible. Based on these findings, we have concluded that our estimated *t*-statistics are reliable.

In another diagnostic test, we measured the magnitude of estimated betas to see how robust the market model is. According to this model, beta coefficients are a measure of a stock’s volatility in relation to the market. The betas in our study are measured over the estimation period, i.e., (–150, –31) and (46, 150). We thoroughly investigated individual betas for each firm and did not find any abnormality. The estimated average beta for addition (deletion) is 0.98 (1.13) and not significantly different from the theoretical value of 1. We also investigated whether the S&P/CITIC 300 index properly represents the Chinese stock market, compared with other proxies. We verified this question by investigating the properties of the

with 2.121 for the market. For stock deletions, the corresponding figures are 0.357 and 2.035 respectively. This provides further evidence that Chinese index additions and deletions are not information-free events.

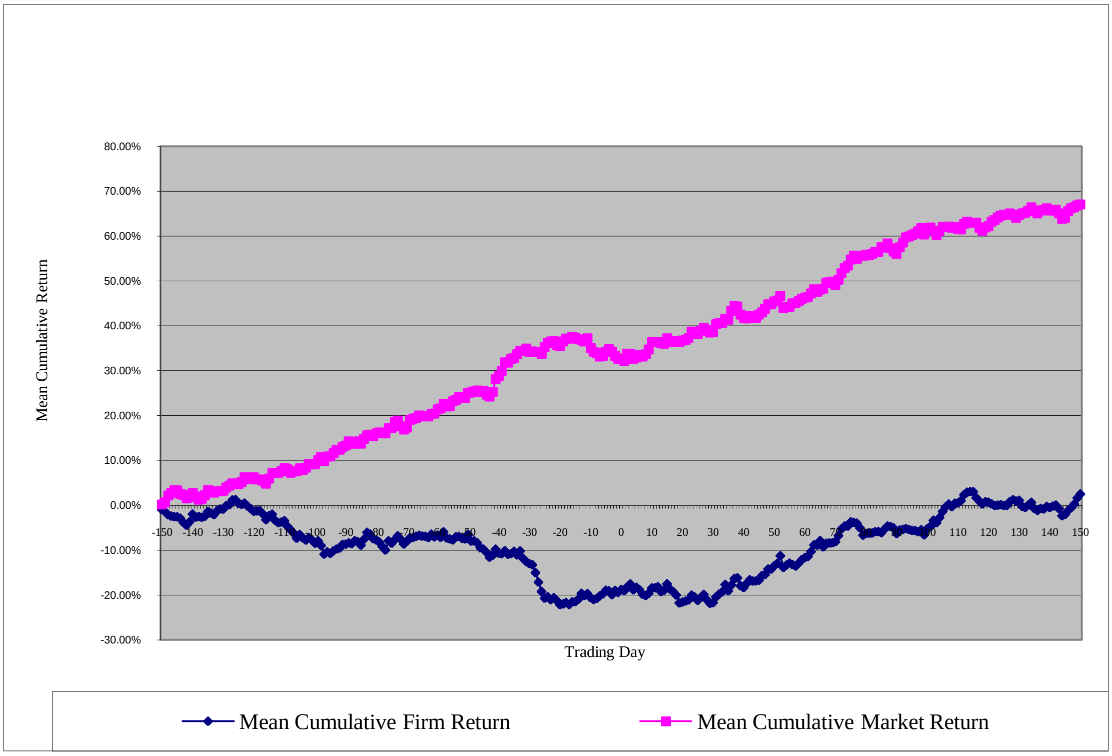

Figure 5 - Cumulative Firm Return and Market Return for Stock Deletion from S&P/CITIC 300

FTSE/XINHUA 400 index[20] as another proxy for the Chinese equity market. Our findings show that the correlation between the FTSE/XINHUA 400 index and the S&P/CITIC 300 index is very high (98.45%), and the results produced by using the FTSE/XINHUA 400 index are quite similar to those based on the S&P/CITIC 300 index. This leads us to believe that S&P/CITIC 300 index is a reasonable proxy for the Chinese equity market and the test results based on this index are robust.

As we discussed earlier, since it is possible that the analysis based on the long event window in Table 1 and Table 2 may be biased by noise from other events, we estimated CAR coefficients for shorter windows of (–5, 5), (–10, 10), (–20, 20), and the results are reported

[20] The FTSE/XINHUA 400 Index is one of the indices established by FTSE/XINHUA Index Limited (FXI), which is a joint venture between the global index provider FTSE Group and Xinhua Finance. The company was created to facilitate the development of financial indices for the Chinese market; it provides combined coverage of the Shanghai, Shenzhen and Hong Kong exchanges.

in Table A1 and Table A2 in the Appendix. These results are consistent with our findings in Table 1 and Table 2, suggesting that our tests are robust.

Table 4. Average daily percentage changes in percentage-spread and in the trading volume due to S&P/CITIC 300 index addition and deletion

		Addition		Deletion	
		Percentage change in percentage spread	**Percentage change in trading volume**	**Percentage change in percentage spread**	**Percentage change in trading volume**
Short term	**(–15, –1)**	40.26%***	14.39%**	4.10%	1.57%
		(3.35)	(2.34)	(0.36)	(0.44)
	(–10, –1)	47.02%***	21.73%**	6.93%	0.56%
		(3.90)	(2.90)	(0.58)	(0.14)
	(–5, –1)	54.78%***	19.87%*	11.82%	5.12%
		(3.58)	(1.70)	(0.83)	(0.81)
	(0, 5)	4.51%	80.88%***	4.16%	42.97%**
		(0.40)	(5.68)	(0.38)	(2.64)
	(0, 10)	19.53%$	58.64%***	3.29%	21.46%*
		(1.64)	(4.86)	(0.30)	(1.88)
	(0, 15)	23.44%*	42.32%***	3.23%	15.15%*
		(2.08)	(3.88)	(0.29)	(1.84)
Long term	**(16, 30)**	42.20%***	52.44%***	3.03%	40.37%***
		(3.46)	(6.39)	(0.27)	(3.96)
	(16, 45)	26.70%**	45.40%***	2.13%	48.08%***
		(2.37)	(7.51)	(0.19)	(7.51)
	(16, 60)	20.02%*	40.02%***	–0.37%	49.44%***
		(1.83)	(7.93)	(–0.03)	(10.06)
	(16, 75)	15.87%$	41.80%***	–1.49%	54.29%***
		(1.48)	(7.98)	(–0.14)	(12.08)

Symbols $,*, **, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a 1-tail test.

3.3 Liquidity Effect

In this section, we examine the liquidity effects of changes in the composition of the S&P/CITIC 300 index by calculating the percentage change in percentage spread and percentage change in trading volume of the added and the deleted firms. Tests were extended to different event windows to distinguish between the short- and long-term effects of the events.

According to the evidence in Table 4, both percentage changes in percentage bid–ask spread and percentage changes in the volume of trade are significantly positive prior to stock additions. The volume of trade reaches a peak of 21.73% over the interval Day –10 to Day –1, while the percentage change in percentage spread rises as high as 54.78% over the interval Day –5 to Day –1, and becomes highly significant at the conventional statistical levels. The percentage change in the volume of trade continues to increase after addition to its highest level of 80.88% over the interval Day 0 to Day 5, before declining to 42.32% over the interval Day 0 to Day 15. In the longer term, this variable increases again to 52.44% over the interval Day 16 to Day 30, then gradually declines to 41.80% over the interval Day 16 to Day 75 and remains highly significant at the 0.1% level throughout the post-addition period. Generally speaking, the magnitude of the percentage change in percentage spread declines in the post-addition period, reaching a peak of 23.44% in the short term over the interval Day 0 to Day 15, then increasing to its highest level of 42.20% in the long term over the interval Day 16 to Day 30, and becomes highly significant at the 0.1% level. The coefficient for this variable gradually declines to 15.87% over the interval Day 16 to Day 75 and remains significant at the 10% level.

Previous studies, such as that by Hegde and McDermott (2003), found that an increase in the volume of trade is accompanied by a decrease in the bid–ask spread following a stock addition to S&P 500 index. In our study, an improvement in liquidity is supported by an increase in the volume of trade in the entire event window; however, there is not a decrease in the bid–ask spread in the short-term[21]. The excess spread increases steadily before the announcement then starts to decline after the event. This outcome may have arisen from liquidity suppliers' behavior: they may revise their short-term bid–ask spread upwards due to

[21] This experience is not unique to Chinese market. Lakhal (2004) found similar pattern of change in the bid–ask spread around the event day in the (order-driven) French market.

increases in adverse selection cost. However, as asymmetric information declines over time, the bid–ask spread is revised downward. As a result, we can conclude that the changes in the bid–ask spread provide evidence of improving market liquidity in the long term.

For stock deletions, the percentage changes in percentage bid–ask spread is not significant prior to or after the event. On the other hand, the percentage change in the volume of trade continuously increases, reaching its maximum level of 42.97% over the interval Day 0 to Day 5, and becomes significant at the 1% level. This variable continues to rise to its highest level of 54.29% over the interval Day 16 to Day 75, and becomes highly significant at the 0.1% level. The trade volume increase following a deletion is not consistent with previous studies from developed markets; however, it is consistent with another characteristic of the Chinese equity market, which prohibits short sales. Baker and Stein (2002) suggested that, in a world with short-sales constraints, market liquidity can be a sentiment indicator. According to this view, an unusually liquid market is largely dominated by irrational investors who tend to under-react to the information embodied in either order flow or equity issues. Thus, high liquidity is a sign of positive sentiment among irrational investors, which may also have affected CARs in the event study tests.

On the other hand, differences in liquidity effects due to index addition and index deletion may have arisen from the extent of investors' awareness about the events. According to Chen et al. (2004) investors' awareness can increase following an index addition, but does not easily diminish following a deletion. This can lead to an upward revision of the bid–ask spread after an addition, but not an equivalent downward revision after a deletion.

Based on the evidence discussed so far, we can conclude that market reaction to a stock addition (deletion) has been generally positive (negative) because of an increase (decrease) in return and liquidity compared with a bench mark. However, these effects are not symmetrical. For instance, a comparison between findings in Table 1 and Table 2 suggests that the magnitude of the price response to additions is less than that for deletions. A comparison of Figure 4 and Figure 5 also shows that the drop in cumulative return for deleted

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stocks totally disappears around day 100 and the trend becomes horizontal for the rest of the study period, while for stock additions the positive trend in cumulative returns continues to Day 150, at a rate that is much higher than that of the market. The latter evidence suggests a permanent price increase for index additions, and a temporary price decline for deletions. These are consistent with the findings of Chen et al. (2004) for developed markets, and especially with the results of the investigations by Hacibedel and Bommel (2006), and Hacibedel (2007) for the emerging markets.

4. Conclusion and limitations

We have investigated the impacts of index addition and deletion on the price and liquidity of a sample of stocks that were added to or deleted from S&P/CITIC 300 index over the period October 2003 to August 2007. We used an event study methodology to estimate cumulative abnormal returns in the days surrounding the event for testing the price effect. Changes in liquidity of the added and deleted stocks were examined by comparing the percentage change in the percentage bid–ask spread and in the trading volume after the event, to a base period before the event.

Our findings for index addition show that cumulative abnormal returns (CARs) are negative before the event day, then start to increase and accumulate for several days after the event day. For deleted firms, CARs are positive before the announcement day, and then start to decline and become increasingly negative after the event day. We suspect that the significant negative (positive) CARs prior to addition (deletion) are caused by the flow of false information from informed syndicate speculators to uninformed investors, urging them to sell (buy) affected shares. This puts temporary downward (upward) pressure on stock prices and affects CARs accordingly. After the event, the uninformed investors revise their view about the added or deleted shares, causing an increase in CARs for the addition and decrease in CARs for the deletion.

Trend analysis based on the cumulative returns for the added and the deleted firms also reveals that stock addition or deletion is not an information-free event. It is, in a sense, the performance of the firms that leads to their addition or deletion in the first place. This rules out the demand-based (information-free) explanations of price change, leaving some room for the information hypothesis to partially explain the index revision effects.

Furthermore, we found evidence of improved liquidity for stock additions and deletions in the longer term. For stock additions, we found a significant increase in the bid–ask spread before the event and a decline after the event, while the volume of trade showed significant increases before and after the event. The positive change in the bid–ask spread in the pre-event period, despite substantial increases in the volume of trade, is attributed to the increase in uncertainty and asymmetric information around the event period. According to the adverse selection models, the bid–ask spread widens in reaction to the increase in asymmetric information if liquidity suppliers suspect that informed traders may benefit from superior information they possess at their expense. However, for stock deletion, the volume of trade increases without significant change in the bid–ask spread. This has been attributed to short-sale constraints by Baker and Stein (2002). According to this view, an unusually liquid market is largely dominated by irrational investors who tend to under-react to the information embodied in either order flow or equity issues. Thus, high liquidity is a sign of a positive sentiment by irrational investors, which may also have affected CARs in the event study tests.

Based on the evidence discussed in Sections 3.1 and 3.2, we can conclude that market reaction to a stock addition (deletion) has been generally positive (negative) because of an increase (decrease) in return and liquidity compared with a bench mark. However, these effects are not symmetrical. A comparison of findings in Table 1 and Table 2 suggests that the magnitude of the price response to the additions is less than that of the deletions. A comparison of the evidence in Figure 4 and Figure 5 also shows a permanent price increase for index additions, and a temporary price decline for the deletions. These findings are consistent with the findings of Chen et al. (2004) for developed markets, and especially with the results of the investigations by Hacibedel and Bommel (2006), and Hacibedel (2007) for the emerging markets.

Acknowledgement

The authors wish to thank two anonymous referees for their constructive comments on an earlier draft of this paper.

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Asian Journal of Finance & Accounting
ISSN 1946-052X
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Appendix

Appendix 1. Cumulative abnormal return for index additions during shorter event periods

Table A1. Cumulative abnormal return for stock addition to S&P/CITIC 300 index

	OLS market model		Scholes-Williams market model	
Event window	Cumulative abnormal return	*t*-statistic	Cumulative abnormal return	*t*-statistic
(–20, 0)	–6.58%	–3.787***	–6.45%	–3.703***
(–10, 0)	–5.28%	–3.926***	–5.19%	–3.881***
(–5, 0)	–1.96%	–2.029*	–1.85%	–1.921*
0	–0.89%	–1.552$	–0.80%	–1.392$
(0, +5)	–1.41%	–1.535$	–1.16%	–1.224
(0, +10)	–0.68%	–0.643	–0.39%	–0.367
(0, +20)	–1.46%	–0.914	–1.34%	–0.831

Note: the symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a 1–tail test.

Estimation period (–150, –21) and (+21,+150)

Appendix 2. Cumulative abnormal return for index deletions during shorter event periods

Table A2: Cumulative abnormal return for stock deletion from S&P/CITIC 300 index

	OLS market model		**Scholes–Williams market model**	
Event window	**Cumulative abnormal return**	***t*-statistic**	**Cumulative abnormal return**	***t*-statistic**
(–20, 0)	4.88%	2.493**	5.54%	2.732**
(–10, 0)	3.06%	2.632**	3.31%	2.819**
(–5, 0)	1.00%	1.257	1.15%	1.422$
0	–0.57%	–1.832*	–0.60%	–1.872*
(0, +5)	–1.25%	–2.133*	–1.44%	–2.383**
(0, +10)	–2.89%	–3.798***	–3.11%	–3.770***
(0, +20)	–5.40%	–4.158***	–5.47%	–4.075***

Note: the symbols $,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a 1-tail test.

Estimation period (–150, –21) and (+21,+150)