China Stock Markets: Does Technical Analysis Incorporating Data on Volumes and Returns Provide Additional Evidence of Return Predictability?

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Abstract

Several earlier studies using aggregate stock price indexes have found that China's stock markets are not weak-form efficient, based on the evidence of return predictability. To revisit this issue, the present paper uses 8 years' daily stock price data of 39 companies listed on the Shenzhen Stock Exchange to examine whether past volumes and returns have a useful role to play in predicting current returns. Both absolute volume data and relative volume data (which allow for different company sizes) are tried, but no evidence at all is generated in support of return predictability. To avoid the possibility that thin trading might be a cause of predictability, the adjusted return data are also used and the results remain qualitatively unaffected. Thus, it can be concluded that technical analysis incorporating data on volumes and returns does not provide additional evidence of return predictability for China's markets; that is, China's stock markets are weak-form efficient.

Key words: Trading volume, thin trading, weak-form efficiency, China stock market.

I. Introduction

There is a widespread belief that the weak-form version of Fama (1970)'s efficiency market hypothesis (EMH) holds for stock markets. In such an efficient market, current stock prices contain all the information carried by past prices, and so technical analysis based on past prices should not be able to help investors to trade profitably.

However, some earlier researchers argue that past stock prices may not be the only information carrier for technical analysts to utilize, since past trading volumes may also contain valuable information that the stock price dada omit (Blume *et al*, 1994). Therefore, in this paper, trading volume is considered to be another important information variable.

Before starting our formal analysis of the role of trading volume in predicting returns on China's stock markets, it is useful to review some of the previous studies on whether China's stock markets are weak-form efficient. The results of these studies are mixed. Some of them find that the weak-form version of EMH holds in China's stock markets. See, for example, Laurence *et al* (1997), Liu *et al* (1997), Long *et al* (1999). On the other hand, Mookerjee & Yu (1999) provide evidence that China's stock markets are not weak-form efficient. The above cited works all use aggregate stock price indexes. We revisit this issue of weak-form EMH by exploring individual shares and by incorporating trading volume into statistical analysis. It is possible that the presence of thin trading may cause bias to the test results for an emerging market such as China. To address this problem, we also take into account and thus correct for the possible impact of thin trading on return predictability in this research.

The rest of the paper is organised as follows. In Section I, we briefly outline the methodology used and present the results based on the absolute volume data. Section II extends the analysis to the relative volume data and reports the results. This is followed by Section IV, which offers some conclusions.

II. Methodology and Results

1. Data Sources

This research uses daily price indexes of 39 individual stocks on the Shenzhen Stock Exchange (SZSE) in China. The sample period spans from 15/08/1994 to 22/08/2002, in which contains a total of 2099 observations. The time series are obtained from DataStream®. The series of returns are calculated by differencing logarithmic prices once. The aggregate SZSE index is used to generate a market return series.

2. Handling Thin Trading

There are circumstances that stocks do not trade at some consecutive intervals. In China, these non-trading intervals may be due to public holidays, no or very few traders for the stock, listed companies being forced by the authorities to carry out rectification, and so on. Whatever reasons it may be, this problem is known as thin trading (Miller *et al*, 1994). Thin trading impacts on stock prices, in that the closing prices recorded at the period after a non-trading interval are the same as the prices before that period of intervals. If the thin trading problem is quite serious, significant return autocorrelation will result. This is why thin trading may cause bias to the test results, and the detected return predictability would lead to a misleading conclusion that the market is not weak-form efficient whereas it in fact is.

This research adopts the method used by Antoniou *et al* (1997) to handle the potential problem of thin trading. That is, an AR(1) model is used to remove autocorrelation caused by thin trading. More specifically, the adjusted stock returns are calculated using the following equation:

$$R_t^{adj} = e_t / (1 - \alpha_1) \qquad (1)$$

where R_t^{adj} denotes returns at time *t*, adjusted for thin trading;

e_t is the residuals from the regression model: $R_t = C + \alpha_1 R_{t-1} + e_t$;

α_1 is the first-order autoregressive coefficient from the same regression model.

Note that this regression model is estimated recursively by the Kalman filter algorithm to generate a time-varying α_{1t}, because for an emerging market it is plausible to assume that the required adjustment varies over time.

If the weak-form efficiency hypothesis holds, R_t^{adj} cannot be predicted on the basis of the past values. In other words, in the AR(1) model, $R_t^{adj} = c + \alpha_1 R_{t-1}^{adj} + \mu_t$,
α_1 equals 0.

Table 1 Stock Returns: $R_t = C + \alpha 1\ R_{t-1} + \mu t$

Stock #	Unadjusted Returns		Adjusted Returns	
	C	α_1	C	α_1
1	0.0456	-.0641 [b]	0.1080	-0.5358
2	0.0515	-0.0413	0.1735	0.0221
3	0.6898	0.0287	-0.8545	0.0142
4	0.0155	0.0305	-0.1847	-0.0136
5	0.0647	0.0373	-2.1569	-0.0001
6	0.0655	0.0057	8.4616	-0.0004
7	0.0731	0.0168	-0.0332	0.0060
8	0.0505	-0.0027	-12.5437	-0.0006
9	0.0470	-0.0073	0.8834	-0.0010
10	0.0905	-0.0183	-0.0856	0.0014
11	0.0151	-0.0467	-0.4060	0.0014
12	0.0297	-0.0058	-0.0264	0.0001
13	0.0252	0.0011	-4.2494	-0.0011
14	0.0774	0.0327	-0.5634	-0.0002
15	0.0476	0.0537	0.6599	0.0030
16	0.0378	0.0471	0.2699	0.0013
17	0.0261	-0.0155	-13.6573	-0.0001
18	0.0444	0.0285	0.9873	0.0006
19	0.0799	0.0371	0.1845	0.0010
20	0.0915	-0.0282	1.1028	-0.0004
21	0.0806	0.0609	-0.0314	0.0054
22	0.0974	-0.0003	-0.3097	0.1167
23	0.0879	0.1936[a]	0.9285	-0.0010
24	0.0377	0.0251	2.0994	-0.0003
25	0.0468	-0.0182	-1.0296	0.0058
26	0.0564	0.0037	-0.1729	0.0011
27	0.0519	0.0142	0.0252	0.0014
28	0.0564	-0.0252	-0.0958	0.0002
29	0.0151	-0.0467	-0.4060	0.0013
30	0.0816	-0.0147	0.8916	-0.0005
31	0.0578	-0.0311	-215.2100	-0.4773
32	0.0343	-0.0586	0.0004	-0.0017
34	0.0573	0.0139	-11.1860	-0.0005
35	0.0448	-0.0193	-1.2109	0.0009
36	0.0759	.0757[a]	0.2341	0.0014
37	0.0854	0.0198	0.2006	0.0024
38	0.0368	.0683[b]	-0.5108	-0.0054
39	0.0408	-0.0019	0.1118	0.0042

Note: [a] Significant at 5% level,
[b] Significant at 10% level.

In our research, after estimating an time-invariant AR(1) model for the unadjusted returns on 39 individual stocks, we find that only a few of them yield a significant autoregressive coefficient. This seems to imply that the thin trading problem might not be very serious in SZSE market, as the majority of returns even not adjusted for thin trading are already unpredictable. However, to obtain the results that are robust to other different circumstances, we decide to try both adjusted and unadjusted return series. Here, the adjusted return series of 38 (out of 39) stocks show no sign of significance in their autoregressive coefficients. Note, again, that, the standard errors of α_1's in Table 1 are based on a Newey-West corrected covariance matrix. The results indicate that only stock No. 33 is able to reject the null hypothesis ($\alpha_1 = 0$) for its adjusted returns. The null hypothesis cannot be rejected in the cases of other 38 stocks. Thus, their past returns (R_{t-1}^{adj}) cannot help predict their current returns (R_t^{adj}); in other words, the weak-form EMH holds for these 38 individual stocks, after the possible thin trading impacts are removed.

One might be wondering if adjustment for thin trading in the aforementioned way may have removed genuine return predictability due to market inefficiency all together with "false" return predictability due to market illiquidity. Antoniou *et al* (1997) provide a good example that this is not the case. They show that many adjusted returns, even if their autocorrelation coefficients are no longer significant, will still demonstrate predictability after taking into account the role of trading volumes. The predictability so detected is then genuine rather than false, according to our definitions implicitly given above.

Following the testing strategy of Antoniou *et al* (1997), these 38 stocks are then used to test whether their trading volumes will contribute to the predictability of their returns. This is practically implemented by forming portfolios on the basis of the trading volumes of each stock. We compute the monthly trading volumes of these 38 stocks. The most liquid 5 stocks will be incorporated into Portfolio 1, the next less liquid 5 stocks into Portfolio 2, and so on. There are totally seven portfolios so formed, ranked from the most actively traded to the least actively traded. Then seven series of portfolio returns (both adjusted and unadjusted) are computed to generate their daily observations. Since the degree of activeness of each stock varies over time, portfolios will comprise different stocks from month to month.

Moreover, in assessing how much of the "false" predictability is present, we carry out reasoning along the following two lines. First, if the "false" predictability is absent or very weak (i.e. if thin trading does not cause autocorrelation in [unadjusted] return series), no significant variations in the degree of predictability between portfolio unadjusted returns should be observed. And if predictability is still detected, it should be due only to the presence of market inefficiency which applies equally to most portfolios under investigation. If predictability is not detected, this should be taken as evidence of the market efficiency which, too, applies equally to most portfolios under consideration. Second, if the "false" predictability is dominant (i.e., if thin trading is a cause of autocorrelation in [unadjusted] return series), then the portfolios with the lower levels of volumes should have a more significant coefficient on lagged returns than portfolios with the higher levels of volume. This finding is due to Antoniou *et al* (1997), and is a useful ground on which to base our judgment.

Table 2 Portfolio Unadjusted Returns: $R_{pt} = c+\alpha_1 R_{pt-1}+ \mu t$

Portfolio #	Using absolute volumes		Using relative volumes	
	c	α_1	c	α_1
1	.0909	-.0017	.1313	-.0116
2	.0497	.0076	.0407	.0202 [a]
3	.0319	-.0090	.0161	.0038
4	.0311	.0047	.0863	.0059
5	.0390	.0015	-.4146	-.0266
6	.0699	.0067	.3327	.0008
7	.0635	.0082	.02906	-.0017

Note: [a] Significant at 5% level.

From the test results based on unadjusted portfolio returns (as in Table 2), it can be seen that nearly all the coefficients α_1's (except the one of Portfolio 2 when using relative volumes, which will be discussed later) are not significantly different from zero . In other words, there is no variation in the degree of predictability between the portfolios when using unadjusted returns. Therefore, it would be possible to draw correct inferences regarding the efficiency without adjusting for thin trading. However, it is still of interest to see whether the results would be different qualitatively if adjusted returns series were used. Robustness of the results is an important goal that our research seeks to achieve.

3. Analysis Incorporating Volume

To incorporate trading volumes into technical analysis is to see whether trading volumes contain some information relating to the fundamentals of companies that prices do not. If the answer is a Yes, then the conclusion of market efficiency drawn from the analysis of only price data needs to be reconsidered or even reversed. Following Antoniou *et al* (1997), we estimate:

$$R_t = c + \alpha_1 R_{t-1} + \beta R_{mt} + \varepsilon_t \qquad (2)$$

for both unadjusted and adjusted returns. R_{mt} denotes market returns on the SZSE stock index. The estimation uses instrumental variables which include lag 1 of volume and lag 2 of returns for lag 1 of returns. A measure of risk in the regression is represented by the variable market returns, and its inclusion can avoid spurious significance of the autocorrelation coefficient α_1 due to omitting market risk from the model (Antoniou *et al*, 1997).

The estimation results are reported in Table 3. Similar to the results presented in Table 1, none of the 38 individual stocks exhibits predictability of returns whether unadjusted or adjusted for thin trading. Accordingly, incorporating trading volumes into technical analysis of returns will not increase predictability of the stock returns. This suggests that on the individual stock level, the weak-form EMH holds in SZSE market, and technical analysis using information on both volume and returns is of no value.

Table 3 Individuals: $R_t=c+\alpha_1 R_{t-1} + \beta R_{mt} + e_t$

Stock #	Unadjusted Returns			Adjusted Returns		
	C	α_1	β	c	α_1	β
1	-0.001	0.117	1.073[a]	0.031	0.694	0.043
2	-0.011	0.067	1.037[a]	0.165	0.097	-0.092
3	-0.075	1.294	0.964 [a]	1.187	0.206	-0.376
4	-0.034	-0.018	0.915 [a]	0.135	1.775	0.118
5	0.004	0.129	0.988 [a]	-0.329	0.871	0.972
6	-0.001	0.117	1.073 [a]	8.329	0.027	-1.843
7	0.016	0.056	0.996 [a]	-0.016	0.582	0.045
8	-0.015	0.121	1.073 [a]	0.669	1.048	-1.314
9	-0.006	-0.025	0.961 [a]	1.103	-0.247	-1.346
10	0.028	0.158	0.847 [a]	-0.052	0.468	0.119
11	0.035	0.104	0.029 [a]	0.283	1.743	0.368
12	-0.025	-0.075	1.033 [a]	0.319	2.142	-0.341
13	-0.022	-0.123	.9085 [a]	-3.821	0.105	0.391
14	0.022	0.005	1.025 [a]	-0.264	0.632	1.084
15	-0.002	-0.065	1.012 [a]	0.323	0.557	-0.569
16	-0.008	-0.193	1.002 [a]	0.131	0.532	-0.087
17	-0.029	0.073	.9451 [a]	-10.07	0.252	-2.867
18	-0.018	0.146	0.912 [a]	1.060	-0.074	0.030
19	0.016	0.203	0.890 [a]	0.127	0.408	-0.339
20	0.053	-0.189	0.953 [a]	-0.245	1.177	0.940
21	0.053	-0.189	0.953 [a]	0.010	1.247	-0.051
22	0.031	0.110	0.995 [a]	-0.058	0.808	-0.014
23	0.009	0.390	1.05 [a]	-0.41	1.424	0.250
24	-0.017	-0.143	1.035 [a]	-0.467	1.222	0.020
25	-0.011	0.060	0.989 [a]	-0.645	0.387	0.175
26	0.006	-0.095	1.013 [a]	0.087	1.553	0.157
27	-0.003	-0.006	1.022 [a]	-0.021	1.162	0.315
28	0.010	-0.298	1.112 [a]	-0.003	1.148	0.332
29	-0.404	0.091	0.961 [a]	0.291	1.763	0.373
30	0.037	-0.072	0.898 [a]	0.727	0.181	0.073
31	0.011	-0.097	0.886 [a]	-347.9	-0.574	175.00
32	-0.015	-0.035	0.861 [a]	0.008	-0.020	0.171
34	0.016	-0.026	0.800 [a]	1.119	1.089	-2.432
35	-0.011	0.096	0.878 [a]	-0.379	0.551	-3.141
36	0.030	0.084	0.810 [a]	-0.261	2.063	0.208
37	0.036	0.040	0.854 [a]	0.523	-1.629	0.123
38	-0.013	0.113	0.792 [a]	-0.017	1.012	0.423
39	-0.008	-0.046	0.875 [a]	-0.016	1.229	-0.186

Note: 1. [a] Significant at 5% level,
[b] Significant at 10% level.

Furthermore, we look at portfolios to see if the above conclusions also hold on the portfolio level. As mentioned earlier, the seven portfolios are formed on the basis of trading volumes, and ranked from the most liquid to the least liquid. However, since the problem of thin trading has been found to be trivial, we expect the degree of return predictability when taking volume into account to be similar across these portfolios. More specifically, if volume does or does not help predicting returns, the results should not vary considerably across these portfolios just because they have different degrees of liquidity. Table 4 confirms the expectation. Although the values of α_1 do change from one portfolio to another, they are all insignificant even at the 10% level. In other words, at the 10% significance level, we can treat all seven α_1's to be zero. This implies that the conclusion reached for individual stocks applies to portfolios with different degrees of liquidity.

Table 4 Portfolio Unadjusted Returns: $R_{pt}=c+\alpha_1 R_{pt-1}+\beta R_{mt}+\varepsilon_t$

Portfolio #	Using absolute volumes			Using relative volumes		
	C	α_1	β	c	α_1	β
1	0.06674	-0.2356	0.87263 [a]	0.07211	0.05695	0.95926 [a]
2	-0.03166	0.43449	1.10240 [a]	-0.04068	0.56428	0.99562 [a]
3	-0.01937	-0.08492	0.97215 [a]	-0.01325	-0.34216	0.62838[a]
4	-0.04011	0.52742	1.0372 [a]	-0.00092	0.33268	1.11510 [a]
5	0.00185	-0.3867	1.01870 [a]	0.00469	-0.47738	1.01083 [a]
6	0.02973	-0.0809	0.88769 [a]	0.03524	-0.04351	0.89210 [a]
7	0.03824	-0.34667	0.91289 [a]	-0.02372	0.20982	0.89370 [a]

Note: [a] Significant at 5% level,

Table 5 Portfolio Adjusted Returns: $R_{pt}^{adj}=c+\alpha_1 R_{pt-1}^{adj}+\beta R_{mt}+\varepsilon_t$

Portfolio #	Using absolute volumes			Using relative volumes		
	c	α_1	β	c	α_1	β
1	-0.05212	0.90764	0.42128[b]	0.13134	1.40257	0.50557 [b]
2	-18.66790	0.61156	45.94860	-0.15340	0.00304	1.66984
3	0.03418	1.36660	0.20601	-1.03474	2.27015	-0.08214
4	0.01737	0.58013	0.04047	184.89600	5.23160	72.69690
5	-2.40668	-1.73660	0.63191	-0.38047	0.06466	0.05120
6	0.50877	3.10404	0.00039	-0.77243	3.30689	0.07822
7	-4.35853	-0.94940	-2.10137	-1.71721	0.01622	-0.94226

Note: [b] Significant at 10% level.

III. Some Extensions

Two extensions to the work reported in the preceding section were made. Here we only give a briefing on these extensions.

The first extension is that we tried various lags of volumes and returns as instruments for lag 1 of returns in estimating equation (2). The insignificance of the autoregressive coefficient α_1 remains unchanged in all cases (i.e. individual stocks and portfolios).

As a second extension, we used relative trading volumes instead of absolute volumes and went through the entire process of analysis as described in the previous section. The reasons are as follows why we also wanted to try on relative trading volumes (by dividing daily trading volume by the total number of shares in circulation). The sizes of the selected 39 companies for this study are vastly different, in that the total number of shares in circulation of each of them varies from 10 million to 1 billion.[1] This implies that daily turnovers might not accurately reflect the genuine liquidity of the shares issued by a company. For instance, on 16/08/1994, the number of *Wenergy Ltd-'A'* shares traded was 500,540. On the same day and the same market, *ChangChai Ltd-'A'* had 462,570 shares traded. At the first glance, one would say that *ChangChai Ltd.-'A'* was less liquid than *Wenergy Ltd-'A'* on that day, but this assertion may not necessarily be correct.

Table 6: Absolute and Relative Volumes - Two Examples

Date	Wenergy Ltd.		ChangChai Ltd	
	Absolute	Relative	Absolute	Relative
15-8-1994	2296	35.44444	4128.4	152.9037
16-8-1994	5005.4	79.45079	4625.7	171.3222
17-8-1994	1527.7	24.24921	2725.1	100.9296
18-8-1994	9985.3	158.4968	7119.5	263.6852

To generate the time series of relative volumes, we obtained from Stockstar[2] the daily data on total shares in circulation of each of 39 companies over the period 15/08/1994 to 29/08/2002.[3] Table 6 shows respectively the absolute and relative volumes of four days for the two companies taken as examples. It can be seen clearly that in terms of relative volumes, *ChangChai Ltd* was more than twice as liquid as *Wenergy Ltd* on 16/08/1994, in sharp contrast to the case of absolute volumes. One important implication of using relative volumes is that the seven portfolios formed on the basis of trading volumes will certainly change their component stocks. The question is: Will such changes affect our results qualitatively?

The answer seems to be negative. Referring back to Tables 2, 4 and 5, one can see that, except for one case, all other estimated autocorrelation coefficients α_1's remain insignificant indicating unpredictability of portfolio returns. The only exception is Portfolio 2 formed on relative volumes with the associated α_1 being significant at the 1% level (See Table 2). Note that it is unadjusted returns that were used in estimating the AR(1) model, which suggests that the significance of α_1 of Portfolio 2 is possibly due to the thin-trading problem and the use of adjusted returns should be considered. However, using adjusted returns (as well as unadjusted returns) together with relative volumes do not alter the conclusion that Portfolio 2's returns are unpredictable, as evidenced by the insignificant estimates of α_1 for this portfolio as presented in Tables 4 and 5.

The two extensions confirm that the results reported in the previous section are robust.

IV. Conclusion

Now it can be argued on the basis of the above results that the stock prices of listed companies in China SZSE market contains enough information about their fundamentals and performances. This is because incorporating an additional variable, trading volume, into technical analysis of returns does

[1] The company size used in this paper is measured by the total number of shares in circulation of a particular company. It should be noticed that not all shares but only a proportion of them issued by a state-owned or mainly state-owned company are allowed to be traded or to be put in circulation. (Fu *et al*, 1999).
[2] URL: stockstar.com.cn (URL, 2002).
[3] The number of shares in circulation may experience a sudden change due to splitting of the shares.

not help increase its ability to predict returns whether on individual stocks or on portfolios. Thus we are confident to say that volume does not contain additional information omitted by prices.

On the theoretical level, our findings based on company data suggest that China's stock markets are characterized by weak-form efficiency, challenging the findings of previous studies that employ aggregate stock price indexes. On the practical level, our findings warn those investors in China's stock markets that technical analysis, now very prevalent in the nation, is not to be trusted or counted on when making their portfolio investment decisions.

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