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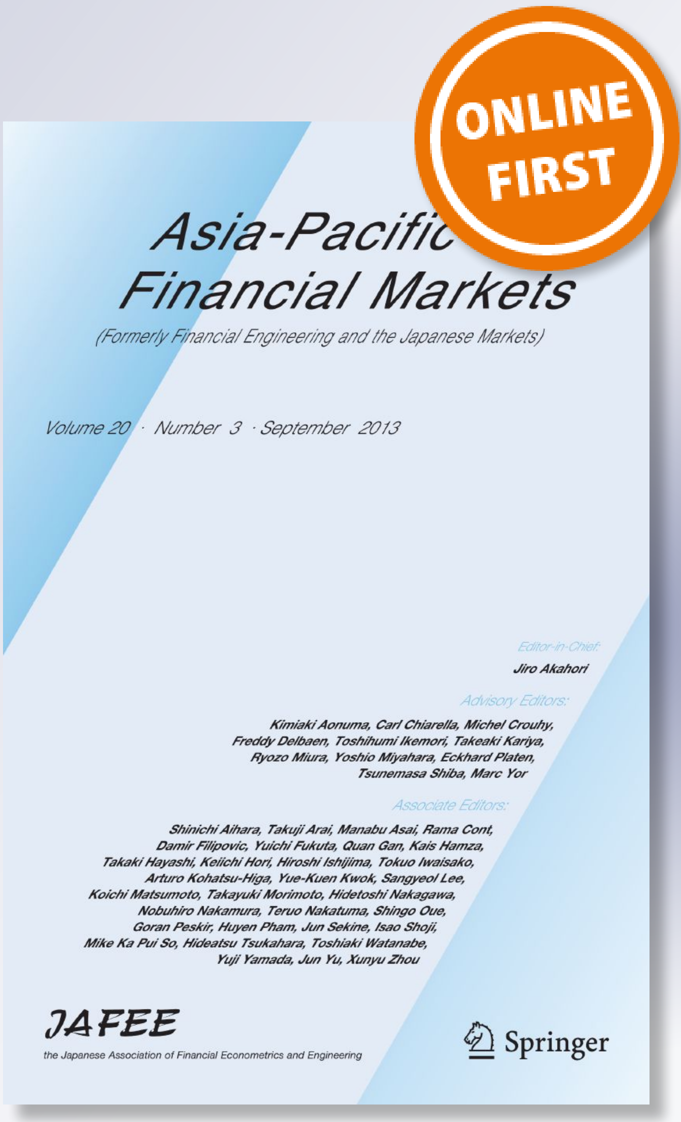
Asia-Pacific Financial Markets

ISSN 1387-2834

Asia-Pac Financ Markets
DOI 10.1007/s10690-019-09290-4



Springer

Asia-Pacific Financial Markets
https://doi.org/10.1007/s10690-019-09290-4

ORIGINAL RESEARCH

The High-Volume Return Premium: Does it Really Exist in the Chinese Stock Market?

Xingjian Zheng[1] · **Dehua Shen**[1]

Abstract

In this paper, we construct long-position portfolios and zero-investment portfolios to study the returns of stocks with high-or-low trading volume. Distinct from previous literature, this study finds that both high-volume return premium and discount effect exist in the Chinese market while the discount effect seems to be more prevalent. However, the dominance of the low volume return premium is not persistent, suggesting that the Chinese stock market is moving from undeveloped towards developed markets.

Keywords High-volume return premium · Discount effect · Zero-investment portfolios · Chinese stock market

1 Introduction

Can investors profit from stocks with high trading volumes? The answers vary in different countries. In the Chinese stock market which is dominated by small and more sentiment retail investors, the price discovery mechanism is distorted even for worse. Phenomena of the High-volume Return Premium might be even stronger owing to higher volatility. It suggests a stronger anomaly awaiting to be utilized by smart money.

For every technical analyst, the volume indicator serves as a crucial leading signal in their daily practice, which tells them if the price is going to rise or fall. Across the academia, this indicator has also aroused great concern and interests, leading to many valuable discoveries. The study of predicting future price movements through trading volumes can be traced back to Ying (1966), who record the correlation between NYSE trading volume data and average yields of the S&P 500's index. One of the discoveries that bears notable economic significance is the High-Volume

✉ Dehua Shen
dhs@tju.edu.cn

[1] College of Management and Economics, Tianjin University, No.92 Weijin Road, Nankai District, Tianjin 300072, People's Republic of China

Published online: 01 November 2019

Return Premium, or HVRP, which is discovered by Gervais et al. (2001, GKM hereafter). In all of the G7 countries, stocks with high trading volumes tend to display significantly excessive returns in the future, while low-volume stocks tend to show a discount in its values. Based on Miller's (1977) visibility hypothesis, GKM pioneer the concept of the High-Volume Return Premium. They conclude because of heterogeneous beliefs and short selling restrictions, stock holders naturally have a strong confidence in the securities that they possess, so they are not likely going to sell them, which creates limited supply. Once a positive volume shock takes place on a stock, investors are going to notice this stock and will be attracted to include it into their portfolios. A smaller amount of stock supply and a larger amount of demand pushed up the price of the stock, which in turn generated a high premium. Researchers also study this abnormal return with high volumes effect from different perspectives. For example, Gordon and Wu (2018) confirm the premium in the Australia stock market with high-frequency data and the theory of investor recognition. Ning and Wirjanto (2009) used a Copula approach to examine the relationship between volume and returns, and they find that in East-Asian equity market, extremely high returns tend to be associated with extremely high trading volumes. However, in some research articles, some developing countries are prone to exhibit high discounts (Kaniel et al. 2012; KOS hereafter; Huang et al. 2011), which implies that the phenomenon of HVRP varies across different countries. A unified conclusion that whether such an anomaly exists in the Chinese Stock Market is never reached. Different studies conducted at different periods of time tend to arrive at different results. Wang and Cheng (2004) believe that both high-volume return premium and high-volume return discount, or HVRD, simultaneously exist in the Chinese stock market. However, Wang, Wen and Singh (2017, WWS hereafter) claim that the average cumulative returns of high-volumes stocks underperform than stocks with normal trading volumes, just like other developing countries. And another researcher surnamed Zhou (2010) concludes that there exists a HVRP because Chinese investors prefer small-sized stocks with high trading volume. While The disturbing inconsistency intrigues me greatly. In our paper, we are eager to figure out whether the information of extreme trading volumes predicts future stock price, and if so, what kind of forecasting can be made, i.e. will there be a premium or a discount. By conducing the research, we also would like to know if there lies a trading strategy that can be adopted when investing based on information of extreme volumes.

In GKM's original research, they contend that when a stock receives a positive volume shock (which means its trading volume rises abnormally as compared to its history volume record), it attracts the attention of investors and resulted in a subsequent price appreciation. It is consistent with Miller's (1977) *visibility hypothesis*. On the other hand, according to KOS's (2012) *investor recognition hypothesis*, after a given shock, the investor base is enlarged and thus risk is shared on a bigger basis and, therefore, the firm's value is increased. But as WWS put it, they postulate that if the increased investor group is made up of speculative investors, then their trading behavior could heavily decrease a firm's value and 'fail to bring the expected long-term impact (WWS 2017). However, as regulations grow tougher and the institutional investor takes a bigger pie of the whole market, the Chinese stock market is now developing at a healthier pace. The question that whether speculative behavior, though still exists pervasively, will turn high volume return premium into discounts remains doubtful. Besides, the data used by previous researchers were outdated and incomplete, so we are inclined to test the HVRP phenomenon with the latest data and a more well-designed research method.

In addition, among various explanations to the abnormal performance of the volume-price relationship as discussed above, many scholars have mentioned the impact of investor behaviors on stock prices. KOS (2012) believe that once investors had noticed those high-volume stocks, they are very likely to overestimate the stock price because of overconfidence and include it into their portfolios, subsequently obtaining a negative return in the long term. Furthermore, because the bubble generated by speculation is doomed to be punctured, so stocks with stronger speculative attributes shall have lower long-term cumulative yields than stocks with lower speculative attributes. WWS (2017) hold the view that when investors are extremely risk-averse because of excessive pessimism, they will require low-volume stocks to have an excessive return premium as a risk compensation.

Considering China's special historical conditions and the status quo, researchers have to dig deep into the structure and composition of the market when studying speculative features and anomalies on the Chinese stock market. The Chinese securities market was established quite later compared to other markets. It has not been more than 30 years since the Shanghai Stock Exchange, or the SHSE, (one of the two biggest stock exchanges in China) officially opened in December 1990. According to the investigation released by the Shenzhen Stock Exchange (the other major stock exchange in China after the SHSE), or the SZSE, in 2017, the market is still dominated by small and medium-sized investors. The proportion of investors with securities account assets below 500,000 yuan (roughly 70,000 US dollars) is 75.1%, and short-term trading investors was 18.1% and 25.9% respectively (SZSE 2017). Investors who believe that the investment experience is insufficient and the investment knowledge is poor account for 52.5% and 49.8% of the totals separately. This huge investor group lacking rational trading (SHSE 2013) concept is the main contributor to market speculation. In the Chinese stock market, which lacks an effective short-selling mechanism, once the stock price is irrationally high, it is difficult for them to spontaneously regress to the reasonable price range by market forces. Instead, stock price is more likely to keep rising due to its momentum (Jegadeesh and Titman 1993).

Meanwhile, we also consider the impact of one of the most critical events that had taken place in the Chinese stock market, which is the Split Share Structure Reform. Years ago, the market was dominated by state-owned enterprises (SOE) whose shares are mostly controlled by the government. If the SOEs wanted to go public on the stock market, then the Initial Issue Privatization (IIP, as opposed to the more liberalized IPO nowadays) had to be carried out under the China Securities Regulatory Commission's watch, and subsequently a small part of the equity could flow to the market, despite the fact that still a large amount of shares still is not tradable, because they were considered as assets owned by the collective or the state. This split share structure has caused management difficulties and agency problems, fueling retail investors' speculative tendency and hindering the discovery of intrinsic values. Out of pure intention to guide the healthy development of

Chinese stock market, the government has taken actions by initiating the split-share structure reform in 2005–2007, which effectively realized the liberalization of share circulation that was formerly restricted. The split-share reform not only changed the fundamentals of the company, but also significantly improved the investors' investment preferences, creating a more rational environment. Prior to the non-tradable shares reform, or the split-share structure reform as mentioned before, SOEs displayed lower performance indicators such as profit yields than private companies (Bai et al. 2004). Besides, they also showed a lower return on total assets than mixed-ownership companies (Tian and Estrin 2008). In an article that comprehensively describes the non-tradable shares reform (Liao et al. 2014; LLW hereafter), researchers had found that after the non-tradable share reform, SOEs had boosted a remarkable output, and their operating efficiency had also been significantly improved. At the same time, the market mechanism was changing for the better because of this reform. As is reasoned, it can be inferred that the market has undergone tremendous changes during the 2-year-long reform. But unfortunately, all of the existing literatures that focused on the effect of HVRP or HVRD in China, except for the paper written by WWS, do not take the non-tradable share reform into good consideration. Some of them only use data long before the reform (Wang and Cheng 2004), others did not segment their data into periods before or after the Split Share Structure Reform (Zhou 2010; KOS 2012). It is unreasonable to conduct research directly without dividing the time series, because under different market circumstances, investors tend to behave differently and as a result, they invest differently. On top of that, the data used by WWS, though having considered the split-share reform, was outdated as compared to our data. Their dataset only ends abruptly in 2014 while our data continue to record until the year 2018.

In our empirical tests, we imitate the research methods used by GKM to determine whether a stock with extreme volumes belongs to the high-volume stock group or the low-volume stock group, and construct a trading interval of 100 days duration and a combination of long-position portfolio and zero portfolio. During the sample period (2007–2018), we test the average cumulative returns of our portfolios under different market capitalization deciles. Then we set out to see whether gambling preference has helped boosted the profits of extreme stocks or not by comparing returns of portfolios consists of lottery-type stocks and portfolios consists of non-lottery-type stocks.

Our findings are summarized as follows. We discover that there exists a significant low-volume return premium phenomenon in the Chinese stock market. This finding is in consistency with Wang and Cheng (2004). Besides, we find there is insignificant high-volume return premium and sometimes even a discount in the market, or the HVRD. According to the results, high-volume stocks generally have a very low and insignificant positive return, while during certain period firms with low capitalizations display a phenomenon of High-Volume Return Discounts. But considering the usual positive drift in the stock prices, we hold doubts on whether there truly exists a strong relationship between high trading volumes and abnormal returns. What's more, our result shows that portfolios performed better in a closer sub-period (2012–2018) to today during the whole sample period (2007–2018) as opposed to the earlier sub-period (2007–2012). Comparing to the study of HVRP across countries (KOS 2012), we think our empirical result implies that China's securities market is gradually becoming effective.

To the best of our knowledge, contributions of this paper which are made on the relationship between volume and price are listed as follows. First, we use the latest dataset, different model as well as time period classification methodology to study the HVRP effect and are able to reach a different conclusion. Secondly, we propose economically significant trading strategies for the Chinese stock market based on the findings and commented on some underlying problems of existing trading strategies which have never been pointed out before.

The writing structure of this paper is as follow: the first section is the introduction; the second section introduces our experiments; the third section describes the empirical results and further researches; the fourth section consists of our comment on trading strategies and robustness test; the last section concludes this whole paper.

2 Research Design

2.1 Methodology and Data

We adopted daily trading data from the Shanghai and Shenzhen A-share markets, which are two of the China's biggest trading exchange centers, with a time spread from 2007–01–04 to 2018–03–30. Several indicators such as daily closing price, daily trading volume, daily trading amount and daily returns having considered the cash reinvestment of dividends were obtained from the Chinese Stock Market and Accounting Research database, or the CSMAR as well. The firms' capitalization was obtained from the RESSET database. Because daily data of every different stock obtained from the CSMAR database is discontinuous due to suspension of trading, so we adopt the continuous Shanghai Stock Exchange (SSE) A-share index as a time series to align with the missing date, so that we can get a comprehensive panel data.

When cleansing our data, considering the IPO premium and the negative effects brought by long-term stock suspension, we exclude stocks that have not been listed for at least half a year and have not been suspended for more than 1 year. And finally, we select stocks with a continuous duration from June 30, 2006 to March 30, 2018 to ensure the stability of the total sample size, which leads us to a total stock quantity of 1265.

We adopt GKM's approach to define extreme volume stocks as those stocks whose trading volumes are inconsistent with their historical volume fluctuations, that is, the trading volume is excessively high or low on a certain date. We set up a trading interval which consists of a reference period, a formation date which is located at the end of this reference period, and a test period just as GKM and KOS did. When setting the length of the reference period, we try different values of 50 days, 30 days and 10 days as robustness checks. Our results show that the significance level is subject to different length of reference periods (i.e. the length being set at 50, 30 or 10 days separately), but our discovery of the prevalent Low Volume

Return Premium remains unchanged, which is consistent to WWS's finding that the length of reference period will not change the result. Once we confirm this, we complete the rest of our study with a reference period length of 50 days. Meanwhile, we set the test period of 50 days, so that it is long enough to observe the premium or discount effects. Finally, we reach a total of 54 non-overlapping 100-day-long intervals from 2007 to 2018.

When it comes to determining the extreme trading volumes, similarly to previous approaches, we define stocks whose trading volumes on its formation day in the top or bottom 10th percentile as compared to its own distribution of trading volumes in the preceding 49-day-long reference period as high- or low-volume stocks, and the remaining 80% stocks are classified into normal-volume stocks. Unlike KOS (2012) and WWS (2017) who set the top or bottom 20% as limits, our filtering condition which sets the threshold level at 10 percent is more stringent, so that it can lead to a stronger result and less noises. After all, KOS set the threshold at 20% to enlarge their stock pool because they are doing a cross-country empirical study and in some Stock Exchange Centers few stocks are listed. On top of that, we do not discard the top or bottom 5 percent of those extreme stocks because we crave for a more significant result.

When further manipulating our data, in each reference period, if the total number of trading days of a stock is less than half of the reference period (i.e. the stock has been suspended for more than 25 days in the reference period when we set reference period 50 days), we do not include the stock in the formation date. If a stock happens to be suspended on the formation date, we also do not use it.

A previous study (Blume et al. 1994) postulates that trading volume properties would be affected by firms' capitalization. For example, the volatility of a large firm which receives a positive volume shock would behave differently to that of a small firm. On the other hand, Merton (1987) also made a theoretical analysis of the difference in return premium of low-trading stocks under different market values. Stocks, therefore, can be classified into three categories: big firms, medium firms and small firms based on its market capitalization of the year preceding the year on which we chose the formation date. We assign every stock which exists on its formation date according to its market capitalization decile into different firm-size groups. The firms in capitalization decile eight to ten represents the big firms; the firms in capitalization decile four to seven represents the medium firms and the firms in decile one to three means small firms. Finally, we obtain Table 1 which describes the intervals and stocks in them.

2.2 Portfolio Formation

We adopt the approaches used by GKM (2001), KOS (2012) and WWS (2017) to construct a long-position portfolio as well as a zero-investment portfolio, are able to obtain the average cumulative returns of our portfolios during the test period in different firm-size groups. Only in this way can we test whether there exists a high-volume return premium or a discount in the Chinese stock market.

Table 1 Summary statistics

	Small firms	Medium firms	Large firms
Panel A: overall sample			
Average stock price	9.87	11.56	17.46
Median stock price	8.32	9.38	12.85
Average share volume	7,046,754	11,756,391	253,000,087
Median share volume	4,020,963	6,738,667	10,881,672
Panel B: first trading interval sample (2007/01/04-2007/03/21)			
Average stock price	7.93	10.15	17.02
Median stock price	7.39	8.57	13.89
Average share volume	6,368,452	10,683,808	17,019,526
Median share volume	5,201,912	7,906,651	9,351,568
Panel C: last trading interval sample (2017/11/24-2018/02/02)			
Average stock price	8.92	10.29	19.86
Median stock price	7.27	8.36	11.38
Average share volume	5,272,557	12,349,766	38,604,739
Median share volume	3,494,702	7,015,661	15,633,875

Panel D: high-or-low-volume stocks in trading intervals	Small firms		Medium firms		Large firms	
	high	low	high	low	high	low
Average	17.18	24.01	26.57	35.16	21.51	26.03
Median	12.5	16.5	20.5	20.0	16.50	17.00
Variance	157.51	511.26	527.56	1156.78	377.49	625.28
Minimum	2	0	5	0	2	0
Maximum	65	77	137	129	93	89
Correlation	−0.641		−0.58		−0.63	

A total of 54 non-overlapping trading intervals consisting of a 50-day long reference period and a 50-day long test period is illustrated in this table. For each trading interval, a stock is classified into a big, medium or small firm based on its preceding market capitalization. If it is in market capitalization decile eight to ten, it is classified as a big firm; if it is in decile four to seven, it is considered a medium firm; and if it is in decile one to four, it is then thought of as a small firm. In panel A, B and C we describe both average as well as median trading volumes and price in the overall trading intervals, the first trading interval and the last trading interval. Panel D presents summary statistics on the number of stocks that are classified as high or low volume stocks in each trading interval under each market capitalization groups

As for the long-position high volume or low volume portfolio, we buy high volume or low volume stocks each for one yuan in total during the formation date, and then assign the same weight to each stock in their portfolios. Because we want to study the HVRP or HVRD effect under different market capitalization deciles, so we do not adjust portfolios based on their market values. And finally, we do not rebalance the portfolio during our test period.

As for long position portfolios, we calculate the total cumulative returns R^i_{Tt} by summing up individual returns of each stock r^i_{cTt}, and we divide the sum by the number of stocks in the portfolio.

$$\mathrm{R}^{\mathrm{i}}_{\mathrm{Tt}} = \frac{\sum_{\mathrm{c}=1}^{\mathrm{M}} \prod_{\mathrm{t}=1}^{50} \left(1 + \mathrm{r}^{\mathrm{i}}_{\mathrm{cTt}}\right)}{M} \tag{1}$$

$$\bar{\mathrm{R}}^{\mathrm{i}}_{\mathrm{Tt}} = \frac{\sum_{\mathrm{c}=1}^{\mathrm{M}} \prod_{\mathrm{t}=1}^{50} \left(1 + \mathrm{r}^{\mathrm{i}}_{\mathrm{cTt}}\right)}{54} = \frac{\mathrm{R}^{\mathrm{i}}_{\mathrm{Tt}}}{54} \tag{2}$$

Among which, r^i_{cTt} denotes daily returns having considered reinvestment of cash dividends on a certain stock, which can directly be obtained from the CSMAR database; c denotes stock codes, T ($T=1, 2,\ldots, 54$) denotes the ith interval; t denotes the tth ($t=1, 5, 10, 20, 50$ in our case)day in the test period; M denotes the stock numbers in our portfolio; i ($i=high, low$) denotes whether the stock is classified as a high volume stock or a low volume stock.

$$\mathrm{i} = \begin{cases} \mathit{high} & \text{high volume on the formation date} \\ \mathit{low} & \text{low volume on the formation date} \end{cases} \tag{3}$$

As for zero investment portfolios, we take a long position for a total of one yuan in all these high-volume stocks and a short position also for a total of one yuan in stocks that are determined as low-volume stocks. Likewise, we assign the same weight to each stock in the portfolio and do not rebalance the portfolios during the test period.

During the 50 day-long test period, we calculate the average cumulative returns of zero-investment portfolios $\overline{\mathrm{NR}}_{\mathrm{Tt}}$ by adding up all the cumulative returns of each stock to the sum $\mathrm{NR}_{\mathrm{Tt}}$, and then divide it by the number of stocks in the interval.

$$\mathrm{NR}_{\mathrm{Tt}} = \mathrm{R}^{\mathrm{high}}_{\mathrm{Tt}} - \mathrm{R}^{\mathrm{low}}_{\mathrm{Tt}} \tag{4}$$

$$\overline{\mathrm{NR}}^{\mathrm{i}}_{\mathrm{Tt}} = \frac{\mathrm{R}^{\mathrm{high}}_{\mathrm{Tt}} - \mathrm{R}^{\mathrm{low}}_{\mathrm{Tt}}}{54} = \frac{\mathrm{NR}^{\mathrm{i}}_{\mathrm{Tt}}}{54} \tag{5}$$

Among which, $\overline{\mathrm{NR}}^{\mathrm{i}}_{\mathrm{Tt}}$ denotes the net returns of long-position portfolios minus short-position portfolios and divided by the total number of the stocks; N denotes the total number of the stocks.

Based on Bai–Perron's pure structural changes model (Bai and Perron 2003), we segment our 11-year long period into two parts so that we can see if the Chinese stock market has changed for the better over time, i.e. if the speculative forces have gradually grown weaker. Since the sequence estimation method in the Bai-Perron's test often covers or tends to over- or underestimate the true location of a break point (Bai and Perron 2003), we use the mutation points obtained by a repartition method to divide. We set a single maximum breaking point, otherwise this paper will end up with facing limited data because of four or five break points. Consequently, we split the whole period by using the Shanghai A share index as a reference and get the break point, i.e. the mutation point as Bai-perron calls it, on 2012/01/09. If we chose the Shenzhen Composite Index as the criterion, the break point shall be on 2009/10/26; and further research which is conducted in the robustness check shows no significant difference between the results made by the Shanghai A-Share Index and the Shenzhen Composite index. By calculating the returns of our portfolios, we will be able to examine whether such a premium or discount exists.

3 Empirical Results

3.1 Main Results

As is illustrated in Table 2, in all periods, (the overall period ranging from 2007/01/04 to 2018/3/30), period two (the earlier sub-period ranging from 2007/01/04 to 2012/01/09) and period three (the later sub-period ranging from 2012/01/10 to 2018/3/30) we are not able to observe significant High-Volume Return Premium nor Discount phenomenon in Chinese stock market. For firms in the big-firm groups, medium-firm groups and small-firm groups respectively, if the long-position portfolios which consists of high-volume stocks were held for 50 days, the return rates are 0.006, 0.023, 0.019 (t stats = 0.280,1.3021.203), inconsistent with WWS's and WC's findings. Considering their less updated data and different approaches when setting the values of extreme trading volume percentages, not to mention the return rate we obtained are daily returns having considered cash reinvestment by dividends supported by CSMAR, distinct from the logarithmic daily return rates used by former literatures. As for portfolios made up of high-volume stocks, the fifty-day return rates for big-firm group are 0.006 and 0.006 (t stats = 0.543, 0.221) in period two and three respectively; as for the medium-firm group the returns are 0.027 and 0.019 (t stats = 1.426, 0.891); as for the small-firm group the returns are 0.020 and 0.018 (t stats = 1.024, 0.878). The results seem quite complicating, and we are not able to derive any significant pattern from this.

However, for period one (the overall period), we find that long-position portfolios consisting of low-volume stocks tend to have a premium, which is quite a novel finding. For the fifty-day holding periods across different firm-size groups, the returns are 0.011, 0.041 and 0.062 (t stats = 0.458, 2.006 and 3.765) suggesting a significant result. When it comes to the two sub-periods, we can see that to a certain extent the Low Volume Return Premium, or LVRP, still exists. For low-volume stock portfolios in period two, the fifty-day returns are 0.025, 0.057 and 0.083 (t stats = 1.498, 2.644 and 4.094) for big, medium and small firm size stocks and for those in period three, the returns are −0.003, 0.023 and 0.043 (t stats = −0.150, 1.042 and 2.347) respectively.

As is more clearly elucidated in the zero-investment portfolio constructed by investing long in high-volume stocks and shorting low-volume stocks, the return rates are almost all below zero across different periods and firm-size groups. For the fifty-day average cumulative returns of zero-investment portfolios, most of the returns stay significantly below zero, and for those portfolios belong to small-firm

Table 2 The cumulative returns of each portfolio

Holding peiods	Cumulative returns of portfolios and t statistics														
	Period I(2007/1/4-2018/3/30)					Period II(2007/1/4-2012/1/9)					Period III(2012/1/9-2018/3/30)				
	1	5	10	20	50	1	5	10	20	50	1	5	10	20	50
Panel A: Big companies															
High volume $\bar{R}_{Tt}^{high}$	−0.003	−0.006	−0.002	−0.006	0.006	−0.001	0.004	0.016**	0.017*	0.006	−0.004	−0.017	−0.018	−0.024	0.006
(t stat)	(−1.033)	(−0.685)	(−0.177)	(−0.405)	(0.280)	(−0.249)	(0.296)	(2.379)	(1.748)	(0.543)	(−1.277)	(−1.600)	(−1.378)	(−1.302)	(0.221)
Low volume $\bar{R}_{Tt}^{low}$	0.000	−0.005	−0.005	−0.006	0.011	0.001	0.007	0.011	0.016	0.025	−0.002	−0.017*	−0.021**	−0.029	−0.003
(t stat)	(−0.173)	(−0.550)	(−0.444)	(−0.368)	(0.458)	(0.218)	(1.137)	(1.466)	(1.519)	(1.498)	(−0.736)	(−1.865)	(−2.065)	(−1.492)	(−0.150)
Net return $\overline{NR}_{Tt}^{i}$	−0.002*	−0.004	0.000	−0.005	−0.013	−0.002	−0.002	0.005	0.001	−0.018***	−0.003	−0.005	−0.004	−0.011	−0.006
(t stat)	(−1.891)	(−0.917)	(0.011)	(−0.689)	(−1.141)	(−1.138)	(−0.322)	(0.676)	(0.201)	(−3.246)	(−1.466)	(−1.097)	(−0.736)	(−1.479)	(−0.401)
Panel B: Medium companies															
High volume $\bar{R}_{Tt}^{high}$	−0.002	−0.004	−0.000	−0.003	0.023	0.002	0.003	0.010	0.003	0.025	−0.005***	−0.010	−0.010	−0.010	0.019
(t stat)	(−0.957)	(−0.623)	(−0.015)	(−0.294)	(1.302)	(0.509)	(0.308)	(0.789)	(0.171)	(1.426)	(−2.601)	(−1.201)	(−0.927)	(−0.627)	(0.891)
Low volume $\bar{R}_{Tt}^{low}$	0.000	0.011	0.009	0.0121	0.041**	0.000	0.014**	0.020**	0.026**	0.057***	0.001	0.007	−0.000	−0.001	0.023
(t stat)	(0.315)	(1.000)	(0.805)	(0.794)	(2.006)	(0.157)	(1.985)	(2.220)	(1.920)	(2.644)	(0.276)	(0.418)	(−0.030)	(−0.049)	(1.042)
Net returns $\overline{NR}_{Tt}^{i}$	−0.003*	−0.017**	−0.013	−0.017*	−0.021*	0.000	−0.010	−0.008	−0.020**	−0.017	−0.006**	−0.022	−0.017	−0.015	−0.024
(t stat)	(−1.835)	(−1.981)	(−1.531)	(−1.893)	(−1.776)	(0.073)	(−2.376)	(−1.243)	(−2.105)	(−1.339)	(−2.430)	(−1.435)	(−1.123)	(−0.958)	(−1.237)

Table 2 (continued)

Holding peiods	Cumulative returns of portfolios and t statistics														
	Period I(2007/1/4-2018/3/30)					Period II(2007/1/4-2012/1/9)					Period III(2012/1/9-2018/3/30)				
	1	5	10	20	50	1	5	10	20	50	1	5	10	20	50
Panel C: Small companies															
High volume $\bar{R}_{Tt}^{high}$	−0.002	−0.006	−0.010	−0.018*	0.019	−0.001	0.004	0.0011	−0.013	0.020	−0.004**	−0.014**	−0.021**	−0.023*	0.018
(t stat)	(−1.414)	(−1.063)	(−1.453)	(−1.704)	(1.203)	(−0.467)	(0.436)	(0.122)	(−0.738)	(1.024)	(−1.971)	(−2.053)	(−2.279)	(−1.771)	(0.878)
Low volume $\bar{R}_{Tt}^{low}$	0.000	0.008	0.010	0.013	0.062***	0.001	0.015*	0.023***	0.024*	0.083***	0.000	0.001	−0.000	0.004	0.043**
(t stat)	(0.432)	(1.498)	(1.519)	(1.339)	(3.765)	(0.512)	(1.764)	(2.508)	(1.958)	(4.094)	(0.023)	(0.151)	(−0.053)	(0.236)	(2.347)
Net returns $\overline{NR}_{Tt}^{i}$	−0.004***	−0.014***	−0.021***	−0.031***	−0.037***	−0.004	−0.011***	−0.019***	−0.035***	−0.051***	−0.004***	−0.016***	−0.020***	−0.028***	−0.026***
(t stat)	(−3.303)	(−6.585)	(−6.466)	(−7.326)	(−5.162)	(−1.737)	(−3.505)	(−3.759)	(−4.452)	(−6.324)	(−3.18)	(−5.478)	(−5.268)	(−6.151)	(−2.777)

In each interval, each stock is classified into the big-firm, small-firm and medium-firm categories based on their trading volume. And they are determined as a high-volume stock or a low-volume stock according to their trading volume on every formation date. In this table, high-volume return $\bar{R}_{Tt}^{high}$, low-volume return $\bar{R}_{Tt}^{low}$ and net return $\overline{NR}_{Tt}^{i}$ denotes the average cumulative returns of portfolios constructed by high-volume stocks or low-volume stocks, or by buying high-volume stocks and shorting low volume stocks separately at a total expense of one dollar. The t statistics are illustrated in the parenthesis. We also segment the overall period into two sub periods with the first from 2007/01/04 to 2012/01/09, and the second from 2012/01/09 to 2018/03/30. We display the test results over five different horizons precisely following its formation date: 1, 5, 10, 20 and50 trading days

Fig. 1 The evolution of stock returns in different trading periods.*Note* The evolution of the average cumulative returns of portfolios constructed of different types of stocks during the overall period of time, in which each stock is assigned the same weight. Following each formation date, the returns of three portfolios are shown in the figures above. The solid lines represent the average cumulative returns of portfolios constructed by high-volume stocks, while the dashed lines represent when the long position is held for low-volume stocks, and the dashed-dotted lines represent zero-investment portfolios when buying high volume stocks and shorting low-volume stocks. Panel A covers a whole trading period (2007/1/4-2018/3/30), Panel B depicts the evolution during the 1st trading period (2007/1/4-2012/1/9) while Panel C covers the 2nd trading period (2012/1/9-2018/3/30)) ▶

groups in period III, the result is more significant, which suggests a stronger LVRP. However, when comparing returns from different periods, we can find that the LVRP effect is becoming less significant with lower returns and t-statistics, just like the way HVRP does.

This result is in consistency with my previous expectation. A negative volume shock does result in investors' panic and freeze the stock market. But after a while, i.e. a few trading periods later, investors are destined to discover the intrinsic value of the underestimated stocks. Consequently, the prices tend to rise, rendering positive returns for portfolios made up of low-volume stocks.

However, one drawback of my empirical study is that the t-statistic are not big enough, with few t-stats staying above 1.96. This is because when doing the Person's t test, we use discrete daily returns on each day to reach the result, and owing to the market volatility, daily returns might be heavily affected. So, we average the daily returns of each interval by aggregating each return and dividing the sum by the number of intervals, which is 54; and we are able to draw an evolution line of the average cumulative return of each portfolio in period one (the overall period). Figure 1 depicts the average cumulative returns of high-and-low volume stock portfolios under different firm-sizes during three periods.

3.2 A Revised Test with OLS Regressions

We use a simple OLS regression to regress the data and were able to obtain coefficients illustrated in the table presented below. The formula is shown as below.

$$\text{return} = \alpha + \beta * \text{day} + \varepsilon \quad \text{day} \in [11, 50] \tag{6}$$

From Table 3, we can see the t-statistic are highly significant, which support our findings on the HVRD and LVRD effect. It can be found that when the portfolio is constructed and held for about 26 days, the average cumulative rate of return begins to become positive, and according to Table 3, date parameters for portfolios constructed are all centered in 26th day during the test period, matching with each other. This implies that investors can identify high-volume stocks in advance and then wait until the 26th day before starting a position to buy. For low-volume stocks, the date parameters do not stay consistent. For stocks with small and medium market capitalization, the investment portfolio of low-volume long-term stocks is always positive, and with the increase in the number of positions held, the average cumulative returns also increase consistently. For high-capital and low-volume stocks, the average cumulative returns for the first 24 days are always negative, and after that date the positive cumulative returns turn out to be positive.

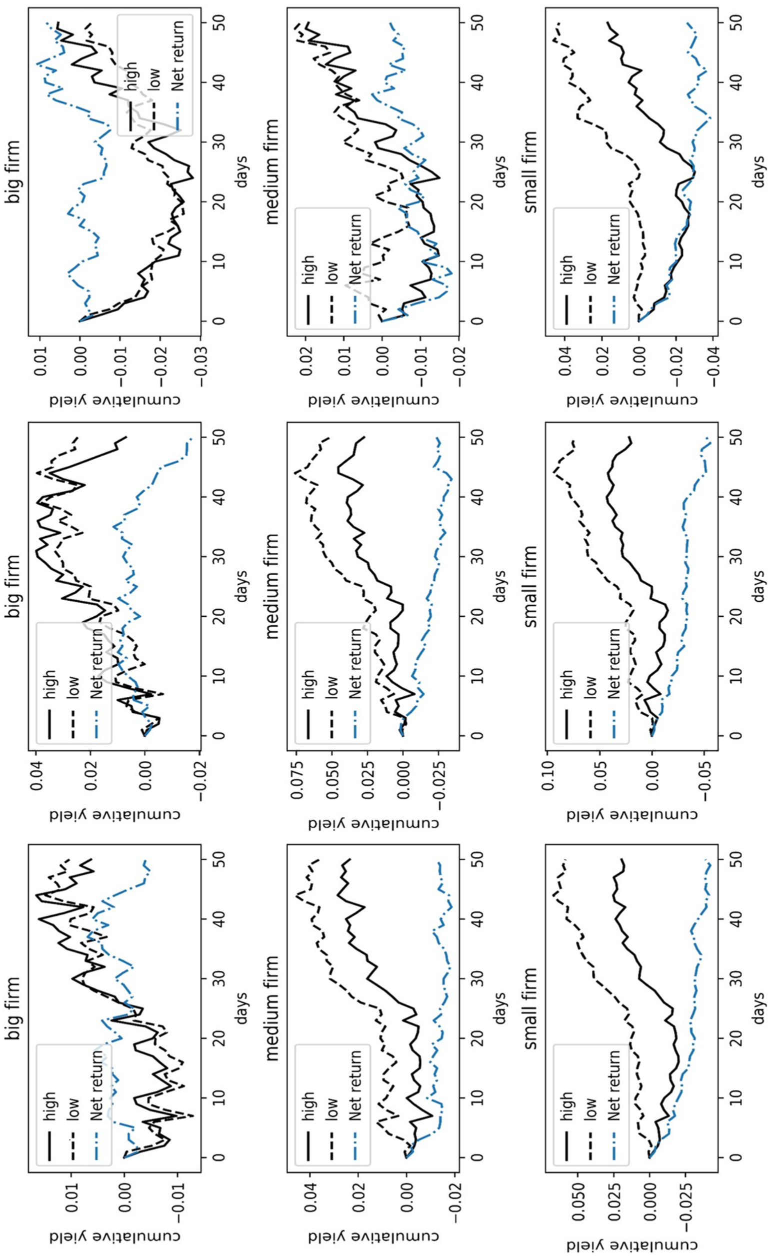

big firm
medium firm
small firm
high
low
Net return
cumulative yield
days

Table 3 The coefficients and t statistics of the cumulative returns

Day	Big firms				Medium firms				Small firms			
	High volume	t-stat	Low volume	t-stat	High volume	t-stat	Low volume	t-stat	High volume	t-stat	Low volume	t-stat
11	−0.006	−3.753	−0.008	−5.881	−0.005	−3.939	0.007	6.615	−0.015	−10.665	0.007	8.955
12	−0.009	−4.525	−0.011	−7.066	−0.006	−4.528	0.005	6.103	−0.017	−12.749	0.006	8.097
13	−0.007	−5.021	−0.008	−7.514	−0.003	−4.490	0.010	6.802	−0.015	−14.244	0.007	8.389
14	−0.005	−5.177	−0.008	−7.731	−0.002	−4.271	0.009	7.428	−0.015	−15.102	0.009	9.219
15	−0.008	−5.795	−0.011	−8.632	−0.005	−4.793	0.007	7.422	−0.019	−17.342	0.007	9.840
16	−0.007	−6.138	−0.011	−9.597	−0.006	−5.331	0.009	6.634	−0.021	−19.754	0.008	9.827
17	−0.005	−6.201	−0.008	−9.744	−0.002	−5.791	0.005	6.500	−0.021	−22.083	0.013	10.189
18	−0.002	−5.571	−0.008	−9.607	−0.001	−5.547	0.010	7.165	−0.019	−21.867	0.014	11.511
19	−0.002	−5.101	−0.006	−8.904	−0.004	−5.127	0.009	7.621	−0.017	−20.823	0.013	12.921
20	−0.005	−5.314	−0.006	−8.904	−0.005	−5.307	0.011	8.313	−0.019	−16.219	0.011	15.829
21	−0.006	−5.643	−0.008	−8.488	−0.005	−5.641	0.010	8.908	−0.019	−15.862	0.012	17.173
22	−0.004	−5.635	−0.007	−8.757	−0.005	−6.009	0.009	9.180	−0.018	−15.741	0.018	18.529
23	−0.002	−4.544	−0.002	−7.487	0.001	−4.904	0.013	10.029	−0.011	−13.745	0.015	20.043
24	−0.003	−4.513	−0.001	−6.776	−0.004	−5.138	0.010	10.505	−0.016	−11.704	0.016	20.880
25	−0.004	−4.566	0.001	−6.186	−0.003	−5.182	0.011	11.077	−0.017	−9.858	0.022	20.884
26	0.001	−4.077	0.001	−5.352	0.003	−4.088	0.019	12.001	−0.010	−7.924	0.025	19.577
27	0.002	−3.599	0.003	−4.471	0.006	−2.932	0.024	12.628	−0.007	−6.235	0.030	18.082
28	0.005	−2.872	0.006	−3.586	0.009	−1.81	0.026	13.224	−0.003	−5.221	0.035	16.699
29	0.008	−2.067	0.007	−2.783	0.013	−0.728	0.029	13.642	0.003	−4.537	0.041	16.650
30	0.010	−1.290	0.006	−2.137	0.017	0.254	0.033	13.826	0.002	−3.861	0.041	17.168
31	0.007	−0.799	0.007	−1.644	0.015	0.925	0.033	14.441	0.007	−3.249	0.041	17.345
32	0.003	−0.575	0.006	−1.309	0.012	1.435	0.032	15.331	0.006	−2.558	0.046	17.661
33	0.007	−0.176	0.007	−0.937	0.017	2.028	0.034	16.136	0.009	−1.89	0.049	18.084
34	0.007	0.173	0.004	−0.729	0.017	2.580	0.034	17.074	0.011	−1.435	0.051	18.666

Table 3 (continued)

Day	Big firms				Medium firms				Small firms			
	High volume	t-stat	Low volume	t-stat	High volume	t-stat	Low volume	t-stat	High volume	t-stat	Low volume	t-stat
35	0.011	0.672	0.007	−0.419	0.021	3.175	0.038	18.762	0.016	−0.933	0.053	19.705
36	0.013	1.189	0.008	−0.419	0.025	3.767	0.039	19.881	0.019	−0.450	0.048	20.748
37	0.010	1.589	0.003	−0.068	0.022	4.304	0.036	21.031	0.016	0.040	0.050	21.679
38	0.013	2.039	0.006	0.069	0.025	4.853	0.041	22.097	0.020	0.433	0.055	22.310
39	0.014	2.498	0.01	0.324	0.024	5.381	0.041	23.228	0.022	0.735	0.061	23.178
40	0.017	3.003	0.011	0.715	0.026	5.914	0.038	24.451	0.025	1.143	0.061	24.230
41	0.012	3.363	0.006	1.074	0.022	6.392	0.038	25.652	0.022	1.546	0.060	24.933
42	0.008	3.594	0.012	1.291	0.018	6.792	0.044	26.828	0.017	1.890	0.067	25.523
43	0.016	4.049	0.015	1.479	0.026	7.318	0.048	27.782	0.025	1.905	0.070	26.662
44	0.017	4.512	0.015	1.851	0.030	8.393	0.041	29.058	0.026	1.994	0.065	27.832
45	0.011	4.831	0.013	2.301	0.027	8.903	0.041	30.278	0.024	2.018	0.066	29.047
46	0.009	5.073	0.014	2.655	0.025	9.445	0.041	31.606	0.024	2.229	0.067	30.275
47	0.010	5.358	0.015	3.018	0.028	9.967	0.043	32.695	0.026	2.583	0.061	31.550
48	0.06	5.459	0.011	3.409	0.026	10.508	0.041	33.904	0.019	2.835	0.063	32.730
49	0.008	5.668	0.012	4.022	0.028	10.803	0.042	34.262	0.018	3.075	0.062	33.323
50	0.006	5.787	0.010	4.293	0.024	10.995	0.038	34.376	0.020	3.336	0.060	32.730

We adopt the Ordinary Least Square Regression to obtain the coefficients of returns of portfolios consists of high-volume and low-volume stocks starting from the 11th day in the test period. This table shows that for any portfolio consisting of different volume stocks held in a long position, how the yield might become. A positive coefficient suggests a positive yield

4 Further Comments and Studies

4.1 Economic Strategies and Critics on Existing Literatures

Having completed studies on the extreme volume return premium and discount, we am eager to know if there exist exploitable trading strategies, or arbitrage strategies, that are feasible enough to be applied to the Chinese Stock market as GKM has found for ones in the United States. However, several problems unveil themselves when we begin considering market frictions and other limitations. Firstly, the daily return rates having considered cash reinvestment by dividends obtained from CSMAR database is somewhat inaccurate, because it is calculated by daily closing price. However, in the real world the price changes intensely, so investors might not be able to settle down a deal at an ideal price. Secondly, when purchasing securities, we consider neither commission fees nor taxes. According to Lesmond et al. (2004), the existence of commission fees could constrain investors' ability to arbitrage market anomalies. So low-volume stock portfolios are prone to underperform than original expectation.

Thirdly, different investors have different transaction costs, and their transaction speed varies greatly. For example, institutional investors have a supreme advantage over retail investors on commission fees. Besides, owing to the limited original stock capitals, retail investors are not able to construct a fully diversified portfolio (Goetzmann and Kumar 2008). Furthermore, when it comes to institutional investors, they need to consider the market holding capacity of capitals especially if they were to invest based on the LVRP effect, which is more significant for small firms. If the market has limited holding capacity, once institutional investors swarm into the market, this low-volume small-firm-sized stock might suddenly change from a low-volume stock to a high-volume stock.

Besides, there lies a common problem when adopting such trading strategies among scholars(Zhou 2010; WWS 2017). Because stocks were bought or shorted on the formation date which is also the same day on which investors determine whether a stock is an extreme stock itself, so the only way to construct a portfolio is building it in on last trading second on the formation date, or directly through a call auction, which increases the uncertainty. Or if an investor decided to make their deal on the following day, then he should bear the risk of a gap opening, which also suggests a greater deal of uncertainty.

However, considering our empirical findings, trading strategies featuring low-volume return premium remain quite promising. If an investor purchases low-volume] stocks in the small-firm group on formation date and construct a portfolio, he will yield a positive return of 6.1% in 50 days, which is equivalent to a 25% net return in a year.

4.2 Robustness Analysis

When trying to decide the length of trading intervals, we also set the reference period to 10 days and 30 days, and our experiments yield similar results. Especially when the reference period is 30 days, the return premium is more significant. That is because when the period is 10 days, the interval contains too little information and thus portfolios are not representative. So, we only study average cumulative returns of high-or-low volume stock portfolios whose reference period is 30 days. The 50-day average cumulative returns are significantly greater than zero, and portfolios consisting of low-volume stocks always outstand those consisting of high-volume stocks. For low-volume stock portfolios which belong to big-firm, medium-firm and small-firm size groups, their fifty-day cumulative returns are 0.027, 0.023 and 0.048 (t stat = 1.001, 1.567, 2.21).

To our surprise, we are able to observe the high-volume return premium effect when we set the reference period to 30 days. Especially for stocks that belongs to the medium firm group. We presume that, the natural tendencies of positive price drifting tend to offset the discount and result in a positive yield.

5 Conclusion

In this essay we illustrate that both the High-Volume Return and Discount effect exist in contemporary Chinese stocks market. When we classify stocks into high volume stocks and low volume stocks based on their trading volumes, we find that portfolios made up of stocks whose trading volumes are extremely lower than average tend to yield a higher average cumulative return in the long-term. For companies with big and medium firm sizes, the HVRP effect is still significant, yet not as strong as the HVRD effect.

By studying the premium or discount patterns during different periods, we find that the anomalies gradually fade away, and we argue changes which took place in the market help explain the result, and the Chinese stock market is becoming more mature.

We also study whether the economic trading strategies based on LVRP effect can be applied to the real world. On top of that, we make some critics which have never been made in previous literatures. Finally, we pertain that it is more reasonable to construct a portfolio consisting of low-volume and non-lottery type stocks which belong to small firms, and by holding the portfolio for a long period of time, the yield might be just as luring as the cherry on top of a sundae.

Acknowledgements This work is supported by the National Natural Science Foundation of China (71701150) and Young Elite Scientists Sponsorship Program by Tianjin (TJSQNTJ-2017-09).

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