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A Study on the Level of Market Efficiency Based on CSI 300 and 300 Constituent Stocks

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Abstract

This paper analyzes CSI 300 index and its 300 constituent stocks with seven market efficiency measures: autocorrelation of daily returns, autocorrelation of absolute daily returns, runs test, forecast ability of other historical data on daily return (the predictive ability of yesterday's change of trading volume on today's return in this paper), the return of specific trading strategy, variance ratio and pricing errors contained in daily return. We do a Principal component analysis to convert these indicators to a single indicator representing the market efficiency. Then we try to find the co-movement among different measures through correlation coefficient and among different stocks through OLS regression: market efficiency values of individual stocks are regressed on market efficiency values of CSI 300 for seven measures respectively. We found that different market efficiency measures are indeed consistent to each other to some extent and the individual stocks are somewhat consistent with the whole market indicating there is a systematic market efficiency in stock market in China. Our finding also support the idea that the market efficiency in Chinese stock market is changing all time without showing a clear upward trend from 2005 to 2020. In the end, we set three hypotheses to explain relatively high level of market efficiency in 2005, 2012, 2017 and 2019: the ability of market detecting and reacting to pricing errors, public information or private information is becoming quickly and accurately. We found that when the market is in a bad condition, the market contains more pricing-errors in daily returns and the ability of market detecting and reacting to private information is also bad.

Keywords: stock market, market efficiency hypothesis, random walk, investment strategy
JEL Classification: G10, G14

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1.Introduction

The market efficiency has alway been a hot issue in empirical finance. The Efficient Market Hypothesis (EMH) predicts that at any point in time market prices should incorporate and reflect all available information (Rossi (2015)). Competition in an efficient market will cause the full effects of new information on intrinsic values to be reflected in actual prices (Fama (1965), Stevenson and Bear (1970)). That is to say, if the equity market is working efficiently, the prices will show the intrinsic values of the equity and the limited savings will be allocated to the productive investment sector optimally (Hamid, Suleman, Shah and Akash(2010)). This kind of market is seen as a rational and developed market in which all the investor make a risk-based return and no one can make excess return with information informed to everyone. Although testing of market efficiency lasts over fifty years, researchers failed to reach an agreement on the final conclusions of market efficiency because of different methods and different results. Some proposed evidence supporting an efficient market and there are also some finding evidence against an efficient market. For example, Chen and Yeh (1997) said that while the short-term nonlinear regularities existed, the search costs might be too high and hence the efficient market hypotheses held. Malafeyev, Awasthi and Kambekar (2017) examined randomness in stock markets of China and India but found that both markets did not follow random walk and all results of tests rejected the hypothesis of weak form market efficiency. This paper also focus on the stock market in China and try to find some more evidence.

The problem is that it is unclear how to compare these different results and summarize them to one comprehensively reasonable result. Therefore, testing market efficiency is difficult and new theoretical model should be developed to take into consideration all changes in market or economic conditions (Titan (2015)).

Fama is one of the most famous researchers who discussed the market efficiency hypothesis clearly in definition and analyzed references before 1970. Fama (1965) defined an efficient market as a market where there were large numbers of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information was almost freely available to all participants. In Fama (1970), it summarized important studies on this topic before 1970, defined a efficient market as a market in which prices always 'fully reflect' available information and proposed the famous terminologies on the classification of types of market efficiency: weak form, semi-form and strong form efficient market. Stevenson and Bear (1970) also pointed out that an efficient market should be characterized by numerous well-formed participants and should create prices which accurately reflect all current information. Detection of and reaction to information seems play a very important role in an efficient market.

The weak form hypothesis of an efficient market says that current stock price fully incorporates information contained in the historical prices. People should not be able to profit from information contained in historical data that is available to everyone. However, many analysts did found a way to make profits which indicated the invalidity of the weak form hypothesis (Fama (1970), Rossi (2015)). In this paper, like what we found in the empirical part, past return series and trading volume data have some predictive ability in predicting future return. Fama (1970) also summarized 'expected return theories' or 'fair game models' with which the modeling of efficient market theory were getting more specific. Anyway, the studies reviewed in Fama (1970) almost supported the conclusion of efficient market in all three types.

Fama, Fisher, Jensen and Roll (1969) is one of the major work on semi-form tests of market efficiency. The semi-strong form of market efficient suggests that the current stock prices fully incorporates all publicly available information, for example, historical data(past prices and past trading volume), data reported in companies' financial statements: earnings, announced merger, expectations regrading macroeconomic factors (Rossi (2015)). However, public information itself is a vague notion that does not have a strict financial definition and therefore may be more difficult and costly to gather compared with historical data. Major newspapers and company-produced publications may not be sufficient sources (Rossi (2015)). Fama, Fisher, Jensen and Roll (1969) solved two questions: First, is there normally some ‘unusual’ behavior in the rates of return on a split security in the months surrounding the split. Second, if spots are associated with ‘unusual’ behavior of security returns, to what extent can this be accounted for by relationships between splits and changes in other more fundamental variables. They concluded that when the information effects of dividend changes were taken into account the apparent price effects of the split would vanish and on the average the market’s judgements concerning the information of a spot were fully reflected in the price of a share at lease by the end of the split month. These findings support the view of an efficient market.

The strong form of market efficiency suggests that the current stock prices full incorporates all exiting information: historical information, public information and private information (Fama (1970), Rossi (2015)). Therefore, there is no information which can be used to make profit for investors. The market completely detects and quickly reacts to all information.

During many papers on the topic of market efficiency, there is not doubt that studies on random walk hypothesis play a vary important role and that most attention has been drawn to the question of whether stock prices or returns deviate from a random walk: future evolution of prices cannot be predicted (Richardson and Smith (1994), Titan (2015)). In simple word, an increase in a specific day does not imply an increase or decrease in the following day or in the following n days. This type of evolution of prices is known as no memory. The random walk theory considers that the movements of stock prices are unpredictable and they follows a random and erratic behavior (AI-Jafari (2011)).

In testing random walk hypothesis, there are many methods used in former studies: autocorrelation of return series, unit root test, runs tests, variance ration test and some other behavior of stock returns able to indicate the inconsistence with the behavior of an efficient market.

Fama (1965) briefly discussed random walk theory. The main process of empirical research testing the random walk hypothesis is testing the dependency of successive price changes. If the test results support the assumption of independence, the random walk hypothesis holds. The other way is construct a trading strategy to see if this kind of strategy could make more profit than just buy-and-hold. However, Fama (1965) also said that it was unlikely the random walk hypothesis provided an exact description of stock market price behavior. Under this viewpoint, if the result of any tests against market efficiency is found, it is not cleat that getting this result is because of an actual inefficient market or somewhat wrong theory.

Anyway, some studies found evidence supporting an approximate random walk in highly competitive, organized and developed markets and others found converse evidence. Pan, Chan and Fok (1997) examined the random walk process for four currency futures prices and found little evidence against the random walk hypothesis. Other studies, like Stevenson and Bear (1970), Malafeyev, Awasthi and Kambekar (2019), found evidence not supporting random walk hypothesis. Stevenson and Bear (1970) found a tendency for negative dependence in short periods of time and positive dependence over longer periods. Malafeyev, Awasthi and Kambekar (2017) tested the daily stock return of SSE and BSE from 1996 to 2016 for whole period and for different sub-periods. The conclusion rejected the random walk hypothesis.

In the meanwhile, Malkile (2003) said that by the start of the twenty-first century, many financial economists and statisticians began to believe that stock prices were at least partially predictable. It also proposed another definition of efficient financial markets: such markets do not allow investors to earn above-average returns without accepting above-average risks, and a concept that markets could be efficient even if many market participants were quite irrational and stock prices exhibit greater volatility. After Malkiel (2003), more and more evidence against ‘an efficient market’ has been gradually increasing. Afego (2012) examined the weak form efficiency for Nigerian stock market with runs test and the results was that Nigerian Stock Exchange displayed a predictable component. Nissan and Hanif (2012) concentrated their efforts on four stock exchange of South Asia and the results suggested that none of the four stock markets follows random walk. Zarei and Jadari (2020) also rejected the random walk and the market efficiency hypotheses in the Tehran stock exchange by finding the existence of long-range dependence (LRD) in the mean and volatility of the TSE log-returns process.

Except these normal tests stated above, some researchers studied the abnormal behavior of daily stock returns like January effect, the day-of-week effect, the calendar month effect and the holiday effect. Yuan, Zheng and Zhou (2006) examined the relation between lunar phases and stock market returns of 48 countries. Their findings were that stock returns were lower on the days around a full moon than on the days around a new moon and they also found that the lunar effect was independent of other calendar-rated anomalies.

Some studies stressed the importance of liquidity for asset pricing like Pastor and Stambaugh (2003). Rosch, Subrahmanyam and van Dijk (2017) said that illiquidity did not necessarily imply return predictability or pricing errors relative to efficient prices but alternative channels could give rise to inefficiencies. Inefficiencies resulting from these channels considered in Rosch, Subrahmanyam and van Dijk (2017) may be reflected in all seven efficiency measures used in this paper. Ozdemir (2008) stated that there might be three reasons for in-continuous market efficiency in an emerging market: not well developed financial system, limited ability of the commercial banks, frequent economic and political instability. Hence, an emerging market can go from an inefficient to efficient state, and vive-versa. Titan (2015) said that one of the reasons for the markets' inefficiency or the phenomenon that prices' responses to event announcements were delayed is that investors were inattentive and this inattention might cause under-reaction of prices and predictability of returns.

Rosch, Subrahmanyam and van Dijk (2017) proposed a new thought on the topic of market efficiency: there might be a significant systematic component to the time-varying behavior of market efficiency measures. It proposed some questions: to what extent do different market efficiency measures vary over time, do different market efficiency measures co-move across stocks, as well as with each other, what are the economic forces that drive it? Their finding support their thought of existence of a systematic market efficiency component across stocks and measures.

Under former studies, in this paper, we try to solve three problems. First, how does severn different market efficiency measures describe the same stock market in China? Second, if there is co-movement in different market efficiency measures and if there is co-movement of market efficiency among different stocks. Third, is stock market improving in efficiency level these years and what aspect is it improving in: detect and react more quickly and accurately to pricing errors or public information or private information or some of them. That is to say, we set three hypotheses for the change trend of market efficiency and want to find which one plays the main role.

The rest of the paper are arranged as follow. Part two states the seven market efficiency measures considered in this paper. Part three briefly analyses stock data of CSI 300 and its 300 constituent stocks. Part four shows the empirical results of seven measures and confirm the results of co-movement across measures and stocks, the results of three hypotheses. Part five summarize all of the paper and raises unresolved questions.

2.Methodology

2.1 Autocorrelation

The first measure used in this paper to test the level of market efficiency is the autocorrelation of daily return series (Safvenblad (1997), Nissan and Hanif (2012), Sewell (2012)). Because of the adjustment function of market to errors, the return series could be negatively related. If there is positive autocorrelation, it can be seen as a sign of predictability. Moreover, we also regard the autocorrelation of absolute return series as the second measure of market efficiency. Ding, Granger and Engle (1993) found that there was more correlation between absolute returns than returns themselves and called this type of phenomenon 'long memory'. Here, only autocorrelation in lag1 is used as the value of market efficiency for all stocks. As for long-term dependence, more complicated and specific, like the ones discussed in Zarei and Jafari (2020), will not be considered in this paper.

2.2 Runs test

The third measure to test market efficiency is chosen as the famous and commonly used non-parametric test: runs test (Karemera, Ojah and Cole (1999), Doria and Simina(2007), Rosa (2009), Al-Jafari and Altaee(2011)). One of the advantages of runs test is that it does not require a normally or identically distributed return distribution (Al-Jafari and Altaee(2011)). Karemera, Ojah and Cole (1999) also found another result related to runs test that the rejection of random walk would be more when return series was expressed in US dollar than in domestic currency because they considered that local investors could have slight information advantage over international investors especially in an emerging market.

2.3 The forecast ability of yesterday's trading volume on today's return

Concentration on the behavior of return series itself may not be enough for the study of forecast ability in a stock market. Models using other variables in the regression of return series may have different implications for stock return behavior and therefore it is meaningful to check some economic variables to find whether they have some relation with stock return or not. Campbell, Grossman and Wang (1993) said that there were numerous papers pointed that high stock market volume was associated with volatile returns but little related the autocorrelations of stock returns to volume and found that serial correlation of stock returns was lower on high-volume days than on low-volume days. This phenomenon appeared both in stock index and individual stocks. Many papers have showed that stock returns could be predicted by financial variables such as the dividend-price ration, the earnings-price ratio and various measures of the interest rate (Campbell and Yogo (2006)). The dividend yield appeared to be the most popular return predictor but the earnings yield also has predictive power (Ang and Bekaert (2007)). Chordia and Swaminathan (2000) found that returns of portfolios containing high trading volume led returns of portfolios comprised of low trading volume stocks. Suominen (2001) said that there was a positive correlation between price variability and trading volume because the trading by informed traders revealed private information. The findings of Mubarik and Javid (2009) suggest that there is a significant effect of the previous-day-trading-volume on the current return. The simple method in those studies is an ordinary least squares (OLS) regression of stock returns onto the lag of the financial variable. Here, the financial data used to predict stock returns are chosen with yesterday's trading volume. The specific regression is the regression of today's return on yesterday's trading volume. Here, we only consider the effect of yesterday's trading volume while Rosch, Subrahmanyam and van Dijk (2017) consider three factors: yesterday's factor, today's factor and tomorrow's factor. The coefficient b is seen as the forecast ability.

$$Y_t = a + b \cdot X_{t-1} + u_t \qquad u_t \sim N(0, \sigma^2) \qquad (1)$$

Y_t: today's return
X_{t-1}: yesterday's trading volume
a :constant
b : the forecast ability

2.4 Strategy

Chan (1988) said that a contrarian stock selection strategy consisted of buying stocks that had been losers and selling short stocks that had been winners. There is also the belief that 'What goes up must come down' and therefore contrarian investment strategies would earn abnormal returns through buying past losers and selling past winners (Chang, Mcleavey and Rhee (1995)). That is to say, individual investment strategies may have the ability to make excess returns than the market. Bessembinder and Chan (1998) said that if technical rules had significant return forecast power, trader could use the rules to improve returns relative to a 'buy-and-hold' strategy without consideration of transaction costs. Since strategies mean frequent transactions investors might not earn an increased returns from return forecastability if transaction costs are under consideration. The strategy process conducted in a certain period is: From the start date of the certain period, find the beginning date of the strategy as the day when the return is higher (lower) than a (b), then buy (sell) one share in the following day. Then find the second trading day as the day when return is lower (higher) than b (a). Next day sell (buy) one share to cover the trading and sell (buy) one more share to open a new trading action. Repeat these processes until the end of the period. This type of strategy is called S(a,b) in this paper. a and b are benchmarks for buying and selling action. It is noteworthy that this type of strategy will make profits higher than a 'buy-and-hold' strategy when the returns have positive autocorrelation relationship themselves.

2.5 Variance ratio

The sixth measure is variance ratio computed as the ratio that long holding period variance is divided by daily return variance. If pricing errors are corrected within three weeks, most of the three-month return reflects a rational assessment of the information arriving during the three-month period and therefore bid/ask and pricing errors have relatively little effect on three-month holding period returns. If daily returns were independent, the variance for a long holding period would equal the cumulated daily variances within the period. If daily returns are affected by trading noise, the longer period variance will be smaller than the cumulated daily variances (French and Roll (1986)). We also use (1 - variance ratio) as the amount of pricing errors. The variance ratio considered here is different from the traditional variance-ratio test of random walk which calculate a final z-values under homoscedasticty or under heteroscedasticity. Liu and He (1991) found evidence rejecting the random walk hypothesis with variance-ratio test while Karemera, Ojah and Cole (1999) conducted the multiple variance-ratio test in fifteen emerging capital markets and found that the returns was consistent with random walk in most markets analyzed.

2.6 Co-movement of different market efficiency measures, co-movement between individual stocks and stock market, systematic market efficiency

In order to check the co-movement of seven market efficiency measures and the co-movement of individual stocks with stock index, correlation coefficient is used for the former one. As for the latter, we use the similar method from Rosch, Subrahmanyam and van Dijk (2017), in which OLS is used:

$$Y_t = a + b \cdot X_t + u_t \qquad u_t \sim N(0, \sigma^2) \qquad (2)$$

Y_t :The value of efficiency measure of individual stock (300 stocks)
X_t:The value of efficiency measure of stock index (CSI 300)
a:constant
b :the coefficient of co-movement

If the coefficient b is significant we can say that there is co-movement between individual stocks and stock index. That is also to say, there is co-movement between different stocks and the market has so-called systematic market efficiency.

2.7 Principal Component Analysis

Principal component analysis (PCA) is a technique in modern data analysis that analyzes a data table in which observations are described by several inter-correlated quantitative dependent variables. It will extract the important information from the table and represent it as a set of new variables called principal components (Abdi and Williams (2010)). During this process, it convert a set of observations of correlated variables into a set of values of linearly uncorrelated variables (Karamizadeh, Abdullah, Manaf, Zamani and

Hooman (2013)). High-dimensional data are common in economic analysis when researchers try to explain the market or explain some phenomena with multiple indicators. PCA will simplifies the complexity in high-dimensional data to fewer dimensions but retain the main information and patterns contained in data. Because we use seven measures to represent the market efficiency level in stock markets of China, we want to use PCA to calculate its first component and use its series as the main change trend of market efficiency level as it did in the Rosch, Subrahmanyam and van Dijk (2017). Then we also do a OLS regression (2) with this data and check if there is a clear systematic market efficiency.

2.8 Possible explanations for higher level of market efficiency

In French and Roll (1986), three possible explanations are proposed for the phenomenon that asset prices become more volatile during exchange trading hours than during non-trading hours: volatility is caused by public information or private information or pricing errors. Their result was that a significant fraction of daily variance was caused by mis-pricing but private information was the principle factor. Mubarik and Javid (2009) also said that the trading volume could serve as a proxy measure for unobservable amount of information that flowed into the market. From the three explanations of French and Roll (1986), we propose three possible explanations (hypotheses) on the change trend of market efficiency in China or for explaining the higher level of market efficiency in some years: First, the pricing-error hypothesis states that when the market is more efficient the pricing errors in daily return is less. If the change trend is caused by this reason, it should be observed that the three-month-pricing-errors is gradually decreasing when the market is gradually efficient. Second, the reaction of stock price series to public information is becoming quick and accurate. Third, the reaction of stock price series to private information is becoming quick and accurate.

In order to verify second and third hypotheses, we do the following regression. We regress daily returns on a variable expressing public information and daily trading volumes expressing private information and use R2 as a criteria.

$$Y_t = a + b_1 \cdot X_{1t} + b_2 \cdot X_{2t} + u_t \qquad u_t \sim N(0, \sigma^2) \qquad (3)$$

Y_t : daily returns of individual stocks

X_{1t}: the arrival of public information expressed with Shibor

X_{2t}: the arrival of private information expressed with trading volume

a : constant

b_1 : the coefficient of public information

b_2 : the coefficient of private information

If both public and private information is important for market efficiency level, both b_1 and b_2 in (3) should be significant. If only public information plays an important role, we hope to see a significant b_1 but non-significant b_2. If only private information plays an important role, we hope to see a non-significant b_1 and a significant b_2. It is important to recognize that these hypotheses are not mutually exclusive. The change trend of market efficiency may be caused by all three possible hypotheses simultaneously. We want to provide some empirical evidence for each explanation.

3.Data

This paper uses data of CSI 300 Index and its 300 constituent stocks which are selected at the time point of January 2021. The data source is NetEase Finance. CSI 300 Index is a index that replicate the performance of the top 300 stocks traded on Shanghai Stock Exchange and Shenzhen Stock Exchange, to represent stock market in China. The time span of CSI 300 Index covers 2005-2020. However, the 300 constituent stocks have different time spans. The earliest year of data available is 1991 like stock 000001, Ping An Bank. For example, stock 601336, New China Life Insurance, started from 2011 and has only less than ten-year-data. Anyway, all data can be collected form the start of timespan to the end date of 2020. To save space, the descriptive analysis of CSI 300 Index and stock 000001, Ping An Bank, is showed in Table 1 including mean, standard deviation, skewness, kurtosis, Jarque-Bera statistic.

Table 1 Descriptive analysis of CSI 300 and stock of Ping An Bank

Note:This table shows the descriptive statistics of CSI 300 and stock of Ping An Bank. Mean is the mean value of daily returns. SD is the standard deviation of daily returns. JB is Jarque-Bera statistic.

	Stock	Mean	SD	Skewness	Kurtosis	JB
2005	CSI 300	-0.00026	0.01331	1.19234	8.09696	317.97697
	Ping An Bank	-0.00027	0.02530	0.63158	6.57926	135.66301
2006	CSI 300	0.00322	0.01404	-0.62286	5.63799	85.10824
	Ping An Bank	0.00383	0.02681	0.08192	6.36474	103.08077
2007	CSI 300	0.00394	0.02340	-1.02355	4.87780	77.48920
	Ping An Bank	0.00470	0.03607	0.03810	2.68570	0.93259
2008	CSI 300	-0.00443	0.03061	0.16536	3.42534	2.96336
	Ping An Bank	-0.00572	0.04596	-1.05736	9.18543	432.65744
2009	CSI 300	0.00264	0.02057	-0.61061	4.21369	30.01468
	Ping An Bank	0.00398	0.03014	0.43126	4.24591	22.10134
2010	CSI 300	-0.00051	0.01593	-0.60559	4.66369	42.52460
	Ping An Bank	-0.00213	0.02336	-0.31374	4.75939	27.76810
2011	CSI 300	-0.00126	0.01300	-0.14597	3.46626	3.06411
	Ping An Bank	-0.00012	0.01684	0.17761	3.64085	5.25685
2012	CSI 300	0.00038	0.01277	0.71082	4.56454	45.06085
	Ping An Bank	0.00024	0.01462	1.28698	7.08008	224.96500
2013	CSI 300	-0.00034	0.01405	-0.25792	5.49843	64.26908
	Ping An Bank	-0.00113	0.04679	-6.39898	77.68127	56453.94550
2014	CSI 300	0.00172	0.01210	0.30446	4.97262	43.33053
	Ping An Bank	0.00106	0.02415	-1.75585	21.87006	3730.16245
2015	CSI 300	0.00010	0.02506	-0.85735	5.08517	73.79213
	Ping An Bank	-0.00119	0.03078	-1.00594	9.04403	410.85251

	Stock	Mean	SD	Skewness	Kurtosis	JB
2016	CSI 300	-0.00019	0.01342	-1.46444	10.22500	615.38715
	Ping An Bank	-0.00090	0.01721	-6.30658	71.91746	49700.67627
2017	CSI 300	0.00077	0.00638	-0.36773	5.18265	53.71175
	Ping An Bank	0.00153	0.01625	0.75692	7.32448	212.55250
2018	CSI 300	-0.00126	0.01352	-0.19377	4.14143	14.65176
	Ping An Bank	-0.00157	0.02122	-0.08138	4.34842	18.60091
2019	CSI 300	0.00132	0.01247	0.05085	7.02186	163.88033
	Ping An Bank	0.00240	0.01991	0.41737	4.67656	35.51479
2020	CSI 300	0.00094	0.01443	-0.97029	8.44374	336.78477
	Ping An Bank	0.00056	0.02165	-0.07529	6.06854	95.17282

The summary statistics in Table 1 has three important implications about the features of stock index and individual stocks: First, generally speaking, because of diversification of risk, the investment lost is lower in investing in stock index than in individual stocks when the mean return in a specific year is minus. In Table 1, this phenomenon is proved in column 'mean' except 2011 and 2015. Of cause, the investment profit is higher in investing in individual stocks than in stock index when the mean return is plus expect 2012, 2014, 2015 and 2020 in column 'mean'. If all the individual stocks are under consideration, this phenomenon would be more clear and remarkable. Second, the standard deviation of stock index is always smaller than the one of individual stocks because the index is a combination of different stocks. Different stocks have increasing trend or decreasing trend in a particular interval and all these trend will be partially eliminated when combining them into one new trend. Third, return distributions of stock index and individual stock are both different from normal distribution in most year for high Jarque-Bera statistic. In Table 1, this conclusion is also proved except 2007 for Ping An Bank, 2008 for CSI 300 and 2011 for both but it can be seen from Table 1 column 'JB' that the return distribution of Ping An Bank rejected the null hypothesis of normal distribution more heavily than that of CSI 300 in most year. Rejection of normal distribution is the similar to Officer (1972) which said that the distribution had 'fat tails' compared to the normal distribution, and also similar to Dorina and Simina (2007), Rosa (2009).

4.Empirical results

4.1 The results of seven market efficiency measures

Calculate seven measures of market efficiency using CSI 300 index and 300 constituent stocks. The results of stock 00001, Ping An Bank, are shown in Table 2.

Table 2 Seven market efficiency measures

Note: The efficiency measures are calculated only when the daily returns in a calendar year are greater than 80. ACF1 shows the autocorrelation at log1 of daily returns. ACF2 shows the autocorrelation at log1 of absolute daily returns. Runs tests shows the z-values of runs test. Beta shows the coefficient of b in regression (1). Strategies shows the value of strategy. Variance-ratios and Pricing-errors are the based on daily returns and 3-month returns. The calculation of variance-ratios is: the variance of 3-month-return series

/ (the variance of daily returns / the number of 3-month return series. There are around sixty days in a 3-month-return series and therefore the number among a year is around four). The Pricing-errors is calculated by (1 - Variance-ratios). *** means very significant with p value lower than 0.01. ** means significant with p value higher than 0.01 but lower than 0.05. * means a little significant with p value higher than 0.05 but lower than 0.1. No * means insignificant.

	ACF1	ACF2	Runs tests	Beta	Strategies	Variance ratios	Pricing-errors
1991	0.067	0.189***	-7.68***	-8.615E-09	1.314	1.786	-0.786
1992	0.104*	0.073	-2.07**	1.873E-08**	-0.402	0.405	0.595
1993	0.006	0.032	-1.97**	-5.701E-10	1.446	0.998	0.002
1994	0.002	0.136**	-0.30	5.673E-09***	0.520	0.509	0.491
1995	0.020	0.035	-0.04	1.038E-08***	-0.764	0.316*	0.684*
1996	0.080	0.087	-0.10	6.78E-10***	1.478	0.559	0.441
1997	0.066	0.112*	-0.78	4.812E-10**	0.852	1.989	-0.989
1998	0.021	0.085	-0.75	1.99E-09***	0.090	0.348	0.652
1999	0.176***	0.454***	0.12	5.668E-10***	0.091	1.857	-0.857
2000	-0.085	0.285***	-0.03	1.081E-09***	0.656	0.164***	0.836***
2001	-0.047	-0.046	0.60	1.021E-09***	-0.074	0.675	0.325
2002	0.144**	0.082	-1.27	8.045E-10***	0.162	1.565	-0.565
2003	-0.063	-0.000	0.98	9.831E-10***	-0.429	0.869	0.131
2004	0.020	0.079	-1.27	8.319E-10***	-0.092	0.285	0.715
2005	-0.033	0.160	1.45	2.089E-09***	0.645	0.116***	0.884***
2006	0.105	0.21***	1.35	6.756E-10***	0.004	1.191	-0.191
2007	0.127*	0.068	-0.11	3.876E-10**	0.023	0.586	0.414
2008	-0.014	-0.040	-0.46	5.081E-10**	0.762	0.293	0.707
2009	0.027	-0.095	0.35	3.478E-10***	-0.007	0.557	0.443
2010	-0.119*	0.019	0.95	2.57E-10***	-0.193	0.4*	0.6*
2011	-0.112*	-0.095	1.66*	3.138E-10***	0.282	0.366	0.634
2012	-0.005	-0.034	0.10	6.224E-10***	-0.115	0.439	0.561
2013	0.034	-0.041	1.81*	2.135E-10***	-0.263	1.228	-0.228
2014	-0.102	0.173***	0.73	1.749E-10***	-0.443	0.540	0.46
2015	-0.010	0.243***	0.39	8.776E-11***	-0.909	0.653	0.347
2016	-0.096	0.001	0.84	1.019E-10**	0.152	0.419	0.581
2017	-0.013	0.157**	-1.65*	8.212E-11***	0.369	0.754	0.246
2018	0.064	0.105*	0.22	7.468E-11***	-0.174	0.891	0.109
2019	-0.029	0.002	0.47	1.474E-10***	0.217	0.423	0.577
2020	0.064	0.151**	0.00	1.038E-10***	0.257	0.894	0.106

The market has the function to constantly correct pricing errors and this functional action would result in negative relation in return series as we said above. Therefore, whether there exits positive relation or not would be more valuable in studying market efficiency.

4.1.1 Autocorrelation of daily return

From autocorrelation of daily returns at log1 in column 2 Table 2, it is clear that before 2000 there exists positive autocorrelation in daily returns although the value is small. What we found is similar to Borges (2008). While after 2000, the negative autocorrelation becomes more frequent. Safvenblad (2000) found that Swedish stock index returns exhibited strong and constantly positive first order autocorrelation and it was observed for return frequencies between one day and three months. The result we found is different from Sewell (2012) which found that the first-order autocorrelation of daily, weekly, monthly and annual log returns was small but positive for all time periods with 0.0138 in daily returns. The reason for difference may be that the period of data in Sewell (2012) is from 1928 to 2012 while the period analyzed in this paper is from 1991 to 2020 and the analysis process is designed to be done in one year-sub-period. Hamid, Suleman, Shah and Akash (2010) used monthly stock market returns of fourteen countries including China, the autocorrelations of these countries were all minus at log1.

4.1.2 Autocorrelation of absolute daily return

From autocorrelation of absolute daily returns at log1 in column 3 Table 2, we found that the result is same as Ding, Granger and Engle (1993) that the absolute return has quite higher autocorrelation compared with daily returns.

4.1.3 Runs test

The z-values of runs test are showed in column 4 Table 2. The results do not find any evidence against efficiency market except 1991, 1992, 1993, 2011, 2013 and 2017. The result is the different from Ozdemir (2008), in which the result of runs test failed to reject the randomness, different from Al-Jafari and Altaee (2011), in which the runs test clearly showed that Egyptian equity market was weak-form inefficient, different from Sewell(2012), which showed that daily returns were the least consistent with an efficient market. The result is similar to Karemera, Ojah and Cole (1999), in which most emerging markets were consistent with random walk, similar to Borges (2008), which found the number of runs was significant less than the expected number of runs, similar to Rosa (2009), in which the results of runs test were different in different sub-periods, and is quite different from Dorina and Simina (2007), in which eight emerging markets were examined and seven of them were found that successive returns were not independent.

Moreover, real runs of return series has less than mean runs (z-value is negative), which indicates positive autocorrelation and has more than mean runs (z-value is positive), which indicates negative autocorrelation. The results of runs tests are similar to the result of autocorrelation. In 1992 and 2011, both runs test and autocorrelation show that there exists positive correlation in daily stock returns.

4.1.4 The forecast ability of trading volume on return

The forecast ability of yesterday's change of trading volume on today's return always has statistical meaning except 1991, 1993, and the coefficient b is always positive except 1991 and 1993 in column 5 Table 2. That is to say, more trading has a positive affect on returns. Our findings is similar to Mubarik and Javid (2009), in which yesterday's trading volume had a positive in predicting today's return. Because the forecast ability of yesterday's change of trading volume on today's return is always significant, we can conclude that from the viewpoint of forecast ability the market is not becoming more and more efficient through 30 years. During 2008, global finance crisis, the coefficient increased. After that, the main trend is downward.

4.1.5 Strategy

The specific strategies process is stated in 2.4. We do S(0.01,-0.01) in this paper and calculate the return of S(0.01,-0.01) for every calendar year. We also calculate returns of holding stocks in the same intervals based on strategies. Without consideration of costs, the results of strategy returns are showed in column 6, Table 2. Although there are years during which strategy makes higher return than buy-and-hold, the returns are not significantly higher. The results of strategies are not consist with the results of autocorrelations and runs tests because of no significance.

4.1.6 Variance ratio and pricing error

The results of variance ratio and pricing error are in column 7 and column 8 Table 2. Here, the period used to calculate long-period-variance is collected with 3-month based on French and Roll(1986). The ratio of 2 or 3 day-period-variance to one-day-variance can be used to examine the autocorrelation of return series: if the ratio is high than 1, positive relation exits and if the ratio is lower than 1, negative relation exits. While the ratio of 3-month-variance to one-day-variance is design to calculate the pricing errors in daily returns with (1 - the ratio). If the market becomes more and more efficient, the possible reactions of the market from perspective of pricing errors have two possibilities: One is, the amount of pricing errors becomes smaller. Another one is, the speed of detection and adjustment to pricing errors becomes quicker. However, the value of pricing errors fluctuates from 1991 to 2020 without a clear downward trend. 2008 has relatively higher pricing errors because of financial crisis. The speed of detection and adjustment to pricing errors can not be concluded from values of pricing errors themselves.

In sum, the results of seven measures are not the same. The results of autocorrelation is similar to runs test but strategy, variance ratio, pricing error, is different from the former two. As for the forecast ability of trading volume on return, it shows a significant forecast ability in almost all years.

4.2 The co-movement of different market efficiency measures

The co-movement of seven market efficiency measures are shown in Table 3. Calculate correlation coefficients pairwise for this seven measures. First calculate correlation coefficients of seven market efficiency measures for individual stocks. Then calculate mean value of 300 stocks.

Table 3 The co-movement of different market efficiency measures

Note: ACF1 means autocorrelation of daily returns at log 1. ACF2 means autocorrelation of absolute daily returns at log 1. Runs tests do not use z-values but use: (mean value of runs - the real number of runs). We rearrange the value of runs tests and therefore when returns are positive correlated, the values are positive and vice versa. Beta is the coefficient of regression of yesterday's change of trading volume today's return. Strategies use the return of S(0.01,-0.01) minus holding return. Variance ratios use the ratios of 3-month variance to one-day variance. Pricing-errors are (1- Variance ratios). Only the market efficiency measures have more than seven year are contained in correlation calculation. There are 232 stocks have more than seven year data.

(A) The mean correlation coefficients of 232 stocks

Note: First calculate the corrections of 21 pairs of market efficiency measures for 232 stocks respectively. Second, calculate the mean value.

	ACF1	ACF2	Runs tests	Beta	Strategies	Variance ratios	Pricing-errors
ACF1	1						
ACF2	0.2421	1					
Runs tests	0.4069	0.0412	1				
Beta	-0.0420	-0.0083	0.0053	1			
Strategies	-0.0744	-0.1215	-0.0181	0.0361	1		

Variance ratios	0.3822	0.1547	0.1862	-0.0318	-0.0594	1	
Pricing-errors	-0.3822	-0.1547	-0.1862	0.0318	0.0594	1	1

(B) The t tests for correlation coefficients

Note: First, calculate the t statistics of correlations of 15 pairs of market efficiency measures for 232 stocks respectively. Second, calculate two ratios that the t statistic is higher than 2 and 3.

	ACF1	ACF2	Runs tests	Beta	Strategies	Variance ratios
ACF1						
ACF2	0.276/0.134					
Runs tests	0.388/0.168	0.034/0.00				
Beta	0.026/0.004	0.06/0.013	0.052/0.013			
Strategies	0.009/0.004	0.004/0.004	0.047/0.009	0.069/0.022		
Variance ratios	0.317/0.185	0.194/0.073	0.06/0.017	0.03/0.009	0.026/0.00	
Pricing errors	0.009/0.00	0.013/0.00	0.00/0.00	0.047/0.009	0.069/0.009	0.00/0.00

Averagely, from Table 3 (A), ACF1 is positively correlated to Runs tests with 0.4069, quite high, indicating positive autocorrelation. However, both ACF1 and Runs tests are negatively correlated with strategies, which is not consistent with the theory: Generally speaking, when the market is positive correlated, the S(a,b) should make profit than a buy-and-hold strategy. Some points should be noticed that there is an implied border like critical value. In order to make profit, the scale of autocorrelation may be requested. When the scale is below the implied critical value, the strategy is going to fail. That may be the reason that negative relationship exits between ACF1 and Strategies and between Runs tests and Strategies. Beta is positively related to Runs tests with 0.0052 and Strategies with 0.0361. As for Pricing-errors, it is positively related to Strategies. Of cause it is reasonable. If the market is full of pricing errors, there will be a lot of chance for investors to make their own strategies for pursuing higher returns.

However, from Table 3 (B), among 21 pairs of variables, the significant t statistics of correlation coefficients are all lower than 0.4. That is to say, among 232 stocks, only a little shows evidence that the different market efficiency measures have significant co-movement.

In a ward, there is a little co-movement among different market efficiency measures. What we found is similar to Rosch, Subrahmanyam and van Dijk (2017) but they found more evidence for co-movement.

4.3 The co-movement of different stocks with the stock market

The co-movement of different stocks with whole market are examined in regression (2). Using seven measure values of 300 constituent stocks as the efficiency level of individual stock and seven measure values of CSI 300 index as the efficiency of whole market in China. It is different from Rosch, Subrahmanyan and van Dijk (2017) which used the mean value of all stocks as the efficiency of whole market. The estimation values of co-movement in different market efficiency measures are the coefficients b from time-series regressions of individual stocks, 300 constituent stocks, on contemporaneous market efficiency, CSI 300 index. Table 4 summarizes three important indicators: the coefficient b, R2 and %-significant.

Table 4 The co-movement of different stocks with the stock market

Note: The results in this table is the regression (2):

$$Y_t = a + b \cdot X_t + u_t \qquad u_t \sim N(0, \sigma^2) \qquad (2)$$

Y_t :The value of efficiency measure of individual stock (300 stocks)
X_t:The value of efficiency measure of stock index (CSI 300)
a:constant
b :the coefficient of co-movement

The regression are done for 300 individual stocks respectively. b is the mean values of the coefficients of b in regression (2). R2 is the mean values of goodness of fit. %-significant means the percentage that is calculated as the ratio when t-statics of b is significant.

	b	R2	%-significant
ACF1	0.4921	0.2425	0.377
ACF2	0.5070	0.2916	0.490
Runs tests	0.1772	0.0867	0.057
Beta	443.8616	0.3533	0.506
Strategies	0.8122	0.3722	0.636
Variance ratios	0.2678	0.1891	0.279
Pricing-errors	0.2678	0.1891	0.279

The mean values of coefficient b range from 0.2678 for Variance ratios and Pricing-errors to 0.81 for Strategies except b for Beta. The b of Beta looks a little strange because the data of change of trading volume have respectively bigger scale. Strategies are the most consistent market efficiency indicator with market efficiency level. %-significant shows that significant regressions are over 50% for Beta and Strategies. Runs tests are the least consistent. Only 5.7% of regressions for Runs tests are significant. The reasonable explanation is that individual stock fluctuates frequently compared with index and their change is somewhat different with each other.

In a ward, there is significant co-movement between individual stocks and the stock market and therefore the systemic market efficiency exist. The result is the similar to Rosch, Subrahmanyan and van Dijk (2017).

4.4 Principal Component Analysis

In order to use one indictor to indicate market efficiency level, here, Principal Component Analysis are used. The first component are used as market efficiency level for 300 stocks and for CSI 300 Index. Table 5 summarizes the mean values of loadings and explained variance ratio for 300 index and for CSI 300 index.

Table 5 Principal Component Analysis for six measures

Note: The results in 300-stocks-1 and the results in CSI 300 index use the basic data of loadings and explained variance ratios from 300 individual stocks and from CSI 300 index to calculate the mean value for both indicators. The results in 300-stocks-2 are the ones which first calculate the mean values of six measures for 300 stocks and then regard the mean value series as a new series to do a Principal Component Analysis. 25%, 50% and 75% are the quintiles of Loadings for 300 stocks.

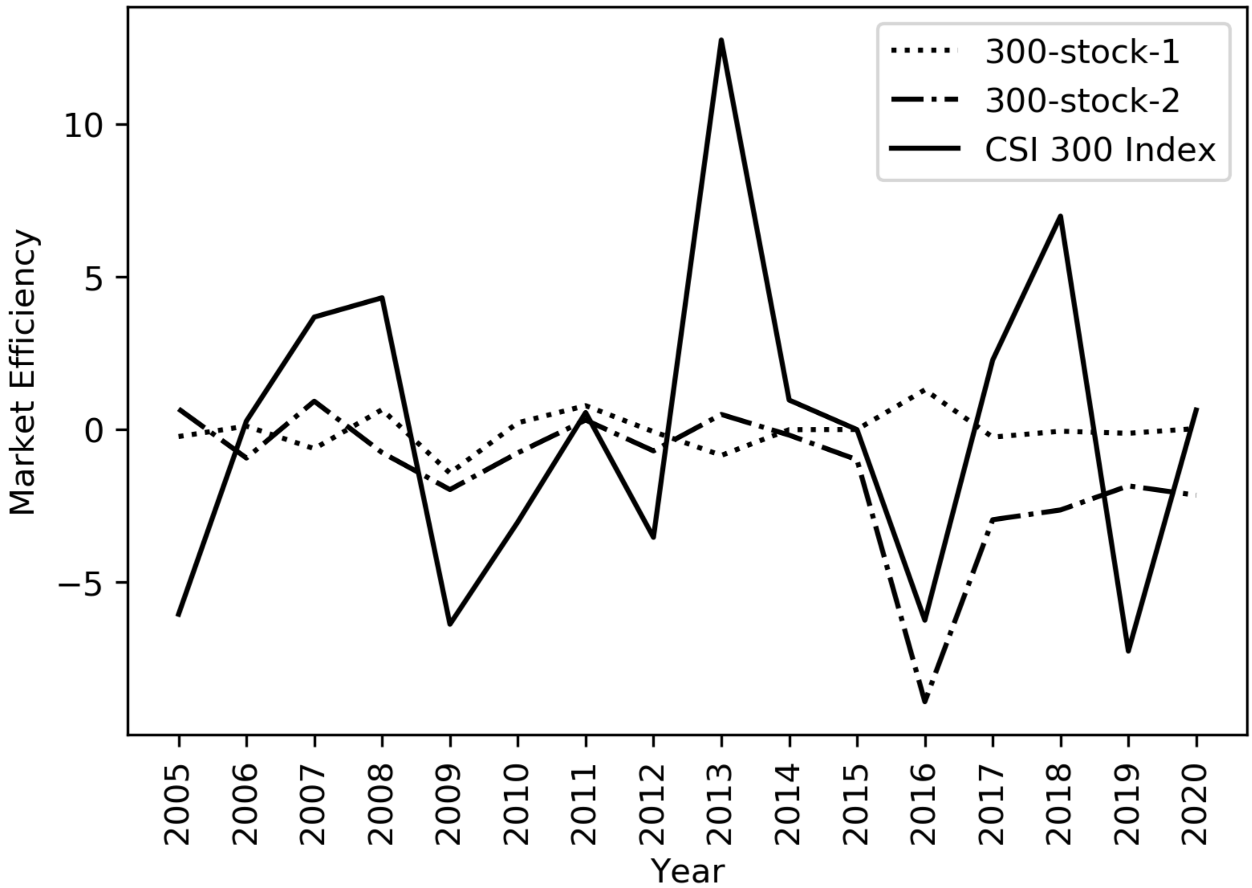
	ACF1	ACF2	Runs tests	Beta	Strategies	Variance ratios
300-stocks-1						
Loadings	-0.0001	0.000048	-0.0087	1.01063E-11	0.0022	-0.0004
25%	-0.0046	-0.0031	-0.9998	-6.28658E-11	-0.0124	-0.0116
50%	-0.0004	-0.0005	-0.9940	-1.53177E-12	-0.0002	-0.0014
75%	0.0045	0.0031	0.9997	4.19418E-11	0.0156	0.0088
Explained variance ratio	0.9873 0.25:0.9849 0.5:0.9898 0.75:0.9931					
300-stocks-2						
Loadings	0.0189	0.0360	0.9745	0.0982	0.0274	0.1959
Explained variance ratio	0.9797					
CSI 300 index						
Loadings	0.0026	-0.0006	0.9997	0.0000	0.0189	-0.0113
Explained variance ratio	0.9841					

Here only six measures are used to do Principal Component Analysis because of the linear relationship between Variance ratios and Pricing-errors. Generally speaking, the first components explain over 95% variance: for 300-stocks-1 and -2, the mean values are 0.9873 and 0.9797, for CSI 300 index, is 0.9841. Therefore, they can be seen as a relatively good indicators representing six market efficiency measures. From 300-stocks-1 and -2, it is clear that not every stock has similar loadings for six measures and the loadings of individual stock range from minus to plus. It may not be a good way to average loadings themselves after calculation of loadings. 300-stocks -2 is better than 1 because all six measures is contained in the first component with different ratios although Runs tests play a bigger and more important role compared with the other measures.

Plot 1 shows the change trend of the first component for 300-stocks-1, -2 and CSI 300 index from 2005 to 2020.

Plot 1 The change trend of market efficiency

Note: 300-stock-1 means that calculate the first component for 300 stocks first and then calculate the yearly mean value of the 300 first component series. 300-stock-2 means that calculate the mean value of six measures from 300 stocks and then do a Principal Component Analysis for the new measure series. All three lines show the first components.



The reason why the change trends for individual stocks are less fluctuate than CSI 300 stock is considered to be the calculation method. The mean value calculation method causes this phenomenon. For example, because we use the mean value of six measures to calculate the change trend of market efficiency in 300 stock 2, the effect of different signs will be eliminated. The efficiency levels of 300-stock-1 and -2 are mixtures of high market efficiency and low market efficiency. Therefore, it may not be a good way to analyze the change trend contained mixed information. And, it is disappointed to see that there is no clear downward trend for market efficiency from 300-stock-1 and -2 or for CSI 300. Anyway, the change trend line of CSI 300 shows high value in 2007 and 2008, financial crisis period, in 2018 and a pretty high value in 2013. When the first component is over 0, the return series have positive autocorrelation and the market is positively predictive. When the first component is minis, the return series have negative autocorrelation and it can not be concluded that to what extent the market is negatively predictive because of adjustment function of the market. The change trend of CSI 300 index also fluctuates from 2005 to 2020 without a clear downward trend. This result is different from Rosch, Subrahmanyam and van Dijk (2017), which found that the market was becoming more and more effective. The reason may be that this paper uses different method to measure stock market efficiency.

Especially in 2020 during which COVID-19 swept across the world, the first component value is positive for CSI 300. The change trend of 300-stock-2 showing different fluctuation may be also caused from the calculation method as we stated above. The value of CSI 300 fluctuated from 2006 to 2020 with negative value in seven times and positive value in nine times.

The result we found above supports the idea that the market efficiency in Chinese stock market is changing all time without showing a clear upward trend from 2005 to 2020.

The results of co-movement of different stocks with stock market using the first component of PCA are summarized in Table 6.

Table 6 The co-movement of different stocks with the stock market (PCA)

Note: Only the stocks which have more than fifteen years are regressed with regression (2).

	b	R2	%-significant
The First Component	0.0329	0.0587	0.0748

It is clear that the co-movement phenomenon is not as significant as what we found in Table 4 in separate seven regression. The reason may be the calculation of PCA which leads to a very different change trend of market efficiency for different stocks.

4.5 Possible explanations for higher level of market efficiency

From Table 2 and Plot 1, we can say that in 2005, 2012, 2017 and 2019 the market has a relatively higher level of market efficiency while in 2008, 2013, 2018 and 2020 the market has a lower level of market efficiency. From Table 2 column Pricing-errors, we found that there is not a clear downward trend for pricing-errors in daily returns. The pricing-errors of Ping An Bank did not support the idea that when the market is more efficient, the pricing-errors contained in the stock is less. For example, the pricing-errors are 0.884, 0.561, 0.246 and 0.577 for 2005, 2012, 2017, 2019 and are 0.707, -0.228, 0.109, 0.106 for 2008, 2013, 2018, 2020. Of cause there is the stock supporting the pricing-error hypothesis among 300 stocks. Moreover, the mean value of pricing-errors of 300 stocks are 0.3077, 0.3833, 0.3445, 0.3065 for 2005, 2012, 2017, 2019 and are 0.4811, 0.3971, 0.4344 and 0.3969 for 2008, 2013, 2018 and 2020. From the average data, when the stock market is more efficient, the pricing-errors in daily returns are less. These evidence supports the pricing-errors hypothesis to some extent.

The results of regression (3) are summarized in Table 7.

Table 7 The results of regression (3)

Note: This table shows results of regression for 300 stocks respectively:

$$Y_t = a + b_1 \cdot X_{1t} + b_2 \cdot X_{2t} + u_t \qquad u_t \sim N(0, \sigma^2) \qquad (3)$$

Y_t : daily returns of individual stocks
X_{1t}: the arrival of public information expressed with Shibor
X_{2t}: the arrival of private information expressed with trading volume
a : constant
b_1 : the coefficient of public information
b_2 : the coefficient of private information

We regress (3) in a calendar year for 300 stocks from 2007 to 2020. There are years during which some stocks do not have data than 50 data. These years are omitted from regression.

(A)

The numbers in the table are the ratios of significant b_1 and b_2 among years from 2007 to 2020 for individual stocks. The stocks that do not have more than three years' data are also omitted from the calculation of the ratios. For saving space, five examples are showed.

	The significant ratio for b_1	The significant ratio for b_2
000001 Ping An Bank	0.077	0.769
000066 Chiese Great Wall	0.231	0.923

000157 Zhong Lian Zhong Ke	0.077	0.769
000338 Wei Chai Dong Li	0.154	0.692
000627 Tian Mao Ji Tuan	0.231	0.846

(B)

The number in the table are the mean ratios of significant b_1 and b_2 in different years.

Year	The significant ratio for b_1	The significant ratio for b_2
2008	0.014	0.741
2009	0.031	0.887
2010	0.006	0.675
2011	0.122	0.76
2012	0.065	0.758
2013	0.282	0.775
2014	0.053	0.811
2015	0.196	0.583
2016	0.045	0.761
2017	0.071	0.802
2018	0.057	0.419
2019	0.011	0.814
2020	0.127	0.715

From Table 7 (A), it is clear that for individual stocks, the private information expressed by daily trading volume plays a more important role in daily return than public information expressed by Shibor. From Table 7 (B), there is no clear trend for significance of public information and private information from 2008 to 2020. In 2012, 2017, 2019 and in 2008, 2013, 2018, 2020, the significant of two variables did not show higher values and lower values for both variables. The hypotheses proposed above are failed to be verified but we found evidence indicating the importance of private information in stock return.

5.Conclusions and further Questions

This paper analyzed CSI 300 index and its 300 constituent stocks with seven market efficiency measures: autocorrelation of daily return, autocorrelation of absolute daily return, runs test, forecast ability of other historical data on daily return (the predictive ability of yesterday's change of trading volume on today's return), the return of specific trading strategy, variance ratio and pricing errors in daily return. We did a Principal component analysis to convert these indicators to a single indicator representing the market efficiency. Then we try to find the co-movement among different measures through correlation coefficient and among different stocks through regression of measures of measures of CSI 300 on individual stocks. We found that different market efficiency measures are indeed consistent to each other to some extent and the individual stocks are somewhat consistent with the whole market in China. In the end, we set three hypotheses for explaining the cause of higher level of market efficiency: the market contains lower pricing-errors and the ability of market detecting and reacting to public information or private information is becoming accurately when the stock market is more efficient.

The result is that there is indeed co-movement among different market efficiency measures, there is also co-movement between individual stocks with stock index and there is a significant part of systematic market efficiency in the stock market in China. As for the three hypotheses, evidence supporting pricing-error hypothesis and for the importance of private information is found. The market contains more pricing-errors in daily returns when the market condition is bad. Private information is more important than public information.

Two questions are proposed for future study. First, what will change when transaction costs are under consideration and how it influences the result of market efficiency. Second, Suominen (2001) said that the source of uncertainty in the asset returns was constantly changing. However, regression (3) is not able to make a random or stochastic structure for the arrival of information. If better model is used to check three hypotheses, the results may be different.

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