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Abstract

This paper examines the weak form market efficiency in five stock markets, China (CSI 300 index), Hong Kong (HSI), Japan (Nikkei 225), the US (NASDAQCOM) and Germany (DAX) from the perspective of random walk hypothesis. The methods for testing random walk are autocorrelation, runs test, strategy. This paper also examine three calendar effects in all stock markets: January effect, the-turn-of-the-month effect (the TOM effect), the day-of-the-week-effect (the DOW effect). The results are: (1)From the viewpoint of autocorrelation, the most efficient market among five stock markets is the market in Hong Kong while strong evidence of autocorrelation is found in China, CSI 300 and The US, NASDAQCOM. (2) The results of runs tests do not found evidence against randomness in daily returns for CSI 300, HSI from 2006 to 2020 but find a little evidence for Nikkei 225, NASDAQCOM, DAX. The higher level of efficient markets among five stock markets are the markets in China and Hong Kong. (3) The strategy analyzed in this paper does not find evidence indicating inefficient market for five indexes. (4) January effect did not exist in five indexes. (5) All five indexes are characterized with a TOM effect in different level and therefore the hypothesis of an efficient market is rejected for five markets. (6) All five indexed are found the-day-of-week effect which also indicates inefficient stock markets. we conclude that all five market are not efficient from 2006 to 2020. (7) After the consideration of time-varying volatility, we found January effect in Nikkei 225 in returns. Except Nikkei 225 all the other indexes are verified with the turn-of-the-month-effect and only CSI 300 are verified with the day-of-the-week-effect in returns.

Keywords: market efficiency hypothesis, random walk, January effect, the-turn-of-the-month effect, the day-of-the-week-effect
JEL Classification: G10, G14, C22

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1.Introduction

We talked about the market efficiency using data of CSI 300 and its 300 constituent stocks with seven market efficiency measures and the systematic market efficiency among the market in China. From this chapter, we also talk about the market efficiency but in different markets and with different data. We try to answer other questions on the study of market efficiency.

The capital market hypothesis has always been the context in which serious discussion of the regulation of financial markets takes place. In order to utilize some theoretical models in economics to analyze problems, many studies consider the financial market in the real world as an efficient market in which there is no cost to get information and the market always quickly and accurately reacts to new information. However, the hypothesis of market efficiency is not a well-defined and empirically refutable hypothesis (Sewell (2012)). On one hand, Gilson and Kraakman (1984) holds the view that market efficiency is easily explained under perfect market assumptions, information is immediately and costlessly available to all participants, but this kind of view is almost 'absolutely accurate and totally useless'. On the other hand, Malkiel (2003) thinks that markets can be efficient even if many market participants are quite irrational and can be efficient even if stock prices exhibit great volatility than can apparently be explained by fundamentals.

From many previous studies, an efficient market is summarized as such a market during which prices at any time fully reflect all available information and therefore available information does not enough for any profitable trading strategies or arbitrage opportunities (Fama (1970), Gilson and Kraakman (1984), Malkiel (2003), Ozdemir (2008), Nisar and Hanif (2012)).

Fama (1970) is one of the famous paper in studying market efficiency, during which lots of studies before 1970 were reviewed and the results were consistent with an efficient market. Around 1990, despite some anomalies, many studies considered that the capital market responded efficiently to information. However, Malkiel (2003) said that after 1990 there were many papers that found evidence against efficient market. The view on the level of market efficiency is gradually changing. According to Fama (1970), there are three types of market efficiency: the weak form, the semi-strong form and the strong form. The weak form market considers that historical return can not predict future return. Th semi-strong form market considers that not only historical information but also public information can not be used to make higher profit than market portfolios. The strong form market considers that all information released is contained in the price series and return series also include private information held by individual investors.

Among many methods for testing the level of market efficiency, the random walk hypothesis is the most examined hypothesis in previous studies. The efficient market hypothesis considers that security prices follow a random walk and it should be impossible to predict future returns based on publicly available information (Thaler (1987)). Liu and He (1991) considered two important features in a random walk process: unit root and uncorrelated increments. If stock price follows random walk process, any shock to stock price is permanent with no tendency in price to return to a trend path over time and this property implies that future returns are unpredictable based on previous observations (Ozdemir (2008)). Some studies also believe that although stock prices or returns do not follow random walk the markets can be efficient.

The studies on stock market are of many types. French and Roll (1986) found evidence that supported the importance of private information in producing a higher volatility in trading-hours compared with non-trading hours. French and Roll (1986) said that if daily returns were independent, the variance for a long holding period would equal the cumulated daily variances within the period while if daily returns are temporarily affected by trading noise, the long period variance will be smaller than the cumulated daily variances. French and Roll (1986) also proposed a viewpoint that if pricing errors were corrected within three weeks and bid/ask errors were corrected overnight, most of the three-month return reflected a rational assessment of the information arriving during the three-month period. Fama and French (1988) said that a slowly mean-reverting component of stock prices tended to induce negative autocorrelation in returns. Jones, Kaul and Lipson (1994) found that public information was the major source of short-term return volatility. Solnik, Boucrelle and Fur (1996) said that international correlation increased in periods of high market volatility and this was bad news for investors because if the domestic market was quite unstable it was the time when international risk diversification was needed. Mubarik and Javid (2009) said that the trading volume could serve as a proxy measure fr unobservable amount of information that flowed into the market and found that there was significant interaction between trading volume and return volatility. More importantly, previous day's returns and volume has explanatory power in explaining the current market returns. All above studies tried to figure out the anomalies in a stock market.

Anyway, the main methods for testing random walk hypothesis are unit root test, autocorrelation of returns, runs test and variance-ratio test. The reason why unit root test can be used to test the market efficiency is that market efficiency demands randomness (non stationary) in security prices and unit root test examines whether time series is non stationary or not (Nisar and Hanif (2012)). If the time series is stationary and the null hypothesis of randomness is rejected. The other tests are normally used and will be reviewed in the next part.

After 1990, the evidence against random walk hypothesis is much. Many paper examined the autocorrelation in daily, weekly and monthly return series. Reliable evidence of nonzero autocorrelation but close to 0 is common. Therefore, they considered that the predictability of returns was not significant and the stock market under study was efficient. Pan, Chan and Fok (1997) found little evidence against the random walks null hypothesis for four current futures and non-randomness was found in Japanese yen. Afego (2012) studied the Nigerian stock market with runs tests and found that Nigerian Stock Exchange displayed a predictable component. Nisar and Hanif (2012) focused on four stock exchange of South Asia and the results suggested that none of the four stock markets followed random walk. Zarei and Jadari (2020) also found evidence against random walk and against the market efficiency hypothesis in the Tehran stock exchange.

Although there are many papers has examined the level of market efficiency using different stock returns from different stock markets, there is no consensus among researchers and economists on the conclusion whether the market is efficient or not (Sewell (2012)). Some found evidence indicating a weak form efficient market like Fama (1970), Ozdemir (2008) and Sewell (2012). Sewell (2012) did an analysis of daily, weekly, monthly and annual Dow Jones Industrial Average log returns and found that the test results were almost the least consistent with an efficient market. However, as Malkiel (2003) said, more researchers are becoming to believe that the stock returns are at least partially predictable, which indicates an inefficient market. Nisar and FCMA (2012) tested the weak form efficient market hypothesis for four stock exchanges of South Asia and found that none of the markets followed random walk and therefore were not weak form efficient market. Rosch, Subrahmanyam and Van Dijk (2017) suggest that there may be a significant systematic component to the time-varying behavior of market efficiency measures and there may be a systematic market efficiency component across stocks. Their results are: (1) The different efficiency measures tend to provide a similar indication of the relative degrees of price efficiency of individual stocks. (2) There exists a systematic market efficiency component.

Calendar anomalies are another evidence for inefficient markets because the existence of consistent patterns in returns is a signal of arbitrage opportunities. They have puzzle financial economists for over sixty years. Thaler (1987) said that abnormal price returns occurred around the turn of the year, the turn of the month, the turn of the week, the turn of the day and before holidays.

The January effect is known to be the most important calendar anomaly: "as goes January, so goes the year" is a popular rule in the stock market (Rossi (2015)). Jones, Lee and Apenbrink (1991) said that the January effect was evidence of return seasonality rather than a misspecification of the Capital Asset Pricing Model. Moller and Zilca (2008) found evidence that the first part of the January had abnormal returns and the second part of January had lower abnormal returns in 1995-2004 period but the overall magnitude of the January effect appeared similar to its magnitude in the previous 1965-1994 period.

The day-of-the-week-effect is another interesting stock market anomaly which attracts researchers. This kind of effect could help investors to make higher profit through buying stocks on days with abnormally Lowe returns and selling stocks on days with abnormally high returns (Basher and Sadorsky (2006)). The day-of-the-week effect refers to the existence of a patten on the part of stock returns. The results from previous papers are: mainly in the USA, the last trading days of the week (Friday) are characterized with positive returns and the first trading days of the week (Monday) are characterized with negative returns (Poshakwale (1996)). Poshakwale (1996) found clear evidence that the average returns were different on each day of the week in Bombay Stock Exchange over a period of 1987-1994. Kenourgios, Samitas and Papathanasiou (2006) investigated the-day-of-the-week effect in the Athens Stock Exchange General Index and found that this effect was present. However, Basher and Sadorsky (2006) examined the day-of-the-week-effect in 21 emerging stock markets from 1992 to 2003 and found that the effect was present for Philippines, Pakistan and Taiwan. Therefore they concluded that the day-of-the-week-effect was not present in the majority of emerging stock markets and some emerging markets exhibited strong day-of-the-week-effect. Apolinario, Satana, Sales and Caro (2006) said that most European markets did not reflect the-day-of-the-week-effect.

Many papers found evidences of the turn-of-the-month-effect for various financial markets. If a stock market shows the turn-of-the-month-effect, it records higher returns during a short time period around the end of the old months and the beginning of the new month, than during the remainder of the month (Arendas and Kotlebova (2019)). Studies find that the turn-of-the-month-effect seems to be persistent across different markets. Martikainen, Perttunen and Puttonen (1995) found significant turn-of-the-month-effect in the Finnish stock index futures, options and cash markets. Kunkel, Compton and Beyer (2003) investigated nineteen country stock market indexes from 1988 to 2000 and found that the four-day turn-of-the-month-effect period accounted for 87% of the monthly return on average. They showed that the turn-of-the-month-effect persisted throughout the 1990s at least in sixteen of nineteen countries. McConnell and Xu (2006) found that the turn-of-the-month-effect persisted over the interval of 1987-2005 using CRSP daily returns and this effect was not confined to small or low-priced stocks, to the December-January turn-of-the-month or to the U.S. Stefanescu and Dumitriu (2011) explored the turn-of-the-month-effect on Bucharest Stock Exchange with two indexes: BET-C and RAQ-C. They found evidence of this effect only for BET-C. Liu (2013) examine the US equity market from 2001 to 2011 and found that the turn-of-the-month-effect still existed but its occurrence had moved to earlier dates. Arendas and Kotlebova (2019) investigated the presence of this kind of effect in the stock markets of eleven Central and Eastern European countries and found that during a twenty-year period, 1999-2018, there was significant turn-of-the-month-effect in returns in seven stock markets.

In this paper, we try to examined the level of market efficiency for five markets with six method using daily and monthly returns. The rest of the paper is organized as follows. Part two states methodology used in this paper to test the level of market efficiency: autocorrelation, runs test, strategy, January effect, day-of-the-week-effect and turn-of-the-month-effect. Part three summarizes statistics of daily and monthly returns for five indexes. Part four shows the empirical results and Part five concludes all the paper.

2.Methodology

In order to test the randomness in return series, three methods are used in this paper: autocorrelation, runs test and a specific trading strategy. We also examine three calendar anomalies: January effect, day-of-the-week-effect and turn-of-the-month-effect.

2.1 Autocorrelation

The autocorrelation in stock returns is one of the most important anomalies in financial market worldwide (Blandon (2007)). A common but important test of the random walk hypothesis for an individual time series is to check the serial correlation of return series. If the returns exhibit a random walk, they should be uncorrelated at all leads and lags (Borges (2010)).

Because the autocorrelation among return series is the most common method for testing the random walk hypothesis, we use the autocorrelation of daily returns at lag1 as the first method for market efficiency level (Mubarik and Javid (2009), Sewell (2012)). When no significant correlations are found, we can judge that the market under consideration is consistent with an efficient market.

The autocorrelation function at lag k denoted by ρ_k is defined as (k = 1, 2, ……, 15 in this paper):

$$\varrho_k = \frac{(cov(R_i, R_{i-k}))}{v(R_i)}$$

R_i: the return on ith day
R_{i-k}: the return on (i-k)th day

2.2 Runs test

Runs tests is always used to check the randomness in a two-valued series. The advantage of runs test is that it dose not require the distribution of return series to be normal distribution and therefore is commonly and widely used as a way to examine the random walk hypothesis. A run of a sequence is a maximal segment of sequence consisting of adjacent equal elements. The number of runs in a sequence, which has n_1 positive values and n_2 negative values, is a random variable whose conditional distribution is approximately normal with:

Mean : $(2*n_1*n_2)/(n_1+n_2) + 1$

Variance : $(\text{Mean}-1)*(\text{mean}-2)/(n_1+n_2-1)$.

If the number of runs is significantly higher or lower than mean value, the hypothesis of independence of returns is rejected. Here, we use runs test as a second way to examine the market efficiency level (Karemera, Ojah and Cole (1999), Borges (2009)).

2.3 Strategy

Strategies have been a hot topic for investors because they are always seeking for higher profits with own asset portfolios but not market portfolio. Chang, Mcleavey and Rhee (1995) said that contrarian strategies recommended buying past losers and selling past winners to earn significant abnormal returns. Because we try to examine the level of market efficiency of different stock markets, the strategy we consider here is the one based on the change of returns.

The strategy constructed in this paper will make higher profit when the stock return series is positively correlated. The specific process is: (1)in a calendar year, form the start date of the year, try to find the first day of the strategy by finding the date on which the return in the day is higher (lower) than a (b). Buy (sell) one share in the following day to start the strategy (action 1). (2) Then find the next day on which the second action will be down by finding the day on which the return in the day is lower (higher) than b (a). Sell (buy) one share to cover the trading and sell (buy) one more share to start a new trading (action2). (3) Repeat (2) until the end of the calendar year. (4) In the last day, only buy or sell on share to end the strategy (action n). The strategy stated above is noted as S(a,b) in the following part. a and b mean the criterion value for buying and selling action. The total return of this strategy is calculated as the following function:

$$\text{Return of one certain strategy} = \quad x_1 + x_2 + \ldots\ldots + x_n$$

x_i: the return of one action in a specific strategy
n: the number of actions in a specific strategy.

If the market is efficient, the return of strategies should not significantly higher than the return of holding the same share in the same period as the strategies.

2.4 January effect

The January effect is the best-known example of anomalous behavior in security markets: at the turn of the year, certain types of securities tend to produce abnormal returns (Jones, Lee and Apenbrink (1991), Haugen and Jorion (1996)). The January effect states: the observations of the month of January appears to have systematically higher returns than other months of the year. This phenomenon is primarily concentrated in smaller firms. From previous studies, two theories provide an explanation for higher return in January: tax-loss selling hypothesis and the window dressing hypothesis. An anomaly would quickly disappear after investors attempt to study and exploit it. However, the January effect was still going strong seventeen years after its discovery (Haugen and Jorion (1996)). Kim (2006) said that the January seasonality was one of the strong empirical inconsistencies with market efficiency. If the market is efficient, investors should eliminate abnormal returns in January by readjusting their portfolios.

Although stocks with small market capitalization tend to produce greater returns than large stocks, we try to find whether the magnitude of the effect have changed significantly in different months with stock indexes. The specific method is the following regression (Patel(2016)):

$$R_t = a + b \cdot JANUARY_t + u_t \quad u_t \sim N(0, \sigma^2) \quad (1)$$

R_t: the monthly returns of stock index

$JANUARY_t$: a dummy variable equal to 1 for January returns and to 0 for the other month returns

a: constant

b: the coefficient of January effect

If b is statistically positive, it indicates the existence of January effect.

2.5 Turn-of-the-month-effect

In order to examine the turn-of-the-month-effect in stock returns, we first calculate the mean returns of a -5 to 5 window (Martikainen, Perttunen and Puttonen (1995), Liu (2013)). 1 (2, 3, 4, 5) means the first (second, third, fourth, fifth) trading day in the month under consideration. -1 means the last trading day in last month and therefore -2, -3, -4, -5 means the trading day before last trading day, two trading days before last trading day, three trading days before last trading day and four trading days before last trading day in last month. Then we calculate the mean return of TOM (here, the -5 to 5 period) period and ROM period (the rest of the month or the other days of the month).

we also do a OLS regression as follow (Kunkel, Compton and Beyer (2003), Razvan and Ramona (2011)):

$$\begin{aligned} R_t = a &+ b_1 \cdot D_{1t} + b_2 \cdot D_{2t} + b_3 \cdot D_{3t} + b_4 \cdot D_{4t} + b_5 \cdot D_{5t} \\ &+ b_{-1} \cdot D_{-1t} + b_{-2} \cdot D_{-2t} + b_{-3} \cdot D_{-3t} + b_{-4} \cdot D_{-4t} + b_{-5} \cdot D_{-5t} + u_t \quad u_t \sim N(0, \sigma^2) \quad (2) \end{aligned}$$

R_t: the daily returns of stock index

a: constant indicating the mean return in ROM period

D_{it}: equals to 1 when the return at time t is on the ith trading days in a month and equals to 0 on other days

D_{-it}: equals to 1 when the return at time t is on the last trading days, the day before last day, two days before last day, three days before last day, four days before last day in one month and equals to 0 on other days

b_i: the coefficient of the turn-of-the-month-effect

If any b_i is significantly different from zero, there is the turn-of-the-month-effect in stock returns.

2.6 Day-of-the-week-effect

In the day-of-the-week-effect case, it considers that a negative equity return on the first trading day in a week and an abnormal high return on the last trading day of the week, usually Friday (Poshakwale (1996), Blandon (2007)). In the USA, low mean returns are observed on Monday and mean returns on Friday are observed to be positive and abnormally higher than the mean returns on other days of the week (Rossi (2015)).

In order to examine the day-of-the-week-effect in stock returns, we also use ordinary least squares regression (OLS) method (Kenourgios, Samitas and Papathanasiou (2005), Apolinario, Satana and Caro (2006), Basher and Sadorsky (2006)):

$$R_t = b_1 \cdot M_t + b_2 \cdot TU_t + b_3 \cdot W_t + b_4 \cdot TH_t + b_5 \cdot F_t + u_t \qquad u_t \sim N(0, \sigma^2) \qquad (3)$$

R_t: the daily returns of stock index
M_t, TU_t, W_t, TH_t, F_t: the dummy variable which equal to 1 when the day is Monday, or Tuesday, or Wednesday, or Thursday, or Friday respectively and to 0 when the day is the other days
b_i: the coefficients of the-day-of-the-week effect
If more than one coefficients from b_i are significant from 0, there exists the-day-of-the-week-effect in returns.

3.Data

This paper try to analyze five stock market from China, Hong Kong, Japan, the US and Germany. The specific index data are respectively the daily close prices of CSI 300, HSI, Nikkei 225, Nasdaq Composite index and DAX stock index for each market. The data are in daily and monthly types from 20060101 to 20201231 collecting from NetEase Finance[1] and Yahoo Finance[2].

The CSI 300 is a stock index which contains 300 stocks listed in Shanghai Stock Exchange and Shenzhen Stock Exchange and is seen as an important indicator in reflecting the market condition in China. The HSI is one of the earliest stock market index in Hong Kong and has become the most widely quoted indicator of the performance of the Hong Kong stock market. The Nikkei 225 consists of 225 stocks in the first section of the Tokyo Stock Exchange and has been used as the indictor of the movement of Japanese stock markets. The Nasdaq Composite index is a index of over 2500 equities listed on the Nasdaq stock exchange. The DAX is a stock index that represents thirty of the largest and most liquid German companies that trade on the Frankfurt Exchange.

Table 1, 2 summarizes descriptive statistics of daily and monthly returns in a calendar year for all indexes.

NetEase Finance[1]: https://money.163.com
Yahoo Finance[2]: https://finance.yahoo.com

Table 1 Summary statistics of daily returns for five indexes

Note: This table shows the summary statistics of daily returns for five indexes including CSI 300, HSI, NIKKEI 225, NASDAQCOM and DAX. Mean is the mean value of daily returns. SD is the standard deviation of daily returns. JB is the value of Jarque-Bera test. The time span is from 20060101 to 20201231.

	CSI 300	HSI	NIKKEI 225	NASDAQCOM	DAX
Mean	0.00047	0.00016	0.00014	0.00046	0.00024
SD	0.01732	0.01494	0.01517	0.01381	0.01398
Skewness	-0.576	-0.035	-0.473	-0.496	-0.241
Kurtosis	6.867	11.778	10.833	12.308	11.089
JB	2473.237	11844.548	9512.961	13783.087	10394.722

Table 2 Summary statistics of monthly returns for five indexes

Note: This table shows the summary statistics of monthly returns for five indexes including CSI 300, HSI, NIKKEI 225, NASDAQCOM and DAX. Mean is the mean value of daily returns. SD is the standard deviation of daily returns. JB is the value of Jarque-Bera test. The time span is from 20060101 to 20201231.

	CSI 300	HSI	NIKKEI 225	NASDAQCOM	DAX
Mean	0.0094	0.00335	0.00279	0.00986	0.00541
SD	0.09303	0.06036	0.05698	0.05069	0.05459
Skewness	-0.479	-0.661	-0.888	-0.653	-0.782
Kurtosis	4.323	4.8	5.374	4.186	4.976
JB	19.918	38.023	65.554	23.721	48.409

From Table 1 and 2, the mean value of both types of returns are all positive with highest daily return 0.00047 in CSI 300 and highest monthly return 0.00986 in NASDAQCOM. The most volatile daily return is CSI 300 with 0.01732 and the most volatile monthly return is also CSI 300 with 0.09303. All ten stock return series are thinner than normal distribution because of kurtosis higher than 3. According to the Jarque-Bera statistics in Table 1 and 2, normal distribution of return series is rejected for almost all markets from 2006 to 2020. Rejection of normal distribution is the same as Mubarik and Javid (2009) and some other papers.

4.Empirical results

4.1 Autocorrelation

We first calculate the autocorrelation at lag1 to lag10 for whole period from 2006 to 2020 and then separate the fifteen years in to three sub-periods, 2006-2010, 2011-2015, 2015-2020, and calculate once more. The results are summarized in Table 3.

Table 3 The autocorrelations of five indexes

Note: This table shows the autocorrelations from lag1 to lag 10 for five indexes. *** 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.

(1) The autocorrelations of CSI 300

Lag	2006-2020	2006-2010	2011-2015	2016-2020
1	0.0273*	0.0273	0.0623**	-0.0380
2	-0.027*	-0.0221	-0.0706***	0.0363
3	0.0314**	0.0473	-0.0208**	0.0441
4	0.0515***	0.0775**	0.0674***	-0.0613**
5	0.006***	-0.0012**	0.0368***	-0.0414**
6	-0.0639***	-0.0541**	-0.0918***	-0.0511**
7	0.0305***	0.0237**	0.0324***	0.0266**
8	0.0092***	-0.022**	0.1004***	-0.0347**
9	0.0117***	-0.0142*	0.0293***	0.0474**
10	0.0055***	0.0346*	-0.0558***	0.0253**

(2) The autocorrelations of HSI

Lag	2006-2020	2006-2010	2011-2015	2016-2020
1	-0.0203	-0.0398	0.0315	-0.0214
2	0.0079	0.0079	0.0136	-0.0034
3	-0.0218	-0.0506	-0.0346	0.0724*
4	-0.0323	-0.0281	-0.0438	-0.032*
5	-0.0024	-0.0102	0.0098	0.0025
6	-0.0144	0.0000	-0.0004	-0.0747**
7	0.0202	0.0134	0.0480	0.0076**
8	0.0258	0.0566	-0.0341	-0.0024*
9	-0.0288**	-0.0646*	0.0361	0.0039*
10	-0.0482***	-0.0673**	-0.0265	-0.0124*

(3) The autocorrelations of Nikkei 225

Lag	2006-2020	2006-2010	2011-2015	2016-2020
1	-0.0373**	-0.0514*	-0.0416	-0.0066
2	0.0106*	-0.0266	0.0407	0.0446
3	-0.0234*	-0.0302	-0.0180	-0.0204
4	-0.0137*	0.0059	-0.0849***	0.0262
5	-0.0173*	-0.0419	0.0382***	-0.0387

Lag	2006-2020	2006-2010	2011-2015	2016-2020
6	-0.0122	-0.0086	-0.0084**	-0.0223
7	0.0025	0.0221	0.0196**	-0.0630
8	-0.0003	-0.0050	0.0135**	-0.0134
9	0.0100	-0.0310	0.0709***	0.0171
10	0.0272	0.0627	-0.0337***	0.0291

(4) The autocorrelations of NASDAQCOM

Lag	2006-2020	2006-2010	2011-2015	2016-2020
1	-0.1182***	-0.0957***	-0.0095	-0.2241***
2	0.0084***	-0.0826***	0.0156	0.1337***
3	0.0182***	0.0815***	-0.1013***	-0.0012***
4	-0.0345***	-0.0434***	-0.0167***	-0.0369***
5	-0.0019***	-0.0081***	-0.0802***	0.0552***
6	-0.0410***	0.0017***	0.0160***	-0.1395***
7	0.0586***	0.0013***	-0.0269***	0.1946***
8	-0.0591***	0.0061***	0.0284***	-0.2112***
9	0.0507***	0.0045***	-0.0404***	0.1727***
10	0.0074***	0.0290***	0.0694***	-0.0650***

(5) The autocorrelations of DAX

Lag	2006-2020	2006-2010	2011-2015	2016-2020
1	0.0020	-0.0325	0.0434	0.0067
2	-0.0089	-0.0455	-0.0290	0.0689**
3	-0.0027	-0.0302	-0.0248	0.0538**
4	0.0033	0.0666**	-0.0408	-0.0394**
5	-0.0265	-0.0468**	-0.0476	0.0263**
6	0.0001	0.0321**	0.0219	-0.0699***
7	0.0248	-0.0286**	0.0454*	0.0816***
8	-0.0370	-0.0076**	-0.0158	-0.1025***
9	-0.0064	-0.0472**	-0.0014	0.0409***
10	0.0092	0.0406**	-0.0087	-0.0140***

Mubarik and Javid (2009) reported significant autocorrelation of first order in return series. Sewell (2012) found that first-order autocorrelation of daily, weekly, monthly and annual log returns was small but positive for all time periods but we find more information than that. From Table 3 (1), (2), (3), (4) and (5), the results of autocorrelation are different among five markets. From Table 3 (1) and (4), there is strong evidence of autocorrelation for CSI 300 and NASDAQCOM, but some evidence for DAX from Table 3 (5), a little evidence for HSI and Nikkei 225 from Table 3 (2) and (3). Hamid, Suleman, Shah and Akash (2010) used monthly stock returns of fourteen countries including China, the autocorrelation of there counties were all minus at log1. In Table 3 (1), there are only two lags at which the autocorrelations are negative for CSI 300 from 2006 to 2020 while there are at least four lags at which the autocorrelations are negative for the other indexes. From the viewpoint of autocorrelation, the most efficient market among five stock markets is the market in Hong Kong.

4.2 Runs test

We first examine the randomness with runs test for whole period for five indexes from 2006 to 2020. Then separate the whole period into three sub-period the same as above. The results are summarized in Table 4.

Table 4 Runs tests of five indexes

Note: This table shows the results of runs tests for five indexes. *** 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.

(1) Runs tests of CSI 300

	2006-2020	2006-2010	2011-2015	2016-2020
Z-value	-0.8797	-0.7955	-0.5965	0.1924

(2) Runs tests of HSI

	2006-2020	2006-2010	2011-2015	2016-2020
Z-value	0.2721	-0.1225	0.400	0.3298

(3) Runs tests of Nikkei 225

	2006-2020	2006-2010	2011-2015	2016-2020
Z-value	2.1553**	2.2819**	0.9128	0.4732

(4) Runs tests of NASDAQCOM

	2006-2020	2006-2010	2011-2015	2016-2020
Z-value	1.3106	-0.0475	-0.1414	2.5227**

(5) Runs tests of DAX

	2006-2020	2006-2010	2011-2015	2016-2020
Z-value	1.7947*	1.1356	-0.0354	1.9110*

From Table 4 (1), (2), (3), (4) and (5), the results of runs tests do not found evidence against randomness in daily returns for CSI 300, HSI from 2006 to 2020 but find a little evidence for Nikkei 225, NASDAQCOM and DAX. The randomness hypothesis is rejected for Nikkei 225 in sub-period of 2006-2010, for

NASDAQCOM in sub-period 2016-2020 and for DAX in sub-period 2016-2020. Moreover, the z-values of runs test for CSI 300 and NASDAQCOM are negative for sub-period 2006-2010 and 2011-2015 indicating the real runs of a return series are less than the mean value of runs and therefore meaning a positive autocorrelation in return series. This is the same as what we found in 4.1 Autocorrelation. Our findings are different from Ozdemir (2008), in which the results of runs test failed to reject the randomness, is similar to Karemera, Ojah and Cole (1999), Dorina and Simina (2007) and Borges (2009). From the viewpoint of runs test, the higher level of market efficiency among five stock markets are the markets in China and Hong Kong. The markets in Japan, The US and Germany are not efficient.

4.3 Strategy

S(0.01, -0.01) are used here for all indexes and all periods, which means buying shares when yesterday's return is higher than 0.01 and selling shares when yesterday's return is lower than -0.01. We calculate returns of holding stocks in the same intervals based on the strategy S(0.01, -0.01). We also calculate the return of every trading and use approximate normal distribution as the distribution of the mean return of S(0.01, -0.01). If the z-value is higher than 2, the S(0.01, -0.01) makes more profit than holding the stock all the time. The results are summarized in Table 5.

Table 5 S(0.01, -0.01) for five indexes

Note: This table shows the results of strategy S(0.01, -0.01) for five indexes. S(0.01, -0.01) means the mean value of strategy. Buy-and-hold means the mean value of holding index in the same period with strategy. *** 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.

(1) S(0.01, -0.01) for CSI 300

	2006-2020	2006-2010	2011-2015	2016-2020
S(0.01, -0.01)	0.28725	0.65404	-0.51503	0.03639
Buy-and-hold	1.68125	1.19001	0.18551	0.45861

(2) S(0.01, -0.01) for HSI

	2006-2020	2006-2010	2011-2015	2016-2020
S(0.01, -0.01)	-0.56409	-0.22136	-0.03966	-0.25952
Buy-and-hold	0.5784	0.10654	-0.10275	0.2862

(3) S(0.01, -0.01) for Nikki 225

	2006-2020	2006-2010	2011-2015	2016-2020
S(0.01, -0.01)	1.06515	-0.03635	0.70223	0.29436
Buy-and-hold	0.5171	-0.4748	0.58473	0.4387

(4) S(0.01, -0.01) for NASDAQCOM

	2006-2020	2006-2010	2011-2015	2016-2020
S(0.01, -0.01)	0.36576	-0.22136	-0.12572	0.65364
Buy-and-hold	1.6973	0.10654	0.62768	0.99299

(5) S(0.01, -0.01) for DAX

	2006-2020	2006-2010	2011-2015	2016-2020
S(0.01, -0.01)	-1.04201	-0.28766	-0.56347	-0.1933
Buy-and-hold	0.90138	0.23417	0.4284	0.32173

From Table 5 (1), (2), (3), (4) and (5), the results are almost the same for five indexes except Nikkei 225. The strategy S(0.01,-0.01) failed to make higher returns than buy-and-hold strategy in any periods except Nikkei 225. Therefore, in long period, S(0.01,-0.01) does not have any advantage. Although in period of 2006-2020, 2006-2010, 2011-2015, from Table 5 (3), S(0.01,-0.01) preformed better than buy-and-hold with Nikkei 225, the result does not have any significance.

4.4 January effect

The results of regression of (1), testing January effect for five indexes are showed in Table 6. The monthly return is calculated as the following function:

$$\ln P_t - \ln P_{t-1}.$$

P_t: the close price on the first trading in this month
P_{t-1}: the close price on the first trading day in last month

Table 6 January effect in five indexes

Note: The January effect is examined by regression:

$$R_t = a + b \cdot JANUARY_t + u_t \quad u_t \sim N(0, \sigma^2) \quad (1)$$

R_t: the monthly returns of stock index
$JANUARY_t$: a dummy variable equal to 1 for January returns and to 0 for the other month returns
a: constant
b: the coefficient of January effect
If b is significantly different from zero, there is January effect in specific indexes. *** 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.
(1)The January effect in CSI 300

Regression Coefficient	2006-2020
a	0.0071
b	0.029

(2) The January effect in HSI

Regression Coefficient	2006-2020
a	0.0041
b	-0.0129

(3) The January effect in Nikki 225

Regression Coefficient	2006-2020
a	0.0046
b	-0.0236

(4) The January effect in NASDAQCOM

Regression Coefficient	2006-2020
a	0.0102**
b	-0.0078

(5) The January effect in DAX

Regression Coefficient	2006-2020
a	0.0062
b	-0.0156

From Table 6 (1), (2), (3), (4) and (5), the coefficient b in regression (1) are not significant for five indexes indicating that the January effect did not exist from 2006 to 2020.

The volatility clustering is common in stock returns. In order to take time-varying volatility into consideration and check if the January effect changes after considering time-varying volatility, we also regress a EGARCH(1, 1) model. The results are showed in Table 7. The EGARCH (1, 1) model are regressed with Stata15.1.

Table 7 The January effect in five indexes—EGARCH(1,1)

Note: This table shows the result of regression:

$$R_t = c + b \cdot JANUARY_t + \varepsilon_t$$

$$\ln(\sigma_t^2) = \lambda_0 + \lambda_1 \cdot JANUARY_t + \alpha \cdot z_{t-1} + \gamma \cdot \left(|z_{t-1}| - \sqrt{\tfrac{2}{\pi}}\right) + \delta \cdot \ln(\sigma_{t-1}^2)$$

$$\varepsilon_t = \sigma_t \cdot z_t \qquad z_t \sim N(0,1)$$

R_t: the monthly return of stock index

b: the January effect in conditional mean function

λ_1: the January effect in conditional variance function

*** 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.

(1)The January effect in CSI 300

Coefficient	Estimate	Standard error	Z-value
b	-0.00443	0.02072	-0.21
c	0.00851	0.00548	1.55
λ_1	0.82122	0.34839	2.36**
λ_0	-0.40159	0.16614	-2.42**
α	0.10681	0.05579	1.91*

Coefficient	Estimate	Standard error	Z-value
γ	0.42052	0.13742	3.06***
δ	0.93165	0.03302	28.21***

(2)The January effect in HSI

Coefficient	Estimate	Standard error	Z-value
b	-0.00847	0.01433	-0.59
c	0.00786	0.00445	1.77*
λ_1	0.48180	0.44752	1.08
λ_0	-1.30259	0.57345	-2.27**
α	-0.89522	0.06460	-1.39
γ	0.40612	0.10455	3.88***
δ	0.77803	0.09823	7.92***

(3)The January effect in Nikkei 225

Coefficient	Estimate	Standard error	Z-value
b	-0.02794	0.01630	-1.71*
c	0.00545	0.00429	1.27
λ_1	0.19371	0.53918	0.36
λ_0	-6.90102	1.46607	-4.71***
α	-0.25088	0.11719	-2.14**
γ	0.28827	0.14393	2.00**
δ	-0.18035	0.25273	-0.71

(4)The January effect in NASDAQCOM

Coefficient	Estimate	Standard error	Z-value
b	0.00123	0.01081	0.11
c	0.00932	0.00377	2.47**
λ_1	0.23321	0.37278	0.63
λ_0	-1.19896	0.46927	-2.55*
α	-0.21922	0.10112	-2.17**
γ	0.39992	0.17835	2.24**
δ	0.80851	0.07513	10.76***

(5)The January effect in DAX

Coefficient	Estimate	Standard error	Z-value
b	-0.017746	0.01768	-1.00
c	0.00610	0.00391	1.56
λ_1	0.72106	0.40939	1.76*
λ_0	-2.35711	0.65044	-3.62***
α	-0.43933	0.08620	-5.10***
γ	0.07724	0.17017	0.45
δ	0.61706	0.10620	5.81***

From Table 7 (1), (2), (3), (4) and (5), after the consideration of time-varying volatility, it is interesting that we found January effect in returns in Nikkei 225 while it did not exist from the result in Table 6 (3) because of insignificant b. The return of Nikkei 225 in January is lower than the other month with -0.02794. The January effect exists in variance in CSI 300 and DAX because of significant λ_1. All five indexes are examined with arch effect or garch effect. Except HSI, other four indexes have a leverage effect because of significant α. Moreover, the leverage in CSI 300 is 0.10681, a positive value, which implies that positive innovations are more destabilizing than negative innovations. The leverage in other three indexes are -0.25088, -0.21922, -0.43933, negative values, which implies that negative innovations are more destabilizing than positive innovations. Because there exists January effect in Nikkei 225, the market in Japan is inefficient.

4.5 Turn-of-the-month-effect

We first calculate the mean returns in -5 to 5 days. The mean returns for five markets are showed in Table 8.

Table 8 The turn-of-the-month-effect in five indexes

Note: 1, 2, 3, 4, 5 means the first, second ,third, fourth, fifth trading day's return in a month. -1, -2, -3, -4, -5 means the last day, the day before last day, tow days before last day, three days before last day, four days before last day's return in last month. 0 means the other days except -5 to 5 days in one month.

(1) -5 to 5 window in CSI 300

	2006-2020	2006-2010	2011-2015	2016-2020
0	-0.00002	0.00049	-0.00048	-0.00006
-5	-0.00110	-0.00084	-0.00366	0.00121
-4	0.00020	0.00019	-0.00028	0.00069
-3	-0.00115	0.00074	-0.00093	-0.00325
-2	-0.00141	-0.00208	-0.00205	-0.00009
-1	0.00217	0.00052	0.00415	0.00185
1	0.00362	0.00613	0.00362	0.00215
2	0.00267	0.00237	0.00122	0.00441
3	0.00205	0.00444	0.00125	0.00045
4	0.00100	0.00170	0.00219	-0.00088

	2006-2020	2006-2010	2011-2015	2016-2020
5	0.00166	0.00191	0.00210	0.00096

(2) -5 to 5 window in HSI

	2006-2020	2006-2010	2011-2015	2016-2020
0	-0.00028	-0.00054	-0.00036	0.00005
-5	0.00010	0.00035	-0.00018	0.00014
-4	0.00085	0.00288	0.00029	-0.00061
-3	0.00081	-0.00051	0.00280	0.00014
-2	0.00159	0.00476	-0.00023	0.00024
-1	0.00101	0.00219	0.00165	-0.00082
1	0.00277	0.00407	0.00171	0.00275
2	-0.00022	0.00079	-0.00155	0.00010
3	-0.00038	0.00167	-0.00138	-0.00145
4	0.00040	-0.00056	0.00047	0.00129
5	-0.00059	-0.00270	-0.00088	0.00181

(3) -5 to 5 window in Nikki 300

	2006-2020	2006-2010	2011-2015	2016-2020
0	0.00001	-0.00109	0.00061	0.00050
-5	-0.00034	-0.00007	-0.00136	0.00041
-4	0.00125	0.00293	0.00147	-0.00064
-3	0.00194	0.00248	0.00049	0.00285
-2	0.00116	0.00299	0.00122	-0.00074
-1	-0.00043	-0.00120	0.00140	-0.00150
1	-0.00058	-0.00212	-0.00007	0.00068
2	0.00036	0.00180	-0.00126	0.00055
3	-0.00052	0.00112	-0.00120	-0.00148
4	0.00056	-0.00131	0.00202	0.00098
5	-0.00067	-0.00324	0.00096	0.00026

(4) -5 to 5 window in NASDAQCOM

	2006-2020	2006-2010	2011-2015	2016-2020
0	0.00037	0.00008	0.00052	0.00050
-5	-0.00092	0.00040	-0.00141	-0.00174
-4	0.00328	0.00461	0.00095	0.00429
-3	0.00100	0.00098	0.00298	-0.00096
-2	0.00085	-0.00028	0.00116	0.00166
-1	-0.00025	-0.00166	-0.00019	0.00110
1	0.00132	0.00146	-0.00001	0.00267
2	0.00027	0.00139	0.00081	-0.00140
3	0.00104	-0.00102	0.00167	0.00248
4	-0.00014	-0.00258	-0.00008	0.00224
5	-0.00077	-0.00132	-0.00129	0.00030

(5) -5 to 5 window in DAX

	2006-2020	2006-2010	2011-2015	2016-2020
0	0.00011	-0.00025	0.00017	0.00041
-5	0.00078	0.00289	0.00182	-0.00236
-4	0.00144	0.00147	0.00343	-0.00057
-3	0.00163	0.00188	0.00213	0.00089
-2	0.00003	0.00012	0.00088	-0.00091
-1	-0.00003	0.00052	0.00104	-0.00165
1	0.00119	0.00274	-0.00054	0.00196
2	-0.00070	0.00110	-0.00316	-0.00005
3	0.00075	0.00101	0.00067	0.00057
4	-0.00145	-0.00373	-0.00114	0.00053
5	0.00026	-0.00121	0.00016	0.00182

From Table 8, it is easy to find that the returns around the turn of the month, -5 to 5 window, seem higher than the other days, showed in Table 8 row 0. From Table 8 (1), in CSI 300, the mean returns on the first day and second day in one month are 0.00362 and 0.00267, seem higher than the mean returns of the former days and the latter days. The other indexes show similar phenomena: in whole period, from Table 8 (2) column 2006-2020, the return on the first day in one month is 0.00277, from Table 8 (3) column 2006-2020, the return on two days before last day in a month is 0.00194, from Table 8 (4) column 2006-2020, the returns on the first day and third day in a month are 0.00132 and 0.00104, from Table 8 (5) column 2006-2020, the return on the first day in a month is 0.00119. They all seem to be higher than the other days.

The results of regression (2) are summarized in Table 9. To save space, only significant coefficients in regression (2) are included in Table 9.

Table 9 The turn-of-the-month effect in five indexes

Note: The results in this table are the results of regression:

$$R_t = a + b_1 \cdot D_{1t} + b_2 \cdot D_{2t} + b_3 \cdot D_{3t} + b_4 \cdot D_{4t} + b_5 \cdot D_{5t} + b_{-1} \cdot D_{-1t} + b_{-2} \cdot D_{-2t} + b_{-3} \cdot D_{-3t} + b_{-4} \cdot D_{-4t} + b_{-5} \cdot D_{-5t} + u_t \qquad u_t \sim N(0, \sigma^2) \qquad (2)$$

R_t: the daily returns of stock index

a: constant indicating the mean return in ROM period

D_{it}: equals to 1 when the return at time t is on the ith trading days in a month and equals to 0 on other days

D_{-it}: equals to 1 when the return at time t is on the last trading days, the day before last day, two days before last day, three days before last day, four days before last day in one month and equals to 0 on other days

b_i: the coefficient of the turn-of-the-month-effect (i = 1, 2, 3, 4, 5, -1, -2, -3, -4, -5)

*** 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.

(1) The turn-of-the-month-effect in CSI 300

Significant coefficients	2006-2020	2006-2010	2011-2015	2016-2020
b_{-3}				-0.00319*
b_{-1}			0.00463**	
b_1	0.00364***	0.00563*	0.0041*	
b_2	0.00269**			0.00447***

(2) The turn-of-the-month-effect in HSI

Significant coefficients	2006-2020	2006-2010	2011-2015	2016-2020
b_{-3}			0.00316*	0.0027*
b_{-2}		0.0053**		
b_1	0.00305***	0.00461*		

(3) The turn-of-the-month-effect in Nikkei 225

Significant coefficients	2006-2020	2006-2010	2011-2015	2016-2020
b_{-2}		0.00408*		

(4) The turn-of-the-month-effect in NASDAQCOM

Significant coefficients	2006-2020	2006-2010	2011-2015	2016-2020
b_{-4}	0.00291***	0.00453**		0.00379**
b_{-3}			0.00245*	

(5) The turn-of-the-month-effect in DAX

Significant coefficients	2006-2020	2006-2010	2011-2015	2016-2020
b_{-4}				
b_2			-0.00333*	
b_4		-0.00348*	0.00327*	

From Table 9 (1), (2), (3), (4) and (5), the turn-of-the-month-effect exists in all indexes for significant b_i although different sub-periods shows different days with positive returns around the turn of the month. First, the TOM window for five indexes are (-3,2), (-3,1), (-2), (-4,-3) and (-4,4). The TOM effect almost exists in the early time of the turn of the month. This result is similar to early studies. In whole period from 2006 to 2020, from Table 9 (1), the returns on the first day and second day in one month for CSI 300 are significant higher than the other days. From Table 9 (2), the return on the first day in one month for HSI is significant higher. From Table 9 (3), the return on the day before last day in one month for Nikkei 225 is significant higher in the sub-period 2006-2010. From Table 9 (4), the return on three days before last day in one month for NASDAQCOM is significant high. From Table 9 (5), the return on fourth day in one month is significant higher in the sub-period 2006-2010. Second, from Table 9 (1) and (2), CIS 300 and HSI, we can find that the turn-of-the-month-effect is becoming earlier and earlier. From Table 9 (1), the results of CSI 300, in sub-period 2006-2010, the abnormal return happened on the first day in one month while in sub-period 2015-2020, the abnormal return happened on two days before last day in one month. This finding is also the same with early papers. Third, the existence of TOM effect is evidence against efficient market. All five indexes examined here is characterized with a TOM effect in different level and therefore the hypothesis of efficient market is rejected for five markets.

Similarly, we regression a EGARCH(1, 1) model in Table 10. Because the excess variables in the conditional variance function failed to be regressed, here we only choose four days (the first day and second day, the last day and the day before last day in one month) for CSI 300, HSI, Nikkei 225 and DAX but two days (two days before last day and three days before last day in one month) for NASDAQCOM.

Table 10 The turn-of-the-month-effect in five indexes—EGARCH(1, 1)

Note: This table shows the result of regression:

$$R_t = c + b_1 \cdot D_{1t} + b_2 \cdot D_{2t} + b_{-1} \cdot D_{-1t} + b_{-2} \cdot D_{-2t} + \varepsilon_t$$

$$\ln(\sigma_t^2) = \lambda_0 + \lambda_1 \cdot D_{1t} + \lambda_2 \cdot D_{2t} + \lambda_{-1} \cdot D_{-1t} + \lambda_{-2} \cdot D_{-2t} + \alpha \cdot z_{t-1} + \gamma \cdot \left(|z_{t-1}| - \sqrt{\tfrac{2}{\pi}}\right) + \delta \cdot \ln(\sigma_{t-1}^2)$$

$$\varepsilon_t = \sigma_t \cdot z_t \qquad z_t \sim N(0,1)$$

R_t: the daily return of stock index

b_i: the turn-of-month-effect in conditional mean function (i = 1, 2, -1, -2)

λ_i: the turn-of-month-effect in conditional variance function (i = 1, 2, -1, -2)

*** 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.

(1)The turn-of-the-month-effect in CSI 300

Coefficient	Estimate	Standard error	Z-value
b_1	0.00406	0.00124	3.29***

Coefficient	Estimate	Standard error	Z-value
b_2	0.00185	0.00089	2.09*
b_{-1}	0.00175	0.00083	2.12*
b_{-2}	-0.00030	0.00106	-0.29
c	0.00017	0.00022	0.78
λ_1	0.59824	0.08632	6.93***
λ_2	-0.51335	0.07541	-6.81***
λ_{-1}	-0.11591	0.09977	-1.16
λ_{-2}	0.03430	0.08233	0.42
λ_0	-0.06190	0.01450	-4.27***
α	-0.00166	0.00495	-0.33
γ	0.15769	0.00906	17.39***
δ	0.99159	0.00166	596.03***

(2)The turn-of-the-month-effect in HSI

Coefficient	Estimate	Standard error	Z-value
b_1	0.00296	0.00096	3.08***
b_2	0.00017	0.00095	0.18
b_{-1}	-0.00045	0.00071	-0.63
b_{-2}	0.00109	0.00085	1.28
c	0.0004	0.00020	0.20
λ_1	0.53445	0.14401	3.71***
λ_2	-0.14663	0.10544	-1.39
λ_{-1}	-0.21310	0.14503	-1.47
λ_{-2}	0.20123	0.10892	1.85*
λ_0	-0.17722	0.20670	-8.56***
α	-0.06482	0.00675	-9.60***
γ	0.13447	0.01036	12.98***
δ	0.98148	0.00232	422.19***

(3)The turn-of-the-month-effect in Nikkei 225

Coefficient	Estimate	Standard error	Z-value
b_1	0.00140	0.00093	1.51

Coefficient	Estimate	Standard error	Z-value
b_2	0.00032	0.00074	0.44
b_{-1}	-0.00101	0.00090	-1.13
b_{-2}	-0.00017	0.00080	-0.22
c	0.00013	0.00020	0.64
λ_1	0.28607	0.11254	2.54**
λ_2	-0.32257	0.08367	-3.86***
λ_{-1}	0.114429	0.12488	0.92
λ_{-2}	0.12701	0.98017	1.3
λ_0	-0.34434	0.03434	-10.03***
α	-0.11494	0.00590	-19.47***
γ	0.20612	0.01265	16.29***
δ	0.96090	0.00392	245.24***

(4)The turn-of-the-month-effect in NASDAQCOM

Coefficient	Estimate	Standard error	Z-value
b_{-3}	0.00129	0.00075	1.74*
b_{-4}	0.00023	0.00077	0.30
c	0.00026	0.00017	1.55
λ_{-3}	-0.06377	0.10832	-0.59
λ_{-4}	0.16477	0.10692	1.54
λ_0	-0.29385	0.02457	-11.96***
α	-0.13290	0.00588	-22.61***
γ	0.15785	0.01186	13.31***
δ	0.96728	0.00269	358.98***

(5) The turn-of-the-month-effect in DAX

Coefficient	Estimate	Standard error	Z-value
b_1	0.00300	0.00093	3.20***
b_2	-0.00198	0.00062	-3.21***
b_{-1}	-0.00076	0.00067	-1.14
b_{-2}	-0.00056	0.00090	-0.62
c	0.00023	0.00018	1.25

Coefficient	Estimate	Standard error	Z-value
λ_1	0.70909	0.12480	5,68***
λ_2	-0.54752	0.10592	-5.17***
λ_{-1}	-0.25627	0.11944	-2.15**
λ_{-2}	0.10337	0.09313	1.11
λ_0	-0.22232	0.02184	-10.18***
α	-0.12962	0.00712	-18.19***
γ	0.13562	0.01243	10.91***
δ	0.97455	0.00251	388.51***

From Table 10 (1), (2), (3), (4) and (5), under the consideration of time-varying volatility, except Nikkei 225, all the other indexes are also verified with the turn-of-the-month-effect in return. For CSI 300, from Table 10 (1), the returns on the first day, second day in one month and the last day in one month are higher than the other days for significant 0.00406, 0.00185 and 0.00175. For HSI, from Table 10 (2), the returns on the first day in one month is higher than the other days for significant 0.00296. For NASDAQCOM, from Table 10 (4), the return on two days before last day in one month is higher than the other days for significant 0.00129. For DAX, from Table 10 (5), the return on the first is higher than the other days for significant 0.003 but the return in the second day is lower than the other days for significant -0.00198.

For variance, from Table 10, except NASDAQCOM, other indexes are examined with the-turn-of-the-month-effect in variance. For CSI 300, from Table 10 (1), the return on the first day in one month is more volatile and the second day is less volatile than the other days for significant 0.59824 and -0.51335. For HSI, from Table 10 (2), the returns on the first day in one month and the day before last day are more volatile for significant 0.53445 and 0.20123. For Nikkei 225, from Table 10 (3), the return on the first day in one month is more volatile and the return on the second day in one month is less volatile for significant 0.28607 and -0.32257. For DAX, from Table 10 (5), the return on the first in one month is more volatile and the returns on the second day and the last day in one month are less volatile for significant -0.54752 and -0.25627.

From Table 10, all five indexes are examined with arch and garch effect for significant γ and δ. Except CSI 300, other four indexes have leverage effect that a fall in returns results in greater volatility than an increase in returns of the same magnitude for significant negative α.

4.6 Day-of-the-week effect

Table 11 shows the mean returns on five weekdays for five indexes.

Table 11 The mean returns on weekdays for five indexes

Note: The returns and standard deviations on five weekdays of five indexes are summarized in this table.

(1) The mean returns for CSI 300

Period	Statistic	Monday	Tuesday	Wednesday	Thursday	Friday
2006-2020	Mean	0.00175	0.00008	0.00059	-0.00110	0.00107
	Sd	0.02127	0.01617	0.01605	0.01655	0.01593
2006-2010	Mean	0.00471	-0.00218	0.00179	-0.00038	0.00107
	Sd	0.02611	0.02056	0.02179	0.02055	0.01946

Period	Statistic	Monday	Tuesday	Wednesday	Thursday	Friday
2011-2015	Mean	-0.00028	0.00008	0.00095	-0.00163	0.00153
	Sd	0.01944	0.01530	0.01458	0.01575	0.01522
2016-2020	Mean	0.00108	0.00226	-0.00094	-0.00130	0.00062
	Sd	0.01612	0.01085	0.00921	0.01232	0.01225

(2) The mean returns for HSI

Period	Statistic	Monday	Tuesday	Wednesday	Thursday	Friday
2006-2020	Mean	0.00010	-0.00007	0.00047	-0.00005	0.00036
	Sd	0.01728	0.01456	0.01447	0.01436	0.01385
2006-2010	Mean	0.00129	-0.00136	0.00061	0.00096	0.00028
	Sd	0.02356	0.01920	0.01909	0.01857	0.01814
2011-2015	Mean	-0.00150	-0.00027	0.00083	-0.00027	0.00089
	Sd	0.01277	0.01185	0.01181	0.01240	0.01085
2016-2020	Mean	0.00054	0.00145	-0.00002	-0.00083	-0.00009
	Sd	0.01300	0.01102	0.01104	0.01095	0.01139

(3) The mean returns for Nikkei 225

Period	Statistic	Monday	Tuesday	Wednesday	Thursday	Friday
2006-2020	Mean	-0.00006	0.00015	0.00041	0.00053	-0.00034
	Sd	0.01540	0.01547	0.01437	0.01553	0.01503
2006-2010	Mean	-0.00033	-0.00094	-0.00079	0.00162	-0.00150
	Sd	0.01799	0.01835	0.01674	0.01934	0.01818
2011-2015	Mean	-0.00097	-0.00014	0.00207	0.00039	0.00096
	Sd	0.01413	0.01458	0.01385	0.01359	0.01296
2016-2020	Mean	0.00126	0.00142	-0.00006	-0.00044	-0.00047
	Sd	0.01348	0.01295	0.01198	0.01273	0.01329

(4) The mean returns for NASDAQCOM

Period	Statistic	Monday	Tuesday	Wednesday	Thursday	Friday
2006-2020	Mean	-0.00017	0.00116	0.00090	0.00030	0.00030
	Sd	0.01563	0.01385	0.01335	0.01382	0.01225
2006-2010	Mean	-0.00085	0.00045	0.00115	0.00023	-0.00041

Period	Statistic	Monday	Tuesday	Wednesday	Thursday	Friday
2006-2010	Sd	0.01854	0.01745	0.01578	0.01649	0.01336
2011-2015	Mean	-0.00048	0.00157	0.00018	0.00071	0.00041
	Sd	0.01139	0.01047	0.01098	0.01140	0.01015
2016-2020	Mean	0.00084	0.00145	0.00137	-0.00004	0.00022
	Sd	0.01602	0.01271	0.01279	0.01308	0.01298

(5) The mean returns for DAX

Period	Statistic	Monday	Tuesday	Wednesday	Thursday	Friday
2006-2020	Mean	0.00023	0.00097	0.00063	-0.00040	-0.00022
	Sd	0.01585	0.01375	0.01302	0.01400	0.01309
2006-2010	Mean	0.00131	0.00028	0.00061	-0.00038	-0.00089
	Sd	0.01842	0.01518	0.01474	0.01487	0.01413
2011-2015	Mean	-0.00095	0.00080	0.00062	0.00120	0.00000
	Sd	0.01391	0.01357	0.01266	0.01336	0.01310
2016-2020	Mean	0.00046	0.00184	0.00066	-0.00202	0.00024
	Sd	0.01454	0.01229	0.01143	0.01352	0.01192

From Table 11 (1), (2), (3), (4) and (5), it is clear that not all weekdays have the same return level. From Table 11 (1), CSI 300, the return on Monday seems higher than the other days in one week with 0.00175. From Table 11 (2), HSI, the return on Wednesday seems higher with 0.00047. From Table 11 (3), Nikkei 225, the return on Thursday seems higher with 0.00053. From Table 11 (4), NASDAQCOM, the return on Tuesday seems higher with 0.00116. From Table 11 (5), the return on Tuesday seems higher with 0.00097.

In order to take a deep look, we regress (3). The results of regression (3) are summarized in Table 12.

Table 12 The day-of-the-week-effect in five indexes

Note: This table shows the results of regression:

$$R_t = b_1 \cdot M_t + b_2 \cdot TU_t + b_3 \cdot W_t + b_4 \cdot TH_t + b_5 \cdot F_t + u_t \qquad u_t \sim N(0, \sigma^2) \qquad (3)$$

Rt: the daily returns of stock index

M_t, TU_t, W_t, TH_t, F_t: the dummy variable which equal to 1 when the day is Monday, or Tuesday, or Wednesday, or Thursday, or Friday respectively and to 0 when the day is the other days

b_i: the coefficients of the-day-of-the-week effect

*** 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.

(1) The day-of-the-week-effect in CSI 300

	2006-2020	2006-2010	2011-2015	2016-2020
b_1	0.00175***	0.00471***	-0.00028	0.00108

	2006-2020	2006-2010	2011-2015	2016-2020
b_2	0.00008	-0.00218	0.00008	0.00226***
b_3	0.00059	0.00179	0.00095	-0.00094
b_4	-0.00111*	-0.00038	-0.00163	-0.00130
b_5	0.00107*	0.00107	0.00153	0.00062

(2) The day-of-the-week-effect in HSI

	2006-2020	2006-2010	2011-2015	2016-2020
b_1	0.00010	0.00129	-0.0015*	0.00054
b_2	-0.00007	-0.00136	-0.00027	0.00145**
b_3	0.00047	0.00061	0.00083	-0.00002
b_4	-0.00005	0.00096	-0.00027	-0.00083
b_5	0.00036	0.00028	0.00089	-0.00009

(3) The day-of-the-week-effect in Nikkei 225

	2006-2020	2006-2010	2011-2015	2016-2020
b_1	-0.00006	-0.00033	-0.00097	0.00126
b_2	0.00015	-0.00094	-0.00014	0.00142**
b_3	0.00041	-0.00079	0.00207**	-0.00006
b_4	0.00053	0.00162	0.00039	-0.00044
b_5	-0.00034	-0.00150	0.00096	-0.00047

(4) The day-of-the-week-effect in NASDAQCOM

	2006-2020	2006-2010	2011-2015	2016-2020
b_1	-0.00017	-0.00085	-0.00048	0.00084
b_2	0.00116**	0.00045	0.00157**	0.00145*
b_3	0.0009*	0.00115	0.00018	0.00137
b_4	0.00030	0.00023	0.00071	-0.00004
b_5	0.00007	-0.00041	0.00041	0.00022

(5) The day-of-the-week-effect in DAX

	2006-2020	2006-2010	2011-2015	2016-2020
b_1	0.00023	0.00131	-0.00095	0.00046
b_2	0.00097*	0.00028	0.00080	0.00184**

	2006-2020	2006-2010	2011-2015	2016-2020
b_3	0.00063	0.00061	0.00062	0.00066
b_4	-0.00040	-0.00038	0.00120	-0.00202**
b_5	-0.00022	-0.00089	0.00000	0.00024

From Table 12 (1), (2), (3), (4) and (5), the day-of-week effect exists in all five markets but with different types. From Table 12 (1), CSI 300, from 2006 to 2020 and sub-period 2006 to 2010, Monday's return are higher than the other days. Friday's return is not as the previous studies, it even shows higher positive returns form 2006 to 2020 in CSI 300 with significant 0.00107. The return on Thursday is less the the other days with significant -0.00111 from 2006 to 2020. From Table 12 (2), HSI shows negative return on Monday in sub-period 2011-2015 with significant -0.0015 and shows positive return on Tuesday from 2015 to 2020 with significant 0.00145. From Table 12 (3), Nikkei 225 shows higher positive return on Wednesday and on Tuesday in sub-period 2011-2015 and 2016-2020, respectively. From Table 12 (4), NASDAQCOM shows higher positive returns almost on Tuesday from 2006 to 2020 and sub-period from 2011 to 2015, which is different from previous studies. From Table 12 (5), DAX, the returns on Tuesday and Thursday are higher than the other days in sub period 2016-2020. Anyway, all markets exist the day-of-week-effect which is significant evidence against an efficient market.

We also regress a EGARCH(1, 1) model as follow.

Table 13 The day-of-the-week-effect in five indexes—EGARCH(1,1)

Note: This table shows the result of regression:

$$R_t = c + b_1 \cdot M_t + b_2 \cdot TU_t + b_4 \cdot TH_t + b_5 \cdot F_t + \varepsilon_t$$

$$\ln(\sigma_t^2) = \lambda_0 + \lambda_1 \cdot M_t + \lambda_2 \cdot TU_t + \lambda_4 \cdot TH_t + \lambda_5 \cdot F_t + \alpha \cdot z_{t-1} + \gamma \cdot \left(|z_{t-1}| - \sqrt{\tfrac{2}{\pi}}\right) + \delta \cdot \ln(\sigma_{t-1}^2)$$

$$\varepsilon_t = \sigma_t \cdot z_t \qquad z_t \sim N(0,1)$$

R_t: the daily return of stock index

M_t, TU_t, TH_t, F_t: the dummy variable which equal to 1 when the day is Monday, or Tuesday, or Thursday, or Friday respectively and to 0 when the day is the other days

b_i: the day-of-the-week-effect in conditional mean function

λ_i: the day-of-the-week-effect in conditional variance function

*** 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.

(1)The day-of-the-week-effect in CSI 300

Coefficient	Estimate	Standard error	Z-value
b_1	0.00144	0.00066	2.23**
b_2	0.01143	0.00057	2.00**
b_4	-0.00089	0.00059	-1.5
b_5	0.00074	0.00058	1.26
c	0.00006	0.00041	0.15
λ_1	0.51480	0.06101	8.44***
λ_2	-0.30038	0.08501	-3.53***

Coefficient	Estimate	Standard error	Z-value
λ_4	0.31511	0.08617	3.66***
λ_5	0.09869	0.06649	1.48
λ_0	-0.18209	0.05220	-3.49***
α	-0.00746	0.00511	-1.46
γ	0.15226	0.00900	16.91***
δ	0.99200	0.00152	653.38***

(2) The day-of-the-week-effect in HSI

Coefficient	Estimate	Standard error	Z-value
b_1	-0.00039	0.00053	-0.74
b_2	-0.00067	0.00054	-1.24
b_4	-0.00070	0.00052	-1.34
b_5	-0.00055	0.00055	-1.01
c	0.00071	0.00038	1.89*
λ_1	0.23057	0.05989	3.85***
λ_2	-0.04907	0.06618	-0.74
λ_4	0.10381	0.08109	1.28
λ_5	-0.00179	0.05509	-0.03
λ_0	-0.20992	0.04351	-4.83***
α	-0.06126	0.00659	-9.30***
γ	0.13098	0.01037	12.63***
δ	0.98200	0.00223	440.31***

(3)The day-of-the-week-effect in Nikkei 225

Coefficient	Estimate	Standard error	Z-value
b_1	-0.00022	0.00083	-0.26
b_2	-0.00010	0.00075	-0.14
b_4	0.00053	0.00075	0.70
b_5	-0.00028	0.00074	-0.37
c	0.00006	0.00051	0.13
λ_1	0.12936	0.04820	2.68***
λ_2	0.15357	0.03179	4.83***

Coefficient	Estimate	Standard error	Z-value
λ_4	0.00041	0.03588	0.01
λ_5	-0.00361	0.04824	-0.07
λ_0	-15.76154	0.06260	-251.81***
α	-0.01112	0.00356	-3.12***
γ	0.09081	0.00392	23.15***
δ	-0.86941	0.00632	-137.65***

(4)The day-of-the-week-effect in NASDAQCOM

Coefficient	Estimate	Standard error	Z-value
b_1	-0.00061	0.00047	-1.28
b_2	-0.00060	0.00048	-1.25
b_4	-0.00033	0.00048	-0.70
b_5	-0.00026	0.00046	-0.57
c	0.00067	0.00034	2.01**
λ_1	0.01980	0.07587	0.26
λ_2	0.05403	0.08616	0.63
λ_4	0.09427	0.08714	1.08
λ_5	-0.05548	0.07004	-0.79
λ_0	-0.30438	0.05754	-5.29***
α	-0.13380	0.00644	-20.77***
γ	0.15430	0.01219	12.66***
δ	0.96810	0.00260	372.33***

(5) The day-of-the-week-effect in DAX

Coefficient	Estimate	Standard error	Z-value
b_1	-0.00042	0.00045	-0.94
b_4	-0.00040	0.00044	-0.92
b_5	-0.00024	0.00044	-0.53
c	0.00041	0.00024	1.69*
λ_1	0.19925	0.05866	3.40***
λ_4	0.25918	0.07132	3.63***
λ_5	0.01864	0.05666	0.33

Coefficient	Estimate	Standard error	Z-value
λ_0	-0.31307	0.03333	-9.39***
α	-0.12468	0.00731	-17.06***
γ	0.12875	0.01197	10.76***
δ	0.97499	0.00245	397.26***

From Table 13 (1), (2), (3), (4) and (5), under the consideration of time-varying volatility, the day-of-the-week-effect only exists in CSI 300 from 2006 to 2020 in return. From Table 13 (1), the returns on Monday and Tuesday in a week are higher than the other days for significant 0.00144 and 0.01143. As for variance, from Table 13 (1), CSI 300, the returns on Monday and Thursday are more volatile and the return on Tuesday is less volatile for significant 0.5148, 0.31511 and -0.30038. From Table 13 (2), HSI, the reruns on Monday is more volatile for significant 0.23057. From Table 13 (3), Nikkei 225, the returns on Monday and Tuesday are more volatile for significant 0.12936 and 0.15357. From Table 13 (4), NASDAQCOM, the returns on every days in a week show the same level of volatility. From Table 13 (5), DAX, the returns on Monday and Thursday are more volatile for significant 0.19925 and 0.25918.

From Table 13, all five indexes are examined with arch effect and garch effect with significant γ and δ. Except CSI 300, other four indexes are found negative leverage effect for significant negative α, -0.06126, -0.01112, -0.13380, -0.12875, which implies that a fall in returns results in greater volatility than an increase in returns of the same magnitude.

5.Conclusions

This paper examined the market efficiency level in five stock markets with five indexes. The methods for testing market efficiency are autocorrelation, runs test, specific strategy, January effect, the-turn-of-the-month-effect (the TOM effect) and the-day-of-the-week-effect (the DOW effect). We found that:(1)There is strong evidence of autocorrelation for CSI 300 and NASDAQCOM. From the viewpoint of autocorrelation, the most efficient market among five stock markets is the market in Hong Kong. (2) The results of runs tests do not found evidence against randomness in daily returns for CSI 300, HSI from 2006 to 2020 but find a little evidence for Nikkei 225, NASDAQCOM and DAX. From the viewpoint of runs test, the higher level of efficient markets among five stock markets are the markets in China and Hong Kong. (3) The strategy analyzed here does not find evidence for inefficient market. (4) The January effect did not exist in five indexes. (5) All five indexes are characterized with a TOM effect in different level and therefore the hypothesis of efficient market is rejected for five markets. (6) All five indexed are also found the-day-of-week effect which indicates an inefficient stock market. (7) After the consideration of time-varying volatility, we found January effect in Nikkei 225. Except Nikkei 225 all the other indexes are verified with the turn-of-the-month-effect in return and only CSI 300 are verified with the day-of-the-week-effect in return.

In a ward, we conclude that all five markets are not weak form efficient from 2006 to 2020 from the viewpoint of autocorrelation, the-turn-of-month effect and the-day-of-week effect.

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