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An empirical analysis of the Adaptive Market Hypothesis with calendar effects:Evidence from China

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ABSTRACT

Adaptive Market Hypothesis (AMH) claims that the degree of market efficiency is related to environmental factors characterizing market conditions. This paper examines the AMH through four calendar effects in China stock market. In particular, we employ subsample analysis and rolling window analysis as well as construct investment strategies based on calendar effects to determine whether they perform as AMH implies. The empirical findings show that both the four calendar effects' performance and excess returns of the investment strategies vary from time to time. Generally speaking, the empirical results suggest that AMH gives a better explanation for the market dynamics in China stock market.

1. Introduction

The Adaptive Market Hypothesis (AMH), which is based on an evolutionary approach to economic anomalies, has been increasingly influential in recent years. Lo (2005) argues that the impact of the competition, mutation, reproduction, and natural selections formulate pressures on financial institutions and market participants, which determines the efficiency of markets and the waxing and waning of investment strategies. This paper aims at examining the AMH in China stock market based on the performance of the well-known calendar effects, which determine whether the AMH is adequate to explain the time-varying calendar effects anomalies. In addition, we construct investment strategies based on the calendar effects and examine whether the investment strategies generate excess return in different time windows. Overall, the time variation of the performance for the calendar effects and the investment strategies provide evidence for the AMH in China stock market.

Unlike other financial anomalies, the calendar effects are very familiar to market participants which were first noticed as early as 1920s (Wachtel, 1942) and have been lasted for years. The major characteristic of the calendar effects is that stock returns are systematically higher or lower on the day of the week, the days of the month, or the month of the year. This paper investigates Monday effect,[1] January effect, turn of the month effect (TOTM), and Chinese Lunar New Year (CLNY) effect in 4 typical stock market indices from the establishments to the end of 2015 by using subsample analysis and rolling window analysis. By using the subsample analysis, we capture the performance of the calendar effects overtime in fixed-length subsample, nonetheless we divide the whole

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[1] In particular, our results suggest the reversed Monday effect. For details, see section 5.

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sample into some subsamples subjectively so as to lose some of the time-varying behavior of the calendar effects (Urquhart and McGroarty, 2014). Therefore, we capture more details of the behavior by using rolling window analysis. For Lo's (2004) another quantifiable implication of AMH, investment strategies will also wax and wane. That is, they perform well in certain environments and perform poor in other environments. So we construct investment strategies based on the 4 calendar effects, examining whether the investment strategies undergo cycles of profitability and loss as AMH implies.

This paper contributes the literature in following aspects. Firstly, it's the first time adding support to the AMH by using the time varying calendar in China stock market; secondly, unlike most of the literatures, this paper uses the GARCH (1,1) model to eliminate the heteroscedasticity of the time series; thirdly we obtain the test results on the details and time varying through subsample analysis and rolling window analysis with a multi-tier approach; finally, this paper thoroughly examines the AMH in China stock market by constructing investment strategies.

The reminder of this paper is organized as follows: Section 2 reviews the 3 calendar effects and AMH; Section 3 introduces the model and the data used in this paper; Section 4 introduces the empirical results; Section 5 concludes.

2. Literature review

The theoretical framework of AMH has been developed for years (Lo, 2004, 2005, 2007). The exploration and empirical research on the AMH of foreign and domestic scholars mainly focuses on the predictability of stock return and the time variability and periodicity of market efficiency. In this paper, the research on the AMH employs the quantitative implications of the theory and selects calendar effects to study if the description under the AMH is suitable for the financial anomalies in China stock market. The following introduces existing literature on the AMH and calendar effects which we employ as the evidence of the AMH in China stock market.

2.1. The AMH

According to the EMH theory by Fama (1970), the asset price can quickly incorporate all the newly released information in the market. Based on that, Grossman and Stiglitz (1980) argued that it is impossible for the market to achieve the equilibrium since arbitraging itself is costly and almost all arbitrage opportunities have been eliminated. Then Campbell et al. (1997) proposed the notion of relative efficiency which distinguishes the market referring to different degrees of efficiency. Following that, Lo (2004) put forward AMH, which states that there is a continuous process of evolution in the market as it is in nature. The present studies generally regard Lo's (2004) basic theory as the symbol of the establishment of the AMH.

Specifically, as Lo (2005) states, the AMH can be viewed as a new version of the EMH, which is derived from evolutionary principles. The primary components of the AMH consist of the following ideas: (1) Individuals act in their own self-interest; (2) Individuals make mistakes; (3) Individuals learn and adapt to different environments; (4) Competition drives adaptation and innovation; (5) Nature selection shapes market ecology; (6) Evolution determines market dynamics. Combining the implications of the AMH (Lo, 2004), we form two ways to examine the AMH in China stock market through calendar effects. One is that the performance of the calendar effects varies from time to time. The other one is that the investment strategies will also wax and wane, performing well in certain periods and performing poorly in other periods.

2.2. Evidence for the AMH

Plenty of studies provide evidence for the AMH in both developed and emerging markets. In the different markets, academics find evidence of the AMH. Lee and Lee (2009) using the energy prices for OECD countries from 1978 to 2006 and observes the presence of the profitable arbitrage opportunities among energy prices. Neely et al. (2009) observe the regularities consisting with the AMH by analyzing the intertemporal stability of excess returns to technical trading rules in the foreign exchange market. From the findings of Charles et al. (2012) which examine return predictability of major foreign exchange rates by testing for martingale difference hypothesis using daily and weekly nominal exchange rates from 1975 to 2009, we see that return predictability occurs from time to time depending on changing market conditions, consistent with the implications of the AMH. Not only in the foreign exchange market have we find evidence for the AMH, but also in the major stock markets (Urquhart and Hudson, 2013; Urquhart and McGroarty, 2016), REIT market (Zhou and Lee, 2013), and derivative product market (Hall et al., 2017). As same as the empirical studies, Butler and Kazakov (2012) analyze variable efficiency and cyclical profitability via computational intelligence to test the AMH. Manahov and Hudson (2014) also find evidence for the AMH from artificial stock markets. Generally speaking, the AMH is widespread in financial markets.

Intuitively, most of the above literature focuses on examining the AMH in major stock markets. Evidence from developed stock markets (Todea et al., 2009; Kim et al., 2011; Noda, 2012, 2016; Urquhart and Hudson, 2013; Urquhart and McGroarty 2014, 2016; Rodriguez et al., 2014), as well as from emerging stock markets (Chong et al., 2012; Hiremath and Kumari, 2014; Hull and McGroarty, 2014; Hiremath and Narayan, 2016) indicate that the AMH is general in global stock markets. In recent years, China stock market has been increasingly influential in global stock markets, whereas the literature studying the AMH in China stock market remains less.

Most of the empirical studies focus on the stock return predictability by using linear and nonlinear methods (Todea et al., 2009; Urquhart and Hudson, 2013; Hiremath and Kumari, 2014; Ghazani and Araghi, 2014). Noda (2012, 2016) employs a time-varying model approach to measure the degrees of market efficiency. In this paper, we choose GARCH (1, 1) model which treats heteroscedasticity as a variance to be modeled (Engle, 2001). Subsample analysis is the most popular idea to investigate the efficiency in stock market (Chong et al., 2012; Rodriguez et al., 2014; Urquhart and McGroarty, 2016). But this paper combines subsample analysis and rolling window analysis as Urquhart and McGroarty (2014) and Hiremath and Narayan (2016).

2.3. Calendar effect

2.3.1. Monday effect

Monday is the first trading day in one week and the phenomenon that daily return of Monday is significantly different from the other 4 trading days is called Monday effect. Studies on Monday effect in developed financial markets starts from 1920s where participants in financial markets have been aware of Monday effect. Kelly (1930) documents that on Mondays, individual investors have a penchant for selling stocks, and this tendency is related to the Monday decline (Maberly, 1995). In line with the anomaly, scholars draw the conclusion that returns on Mondays are significantly lower than other weekdays (Siegel, 1998). Gibbons and Hess, (1981) found that average returns of DJIA, individual stocks and T-bill on Mondays are all lower than those of the other four weekdays. Connolly (1989) studies the weekday effect from 1963–1983, he finds out that after 1974 even returns on Mondays are negative and they are not significantly different with other trading days. Also, plenty of literature show that Monday effect has a reversal in S&P500, NYSE, DJIA and weighted average CRSR, indicating that returns on Mondays are significantly higher than those on other four trading days (Brusa et al., 2000, 2004, 2005). The reversal has also happened in international financial markets. Doyle and Chen (2009) investigate 11 financial markets and observe significant reversal for Monday effect.

2.3.2. January effect

January effect refers to the fact that the average return for the first month is significantly different from returns for other months. Rozeff and Kinney (1976) find statistically significant differences in mean returns among months due primarily to large January returns on the New York Stock Exchange from 1904 to 1974 except 1929–1940. Other studies find that small firms experience large returns in January and even in years when, on average, large firms earn larger risk adjusted returns than small firms (Keim, 1983; Kato and Schallheim, 1985). Some scholars also provide evidence that the so-called January effect is independent of the small firm effect (Kohers and Kohli, 1991). As more investors become familiar with January effect, the anomaly in the stock market may not be stable over time (Mehdian and Perry, 2002). Gu (2003) shows that the January effect exhibits a declining trend for both large and small stock indices since 1988 and the anomaly is disappearing in the Russell indices. Strong evidence is found that the January effect has disappeared after it has been published and the timing of disappearing or reappearing anomalies typically often coincides with the timing of academic publications. Sun and Tong (2010) find strong evidence that the January effect is due to higher compensation for risk in the month.

2.3.3. TOTM effect

TOTM refers to an anomaly that in the turn of the months, average return is significantly higher than those of the other days within the month. Early literature finds that the mean return for the stocks is positive only for days before and during the first half of calendar months, and indistinguishable from zero for days during the last half of the month (Ariel, 1987). Lakonishok and Smidt (1988) use 90 years of daily data on the Dow Jones Industrial Average to test the existence of persistent seasonal patterns in returns and find evidence of persistently anomalous returns around the turn of the month. Kunkel et al. (2003) examine 19 country stock market indices for recent evidence of the turn of the month effect in daily stock returns and find that the 4-day TOTM period accounts for 87% of the monthly returns in the stock market of 15 countries where the TOTM effect exists.

2.3.4. CLNY effect

According to Wong et al. (1990), the earliest scholar investigating the impact of the CLNY effect, such effect may be peculiar to markets with a large population of Chinese. Yen and Shyy (1993) find that there are excess returns prior to the Chinese Lunar New Year in Hong Kong, Japan, Malaysia, Singapore, South Korea, and Taiwan. Chan et al. (1996) find that there are significant CLNY effect in Malaysia and Singapore. Also, Gao and Kling (2005) show us that there is a statistically and economically significant Chinese Lunar New Year effect. Most recently, Yuan and Gupta (2014) use an ARMA (1, 1)-GARCH (1, 1) model and find that there is a significant CLNY effect.

3. Model

In this paper, we examine the performance of the calendar effects in the time dimension by studying the daily returns of the 4 representative indices in China stock market. We observe the reasonability of the AMH of explaining the anomalies in China stock market through the performance of the calendar effects. The regression equation we use is as follows:

$$R_t = c + \beta D_t + \varepsilon_t \tag{1}$$

where R_t is the return on an index, D_t is a dummy variable indicating calendar effect and ε_t is the error term.

We do not use an OLS regression, considering the financial time series with volatility cluster effect and the empirical results may be affected by the interference of heteroscedasticity, while the GARCH model allows for heteroscedasticity, and the GARCH (1, 1) model is the most widely used and most reasonable in the studies of financial time series (Engle 2001). Modeling the error term with GARCH (1,1), we can control the mutual influence of the return series of the index and dummy variable series of calendar effect in time t and time t − 1, in order to eliminate the influence of return of calendar effect series on the return of non-calendar effect. The conditional variance equation is:

$$h_t = \alpha_1 + \alpha_2 \varepsilon_{t-1}{}^2 + \theta h_{t-1} \tag{2}$$

where h_t and h_{t-1} are the conditional variance of index return at time t and $t-1$ respectively and α_1, α_2, θ are the GARCH model coefficients.

4. Data

In this paper, we select four representative indices from the days of their establishment respectively to 31st December 2015 in China stock market as the empirical data, which fully captures the characteristics in China stock market. The indices include SSE50, SSE180, CSI300, and ChiNext index.

SSE50 consists of 50 stocks with large scale, good fluidity on Shanghai Stock Exchange (SSE), such stocks can reflect the overall trend of the most influential group of leading enterprises in SSE. All the common stocks are ranked in descending order according to the market value and transaction volume, and the index is made up of the top 50 stocks based on adjusted-market-cap weighted calculation method. The index is generally adjusted every half year.

SSE180 consists of 180 stock with some of the large scale, good fluidity, and strong industry representative stock in SSE. The market capitalization accounts for 50% of SSE's total capitalization and trading volume accounts for 47% of SSE's, which can reflect SSE's overall tendency. All the common stocks are ranked in descending order comprehensive according to market value, negotiable market value, trading volume and turnover rate and the index is made up of the top 180 stocks using adjusted-market-cap weighted calculation method. The index is generally adjusted every half a year.

CSI300 consists of the mainstream shares in SSE and Shenzhen Stock Exchange (SZSE) with high liquidity and actively trading, can reflect the overall trend of SSE and SZSE. The index is made up of 300 stocks selected form the ranked common stocks in SSE and SZSE in descending order according to market value and liquidity. The index is negotiable value weighted and adjusted every half year.

ChiNext index can comprehensively and objectively reflect the overall price movements of the Growth Enterprises Market stocks. All the common stocks are ranked in descending order according to negotiable value and trading volume. The index is negotiable value weighted and adjusted quarterly.

The daily return of the index for day d is R_d, which is calculated as follows:

$$R_d = (C_d - O_d)/O_d \tag{3}$$

where C_d is the closing price on day d and O_d is the opening price of the index on day d.

We make some descriptive statistics of the 4 indices to verify the rationality of the selected model. According to the kurtosis, skewness, Jarque–Bera test of the daily return of the indices, we can draw the conclusion that the series are not normally distributed.

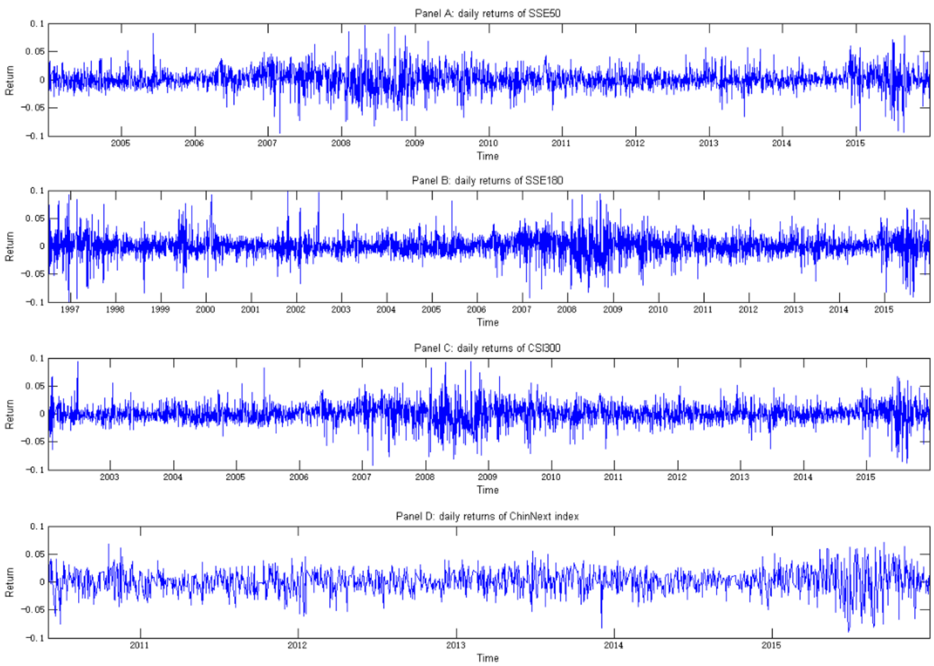

Fig. 1. Daily returns of the 4 indices.

Table 1
Descriptive statistics of indices.

	Observations	Mean	St.d	Skewness	Kurtosis	Jarque–Bera test
SSE50	2918	0.000437	0.018633	−0.114573	6.258058	118.4813***
SSE180	4731	0.000433	0.018163	−0.077942	7.155840	95.3417***
CSI300	3396	0.000429	0.017825	−0.227402	6.447047	65.4210***
ChiNext	1361	0.000856	0.021773	−0.421925	4.377455	230.7537***

Note: This table reports the summary statistics of the 4 indices. All the 4 indices have leptokurtosis and heavy tails with all the kurtosis greater than 3. As well as the Jarque–Bera test are significant at 1% level indicating the series are no-normal. ***, indicate significance at 1% level.

Due to the volatility clustering effect, selected data is heteroscedastic significantly, which particularly fits our model.

Fig. 1 shows the daily returns of the four indices since establishment to 31st December 2015, we can obviously see the volatility clustering effect in different periods. The characteristics are the basis for this paper in choosing models.

5. Empirical results

5.1. Descriptive statistics of the calendar effects

We divide the time series of the 4 indices into calendar effect series and non-calendar effect series, and then we have the whole sample descriptive statistics of the calendar effect in the four indices and we construct K–S test of calendar effect and non-calendar effect (*P* value of less than 0.01 is very significant).

In order to eliminate the statistical interference from the different lengths of the calendar effect series and non-calendar effect series, we further process calendar effect series and non-calendar effect series for the same length, continuing to do descriptive statistical test. The 3 calendar effects are defined as follows. Monday effect: Monday series are made up of all the Mondays' daily returns and non-Monday series are made up of all the average daily returns from each Tuesday to the Friday in the same week; January effect: January series are composed of average daily returns of each Januarys and non-January series are composed of average daily returns from each February to the December in the same year; TOTM effect: Average daily returns of four trading days of the each turn of the months make up TOTM series and non-TOTM series are made up of average daily returns after each TOTM and before next TOTM; CLNY effect: average daily return of the three days prior to and after the Chinese Lunar New Year make up CLNY series and non-CLNY series are made up of average daily returns of the other days in the year (HYPERLINK \l "tbl0001" Table 1).

The inspection results are shown inTable 2.

Through descriptive statistics of the four indices, returns of Mondays of the four indices are all positive, significantly greater than the non-Monday's, which proves that not the Monday effect, but the reversed Monday effect exists in China stock market; The returns in Januarys and non-Januarys are not significantly different in SSE50 and ChiNext index, but the returns in Januarys in SSE180 are significantly higher than in non-January trading days, and the returns in Januarys in SCI300 is greater than non-Januarys, but not significant; TOTM effect in the 4 indices are very strong, the returns in TOTMs are significant higher than in non-TOTMs. Returns of Chinese Lunar New Year period are all positive, significantly greater than the non-CLNY's, which proves that the CLNY effect exists. Therefore, we can draw the conclusion that in the whole sample of the four indices, Monday effect, CLNY effect and TOTM effect are significant, but January effect is only significant in SSE 180. In order to further analyze the performance varying of the calendar effects in different periods of the whole sample, we combine the sub-sample analysis and rolling window analysis methods to study the changing behavior of the calendar effects.

5.2. Subsample analysis on calendar effects

We study the time-varying performance of calendar effects through subsample analysis and rolling window analysis. Subsample analysis generates more details on the empirical results and rolling window analysis can get the time-varying results, so combining these two methods can overcome their own shortcomings. We segment every sample into several subsamples: SSE 50 from 2004 to 2015 was divided into 4 subsamples equally; SSE 180 from 1996 to 2015 was divided into 5 subsamples equally; CSI 300 from 2002 to 2015 was divided into 4 subsamples of which the first sample was 2 years long and the rests were all 4 years long; ChiNext index was not divided because it was newly set up and have shorter sample. Table 3–6 report the regression results under model (1) and (2) on SSE 50, SSE 180, CSI 300 and ChiNext index respectively.

As shown in Table 3, different subsamples of SSE50 are with different coefficients and significant levels. Reversed Monday effect subsamples generate 2 positive and 1 negative coefficients, indicating a reversed Monday effect reversal in different periods, although not significant at 10% level, but with an increase in the degrees as time goes on, supporting the AMH; January effect subsamples generate 2 negative and 1 positive coefficients, showing that January effect is also changing, supporting the AMH; TOTM effect subsamples generate 3 significantly positive coefficients, but the significant degree is consistent with the time-varying behavior of the AMH. CLNY effect subsamples generate 3 positive coefficients, although not significant at 10% level, but with a decrease in the degrees as time going on, supporting the AMH.

Table 4 reports the regression results of 5 subsamples of SSE180. Reversed Monday effect subsamples generate 3 negative and 2 positive coefficients and reversals occurs in 2004–2007 and 2012–2015 subsamples, with changing magnitude of significant degrees,

Table 2
Descriptive statistics after adjusted the length of the series.

	No. of days	No. of days after adjusted	Mean	St.d	% of +days	P value of K–S test
Panel A: SSE50						
Monday	571	570	0.001600	0.022300	52.71%	0.0000***
Non-Monday	2343	570	0.000337	0.008800	49.81%	
January	222	12	0.000726	0.005200	50.90%	0.0656*
Non-January	2692	12	0.000491	0.002100	50.33%	
TOTM	572	142	0.002300	0.009100	54.90%	0.0003***
Non-TOTM	2342	142	−0.000039	0.004700	49.27%	
CLNY	72	12	0.002718	0.021764	55.56%	0.0656*
Non-CLNY	2842	12	0.000416	0.018488	50.60%	
Panel: SSE180						
Monday	933	932	0.001200	0.021400	51.34%	0.0000***
Non-Monday	3792	932	0.000386	0.008300	50.98%	
January	352	19	0.001400	0.004400	54.83%	0.0486**
Non-January	4373	19	0.000362	0.001800	50.74%	
TOTM	932	232	0.002100	0.009000	55.47%	0.0000***
Non-TOTM	3793	232	−0.000013	0.004700	49.96%	
CLNY	114	19	0.003980	0.023470	63.16%	0.0018***
Non-CLNY	4611	19	0.000371	0.017962	51.29%	
Panel C: CSI300						
Monday	667	666	0.001500	0.021200	55.32%	0.0000***
Non-Monday	2725	666	0.000291	0.008300	51.63%	
January	262	14	0.001200	0.004800	54.58%	0.1106
Non-January	3130	14	0.000433	0.002000	52.17%	
TOTM	668	166	0.002500	0.008800	57.34%	0.0000***
Non-TOTM	2724	166	0.000055	0.004600	51.14%	
CLNY	84	14	0.004155	0.019888	65.48%	0.0030***
Non-CLNY	3308	14	0.000371	0.017687	52.45%	
Panel D: ChiNext index						
Monday	264	263	0.002000	0.025200	57.20%	0.0000***
Non-Monday	1093	263	0.000624	0.010000	51.97%	
January	96	5	0.001200	0.006700	56.25%	0.2090
Non-January	1261	5	0.000895	0.001700	52.74%	
TOTM	264	66	0.004200	0.011200	61.36%	0.0002***
Non-TOTM	1093	66	0.000367	0.005700	50.96%	
CLNY	30	5	0.007930	0.019272	70.00%	0.0361*
Non-CLNY	1327	5	0.000832	0.021565	52.75%	

Note: Kolmogorov-Smirnov test compares the distributions of the values in two samples x1 and x2. The null hypothesis is that x1 and x2 are from the same continuous distribution. The alternative hypothesis is that they are from different continuous distributions. It is significant at 1% level when p value is less than0.01, at 5% level when p value is more than 0.01 and less than 0.05, at 10% significant when p value is more than 0.05 and less than 0.1. ***, **, * indicate significance at 1%, 5%, and 10% levels respectively.

supporting the AMH; January effect subsamples generate 3 negative and 2 positive coefficients also being significant in 2000–2003 and 2004–2007 subsamples, showing a very good evidence for the AMH; TOTM effect subsamples generate 5 all significant positive coefficients and the significant level increases at first and decreases subsequently, in accordance with the AMH. CLNY effect subsamples generate 3 positive and 2 negative coefficients, with a changing form negative to positive, supporting the AMH.

Table 5 shows the regression results of 4 subsamples of CSI 300. Reversed Monday effect subsamples generate 2 positive and 2 negative coefficients, although only the first two are significant, the 4 subsamples experience 2 reversals, supporting the AMH; January effect subsamples generate 3 positive and 1 negative results, of which there is a reversal in 2014, consisting with the behaviors under the AMH; TOTM effect subsamples generate 4 positive coefficients, with the significant degrees increasing at first and decreasing subsequently, indicating that the performance of TOTM effect being in accordance with the AMH. CLNY effect subsamples generate 4 positive coefficients, with a changing significant level, supporting the AMH.

Since the ChiNext index is established lately, there is no need to divide the sample. However, we still find that the three calendar effects' performance are consistent with the previous empirical results, also the TOTM and CLNY effects are the more significant two of the four across the whole samples.

5.3. Time-varying calendar effects

Because of the relatively short history of China stock market, when using the rolling window analysis, we do not have enough data to study January effect and TOTM effect. So in this paper, when we study the time-varying performance of calendar effects we choose the reversed Monday effect and study the time-varying performance of the reversed Monday effect in the 4 indices. We use a Student's *t*-test over 12-month window length rolling 1-month forward. Index data window is set to 12 months, each move forward a month, so that we obtain more convincing evidence.

Fig. 2 shows the time-varying *p*-values of Student's *t*-test using a 12-month window. The solid line is the *p*-values and the dotted

Table 3
Subsample analysis of the calendar effects in SSE50.

SSE50	Conditional mean		Conditional variance		
	c	β	α_1	α_2	θ
Reversed Monday effect					
2004.1.2–2015.12.31	0.000451	0.000039	0.936716***	0.055893***	0.000000***
	(1.43)	(0.06)	(173.04)	(10.88)	(4.84)
2004.1.2–2007.12.31	0.000863*	0.000630	0.932428***	0.058839***	0.000000**
	(1.79)	(0.61)	(71.47)	(5.06)	(2.27)
2008.1.2–2011.12.31	−0.000626	0.001287	0.953974***	0.040599***	0.000000*
	(−0.98)	(1.06)	(101.58)	(4.81)	(1.85)
2012.1.2–2015.12.31	0.000733	−0.001491	0.925448***	0.063329***	0.000000***
	(1.34)	(−1.49)	(115.50)	(7.83)	(3.83)
January effect					
2004.1.2–2015.12.31	0.000454	0.000053	0.936638***	0.055960***	0.000000***
	(1.60)	(0.06)	(173.39)	(10.92)	(4.85)
2004.1.2–2007.12.31	0.000824*	0.002141*	0.931148***	0.060531***	0.000000*
	(1.82)	(1.65)	(71.35)	(5.14)	(2.24)
2008.1.2–2011.12.31	−0.000080	−0.003288	0.951027***	0.043407***	0.000000*
	(−0.14)	(−1.58)	(94.75)	(4.74)	(1.89)
2012.1.2–2015.12.31	0.000462	−0.000373	0.925041***	0.063464***	0.000000***
	(0.95)	(−0.21)	(114.65)	(7.94)	(3.83)
TOTM effect					
2004.1.2–2015.12.31	−0.000106	0.002889***	0.934483***	0.057976***	0.000000***
	(−0.34)	(4.46)	(171.23)	(11.16)	(4.88)
2004.1.2–2007.12.31	0.000601	0.001877*	0.929383***	0.062002***	0.000000*
	(1.19)	(1.92)	(71.36)	(5.35)	(2.27)
2008.1.22011.12.31	−0.001218**	0.004439***	0.952590***	0.041868***	0.000000*
	(−2.00)	(3.32)	(98.53)	(4.82)	(1.86)
2012.1.2-–2015.12.31	−0.000658	0.002782***	0.203813***	0.796187***	0.000000***
	(−1.29)	(2.73)	(6.15)	(8.83)	(11.05)
CLNY effect					
2004.1.2–2015.12.31	0.000393	0.002707	0.936520***	0.056093***	0.000000***
	(1.43)	(1.55)	(172.96)	(10.91)	(4.86)
2004.1.2–2007.12.31	0.000896**	0.003100	0.932737***	0.059022***	0.000000**
	(2.06)	(1.33)	(72.54)	(5.11)	(2.19)
2008.1.2–2011.12.31	−0.000491	0.004384	0.955161***	0.039618***	0.000000*
	(−0.90)	(0.92)	(102.59)	(4.69)	(1.81)
2012.1.2–2015.12.31	0.000419	0.001092	0.924776***	0.063712***	0.000000***
	(0.88)	(0.31)	(114.40)	(7.94)	(3.84)

Note: This table reports the performance of the 3 calendar effects in the whole sample and 3 four-year subsamples of SSE50. The coefficient β indicates the directions and degrees of the calendar effects. ***, **, * indicate significance at 1%, 5%, and 10% levels respectively.

lines represent the 90% confidence intervals. Panel A provides evidence from the returns of SSE50 of the reversed Monday effect. The *p*-value fluctuates around 0.1 and we can clearly see significant reversed Monday effect in the middle of 2004, the year of 2006 and 2008, by the end of 2009 and the second half of 2011. Panel A suggests that the reversed Monday effect fluctuates over time and has actually reversed in recent years indicating evidence for the AMH. Panel B presents the time-varying reversed Monday effect in SSE180 where it is clear that there is much evidence of significant reversed Monday effect in 1998, 2001, 2006, 2011 and some other short periods showing a sign of the reversed Monday effect changing consistently over time which indicates evidence for the AMH. The reversed Monday effect on CSI300 is reported in Panel C and again there is strong evidence that the reversed Monday effect fluctuates over time. In 2006, 2009, and 2011, there is obviously reversed Monday effect in the index. Although there is a short history of ChiNext index and Panel D shows a relatively little evidence of a significant reversed Monday effect throughout the sample, the *p*-values do fluctuate around 0.1 in some periods. Thus the reversed Monday effect in ChiNext index may be relatively weak, but the sign of the Monday effect does vary consistently which provides evidence of the AMH.

The above analysis shows that the changes of the significant degrees of reversed Monday effect in accordance with the AMH. The time-varying performance of reversed Monday effect indicates that the reversed Monday effect after being well-known to investors had not disappeared, and its strength is also in constant fluctuation with no slowing down trend in recent years, all those findings present a strong evidence for the AMH.

5.4. Investment strategies analysis for AMH

An important quantitative implication of AMH is that investment strategies will also wax and wane, performing well in certain periods and performing poorly in other periods. We then construct investment strategies based on calendar effects analyzing weather the performance being consistent as the AMH implies.

Reversed Monday effect investment strategy: Buy at the close order in the first Friday after the index was founded and sell at the close order in the next Monday, holding 1 trading day on Monday, and thus repeating the operation until December 31, 2015.

Table 4
Subsample analysis of the calendar effects in SSE180.,

000010 (SSE180)	Conditional mean		Conditional variance		
	c	*β*	α_1	α_2	θ
Reversed Monday effect					
1996.6.26–2015.12.31	0.000228	−0.000180	0.909267***	0.082034***	0.000000***
	(1.03)	(−0.40)	(218.83)	(18.25)	(7.51)
1996.6.26–1999.12.31	0.000115	−0.001171	0.653505***	0.289045***	0.000000***
	(0.19)	(−1.04)	(19.96)	(8.74)	(5.23)
2000.1.1–2003.12.31	−0.000147	−0.000646	0.747623***	0.228889***	0.000000***
	(−0.43)	(−0.81)	(32.30)	(10.54)	(5.18)
2004.1.1–2007.12.31	0.000800*	0.000882	0.929536***	0.060944***	0.000000**
	(1.68)	(0.83)	(73.51)	(5.31)	(2.37)
2008.1.1–2011.12.31	−0.000621	0.001179	0.952922***	0.040772***	0.000000**
	(−0.97)	(0.95)	(97.65)	(4.81)	(2.00)
2012.1.1–2015.12.31	0.000646	−0.000423	0.928160***	0.060463***	0.000000***
	1.25	−0.44	(108.24)	(7.26)	(3.29)
January effect					
1996.6.26–2015.12.31	0.000151	0.000776	0.909610***	0.081768***	0.000000***
	(0.75)	(1.15)	(221.52)	(18.33)	(7.52)
1996.6.26–1999.12.31	−0.000207	0.001424	0.640505***	0.298848***	0.000000***
	(−0.39)	(0.62)	(19.44)	(9.01)	(5.29)
2000.1.1–2003.12.31	−0.000182	−0.003220***	0.728615***	0.243527***	0.000000***
	(−0.56)	(−3.53)	(30.56)	(11.36)	(5.32)
2004.1.1–2007.12.31	0.000767*	0.002725**	0.928859***	0.062314***	0.000000**
	(1.73)	(2.00)	(74.10)	(5.42)	(2.32)
2008.1.1–2011.12.31	−0.000241	−0.002262	0.952940***	0.040876***	0.000000**
	(−0.43)	(−1.09)	(96.51)	(4.74)	(1.99)
2012.1.1–2015.12.31	0.000591	−0.000419	0.927887***	0.060671***	0.000000***
	(1.28)	(−0.26)	(108.54)	(7.38)	(3.29)
TOTM effect					
1996.6.26–2015.12.31	−0.000325	0.002634***	0.908305***	0.083217***	0.000000***
	(−1.50)	(5.31)	(222.74)	(18.53)	(7.55)
1996.6.26–1999.12.31	−0.000232	0.000564	0.641117***	0.299510***	0.000000***
	(−0.39)	(0.44)	(18.46)	(8.18)	(5.15)
2000.1.1–2003.12.31	−0.000561*	0.001490*	0.755782***	0.222345***	0.000000***
	(−1.67)	(1.61)	(32.79)	(10.41)	(5.05)
2004.1.1–2007.12.31	0.000458	0.002468**	0.924456***	0.065978***	0.000000**
	(0.91)	(2.45)	(70.77)	(5.59)	(2.37)
2008.1.1–2011.12.31	−0.001305**	0.004889***	0.949314***	0.043949***	0.000000**
	(−2.14)	(3.56)	(91.45)	(4.84)	(2.08)
2012.1.1–2015.12.31	−0.000014	0.002929***	0.926351***	0.061938***	0.000000***
	(−0.03)	(2.61)	(105.30)	(7.33)	(3.32)
CLNY effect					
1996.6.26–2015.12.31	0.000140	0.002570**	0.910886***	0.080683***	0.000000***
	(0.72)	(2.10)	(223.54)	(18.32)	(7.40)
1996.6.26–1999.12.31	−0.000002	−0.002846*	0.653276***	0.288936***	0.000000***
	(0.00)	(−1.65)	(17.71)	(7.51)	(4.82)
2000.1.1–2003.12.31	−0.000213	−0.003122*	0.734154***	0.239031***	0.000000***
	(−0.66)	(−1.72)	(30.85)	(11.05)	(5.21)
2004.1.1–2007.12.31	0.000851	0.003832*	0.930326***	0.060948***	0.000000**
	(1.99)	(1.68)	(74.97)	(5.32)	(2.24)
2008.1.1–2011.12.31	−0.000543	0.005815	0.953825***	0.040184***	0.000000**
	(−0.99)	(1.15)	(97.91)	(4.68)	(1.96)
2012.1.1–2015.12.31	0.000531	0.001693	0.927491***	0.061028***	0.000000***
	(1.19)	(0.50)	(108.08)	(7.39)	(3.30)

Note: This table reports the performance of the 3 calendar effects in the whole sample and 5 four-year subsamples (the first subsample is 3 and half years) of SSE180. The coefficient β indicates the directions and degrees of the calendar effects. ***, **, * indicate significance at 1%, 5%, and 10% levels respectively.

January effect investment strategy: Buy at the close order in the last trading day of the first December after the index was founded, and sell at the close order in the last trading day of the next January, holding 1 trading month in each January, and thus repeating the operation until December 31, 2015.

TOTM effect investment strategy: Buy at the close order in the penultimate day of the first month after the index was founded, and sell at the close order in the third trading day of next month, holding 3 trading days (−1 to +3) at the turn of the month, and thus repeating the operation until December 31, 2015.

CLNY effect investment strategy: Buy at the close order three days prior to the Chinese Lunar New Year holiday, and sell at the close order three days after the Chinese Lunar New Year holiday, holding 6 trading days (−3 to +3) around the CLNY holiday, and thus repeating the operation until December 31, 2015.

Table 5
Subsample analysis of the calendar effects in CSI300.,

000300 (CSI300)	Conditional mean		Conditional variance		
	c	β	α_1	α_2	θ
Reversed Monday effect					
2002.1.4–2015.12.31	0.000242	0.000519	0.925437***	0.065362***	0.000000***
	(0.90)	(0.97)	(157.65)	(12.15)	(5.07)
2002.1.4–2005.12.31	−0.000175	−0.001360*	0.789377***	0.144619***	0.000000***
	(−0.43)	(−1.60)	(22.13)	(8.04)	(3.30)
2006.1.4–2009.12.31	0.001208*	0.005741***	0.903237***	0.088398***	0.000000***
	(1.70)	(4.11)	(69.15)	(6.80)	(2.72)
2010.1.4–2013.12.31	−0.000289	−0.000291	0.126250***	0.000000	0.000000***
	(−0.54)	(−0.29)	(10623989.57)	(0.00)	(24.27)
2014.1.4–2015.12.31	0.000838	0.001543	0.918402***	0.080577***	0.000000*
	(1.17)	(1.20)	(82.47)	(5.75)	(1.57)
January effect					
2002.1.4–2015.12.31	0.000273	0.001098	0.925472***	0.065481***	0.000000***
	(1.12)	(1.36)	(158.64)	(12.21)	(5.05)
2002.1.4–2005.12.31	−0.000566	0.003100**	0.792245***	0.141931***	0.000000***
	(−1.43)	(2.51)	(21.94)	(7.84)	(3.24)
2006.1.4–2009.12.31	0.002226***	0.002253	0.907861***	0.084158***	0.000000***
	(3.61)	(0.97)	(72.77)	(6.79)	(2.71)
2010.1.4–2013.12.31	−0.000370	0.000320	0.493835	0.000874	0.000000
	(−0.77)	(0.22)	(0.03)	(0.04)	(0.03)
2014.1.4–2015.12.31	0.001385**	−0.004244*	0.917277***	0.081056***	0.000000*
	(2.17)	(−1.76)	(82.32)	(5.79)	(1.67)
TOTM effect					
2002.1.4–2015.12.31	−0.000310	0.003297***	0.922684***	0.068189***	0.000000***
	(−1.19)	(5.64)	(153.92)	(12.41)	(5.07)
2002.1.4–2005.12.31	−0.000943**	0.002506***	0.793311***	0.144174***	0.000000***
	(−2.21)	(2.84)	(22.73)	(7.85)	(3.31)
2006.1.4–2009.12.31	0.001279**	0.006145***	0.897809***	0.094443***	0.000000***
	(2.01)	(3.96)	(64.50)	(6.68)	(2.70)
2010.1.4–2013.12.31	−0.000934*	0.002963**	0.349982***	0.000000	0.000000***
	(−1.88)	(2.57)	(167190819.86)	(0.00)	(22.46)
2014.1.4–2015.12.31	0.000654	0.002454	0.918002***	0.080254***	0.000000*
	(0.95)	(1.42)	(81.22)	(5.75)	(1.71)
CLNY effect					
2002.1.4–2015.12.31	0.000246	0.004020**	0.925679***	0.065322***	0.000000***
	(1.05)	(2.51)	(158.85)	(12.17)	(5.04)
2002.1.4–2005.12.31	−0.000545	0.005496**	0.793170***	0.140799***	0.000000***
	(−1.42)	(2.26)	(22.05)	(7.82)	(3.26)
2006.1.4–2009.12.31	0.002494***	0.001809	0.326413***	0.223521***	0.000000***
	(3.52)	(0.80)	(3.85)	(5.13)	(5.91)
2010.1.4–2013.12.31	−0.190971***	2.551917***	0.000000	0.996571***	0.000000
	(−33.24)	(9.80)	(0.00)	(4.55)	(0.00)
2014.1.4–2015.12.31	0.001025	0.004748	0.917974***	0.080575***	0.000000*
	(1.64)	(0.86)	(82.51)	(5.77)	(1.67)

Note: This table reports the performance of the 3 calendar effects in the whole sample and 4 four-year subsamples (the last subsample is 2 years) of CSI300. The coefficient β indicates the directions and degrees of the calendar effects. ***, **, * indicate significance at 1%, 5%, and 10% levels respectively.

We compare cumulative returns of the investment strategies for four different indices against the buy-and-hold strategy as benchmark over time, and then plotting the cumulative difference of these strategies. The four investment strategies are executed in a full sample of the 4 indices, with the results of Figs. 3–6 below.

The cumulative return of the investment strategies based on the calendar effects and the ChiNext index are showing in Fig. 3 below. It shows that the reversed Monday effect investment strategy in first 100 trading days gains excess return, but after a period of time, it has no excess return. Its performance is getting worse, as the AMH's description; January effect investment strategy has no excess return around the first 350 trading days, but it gains in the 400–600 trading days, and continue having no excess return in the time remaining, as the AMH's description; the TOTM effect investment strategy has poorer performance than the index in the first 250 trading days and 1100–1200 trading days periods, but in other periods performs better than the index, consistent with the description of the AMH; CLNY effect investment strategy has no excess return around the first 270 trading days, but it gains in the 300–800 trading days, and continue with no excess return in the time remaining, as the AMH's description. Therefore, we observe the evidence that the AMH is more suitable to describe the situations of ChiNext index.

Fig. 4 shows the comparison of the cumulative returns between the calendar effect investment strategies and CSI 300. We can see reversed Monday effect investment strategy performs badly, it has never gained excess return; January effect investment strategy gains excess return in the first 1100 trading days, but no excess return for the subsequent period, which is consistent with the AMH;

Table 6
Subsample analysis of the calendar effects in ChiNext index.

399006 (ChiNext index)	Conditional mean		Conditional variance		
	c	*β*	α_1	α_2	θ
Reversed Monday effect					
2010.6.01–2015.12.31	0.000413	0.001363	0.938447***	0.048809***	0.000000**
	(0.70)	(1.16)	(68.81)	(4.56)	(2.20)
January effect					
2010.6.01–2015.12.31	0.000575	0.001611	0.938400***	0.048973***	0.000000**
	(1.10)	(0.79)	(69.31)	(4.59)	(2.18)
TOTM effect					
2010.6.01–2015.12.31	−0.000204	0.004424***	0.940147***	0.047973***	0.000000**
	(−0.37)	(3.47)	(72.73)	(4.68)	(2.15)
CLNY effect					
2010.6.01–2015.12.31	0.000503	0.008477**	0.937167***	0.049895***	0.000000**
	(0.99)	(2.25)	(68.20)	(4.63)	(2.20)

Note: This table reports the performance of the 3 calendar effects in the whole sample of ChiNext index. The coefficient β indicates the directions and degrees of the calendar effects.***, ** indicate significance at 1%, 5%, and 10% levels respectively.

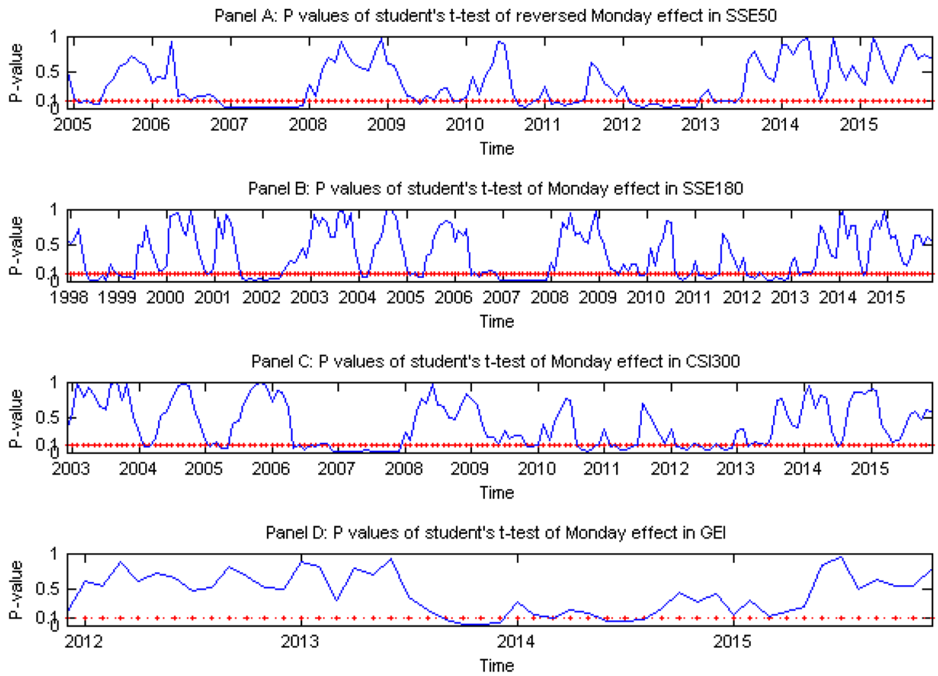

Fig. 2. The time-varying *p*-values of Student's *t*-test in the 4 indices.

TOTM effect investment strategy does not produce excess returns in the 1200–2300 trading days period, but outperforms CSI300 in the other periods, providing a good evidence for the AMH; CLNY effect investment strategy gains excess return in the first 1200 trading days, but no excess return in the subsequent period, consisting with the AMH. Therefore, the evidence from CSI300 shows that the AMH can better describe the development and change of the mainstream stocks in Shanghai and Shenzhen stock exchange.

Fig. 5 shows the results of comparing cumulative returns of the calendar effect investment strategies and SSE50. We can find that the reversed Monday effect investment strategy generates no excess returns since the establishment; January effect investment strategy outperforms the index in the first 600 trading days, but has bad performance in the subsequent period, which is the same as what the AMH implies; TOTM effect investment strategy outperforms the index in the first 600 trading days, however the performance reverses in the 600–1800 trading days, then it almost have excess returns (except 2850–2900 trading days), providing a good proof of the AMH; CLNY effect investment strategy outperforms the B&H strategy in the first 700 trading days, but has bad performance in the subsequent period, being same with what the AMH implies. Therefore, the evidence from SSE50 shows that the situation of China stock market is more correspond to the AMH's implication.

Fig. 6 shows the comparison of the cumulative returns between the calendar effect investment strategies and SSE180. Reversed Monday effect investment strategy almost never generates excess return; January effect investment strategy generates excess return only in the 2200–2300 trading days and performs poorly in other periods; TOTM investment strategy outperforms SSE180 in

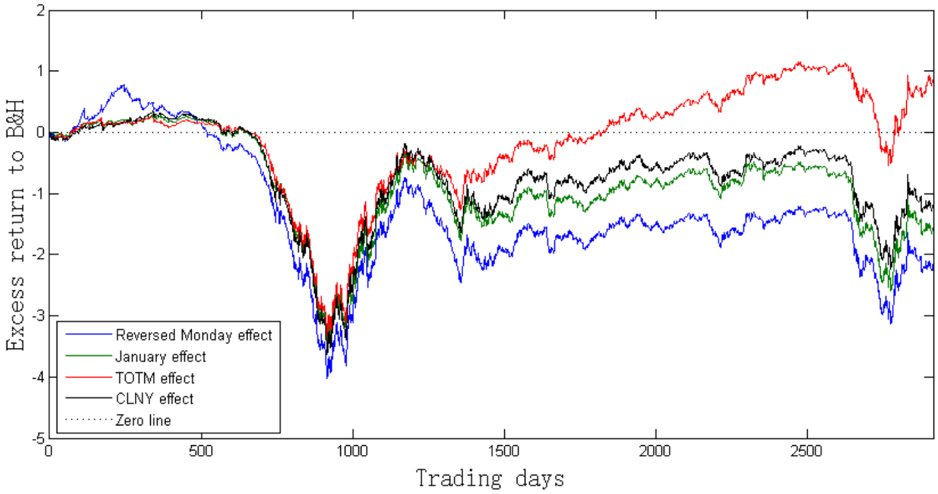

Fig. 3. Comparison of the cumulative returns of calendar effect investment strategies and ChiNext index.

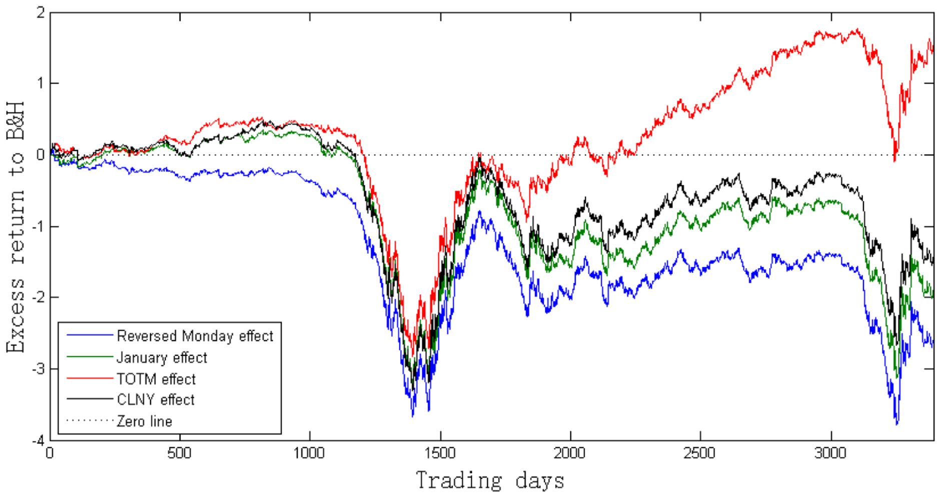

Fig. 4. Comparison of the cumulative returns of calendar effect investment strategies and CSI300.

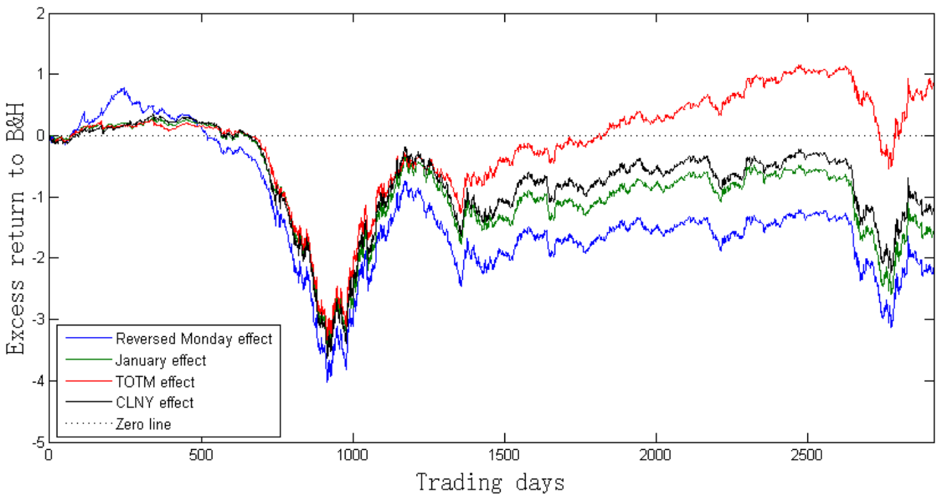

Fig. 5. Comparison of the cumulative returns of calendar effect investment strategies and SSE50.

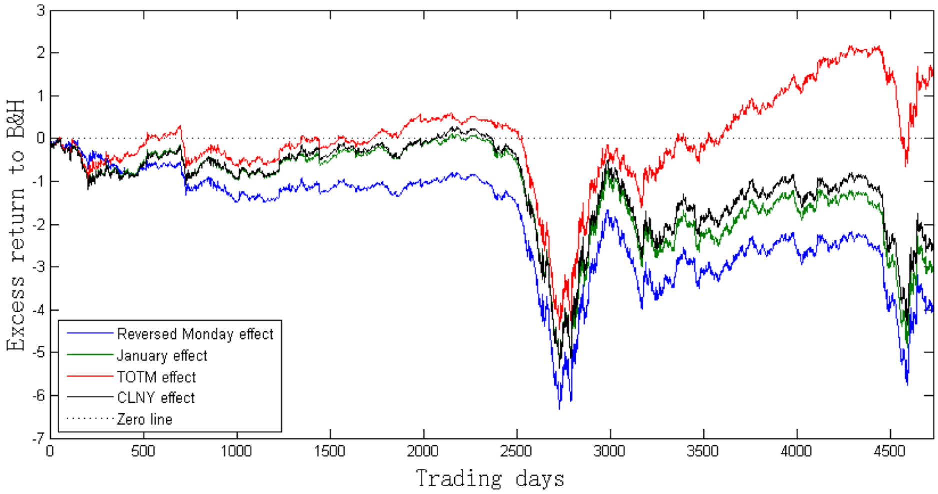

Fig. 6. Comparison of the cumulative returns of calendar effect investment strategies and SSE180.

500–700, 1800–2500, 3500–4700 trading days, and does not generate excess return in other periods, which is good proof for the AMH; CLNY effect investment strategy generates excess return only around the 2200th trading day and performs poorly in other periods. Therefore, the evidence from the SSE180 shows that the AMH can better describe the development and change of leading enterprises in China stock market.

After constructing the investment strategies based on calendar effects, this paper compares the cumulative returns of the reversed Monday effect investment strategy, January effect investment strategy, TOTM effect investment strategy, and CLNY effect strategy to the B&H strategy from their establishment to December 31, 2015. We find the calendar effect investment strategies perform either better or worse than the markets time to time. The evidence is consistent with what Lo (2004) describes and what the AMH implies, "investment strategies will also wax and wane, performing well in certain environments and performing poorly in other environments, investment strategy in some period of time". Hence, we provide a relatively convincing evidence for the AMH in China stock market.

6. Conclusion

In this paper, we choose 4 indices with different characteristics in China stock market to study the time variation of properties for the calendar effect on different levels of the market. Through the research of the whole sample, this paper proves the existence of reversed Monday effect, January effect, TOTM effect, and CLNY effect in China stock market, and the returns in these calendar effect periods are significantly different from other periods. In order to further verify the performance of the calendar effects over time like the process of the evolution through continuous adaptation in nature, we use GARCH (1, 1) model to analyze the subsamples of the 4 indices. The empirical results show that the performance of the reversed Monday effect, January effect, TOTM effect, and CLNY effect fluctuates among subsamples, even with positive and negative coefficients, indicating that each subsample and full sample are not consistent on these calendar effects, which presents a good evidence for the AMH. In addition, we combine rolling window analysis with subsample analysis and find that the *p*-values are constantly fluctuating as time goes on, and the Monday effect has different performance for different periods. This is a good description for the magnitudes of significance of reversed Monday effect across the time dimension, which also supports the AMH. We then construct investment strategies on the 4 calendar effects and find that the profitability fluctuates from periods to periods, which is consistent with what the AMH implies and provides further evidence for the AMH.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2018.11.020.

References

Ariel, R.A., 1987. A monthly effect in stock returns. J. Financ. Econ. 18 (1), 161–174.
Brusa, J., Liu, P., 2004. The day-of-the-week and the week-of-the-month effects: an analysis of investors' trading activities. Rev. Quant. Finance Account. 23 (1), 19–30.
Brusa, J., Liu, P., Schulman, C., 2000. The weekend effect, 'reverse' weekend effect, and firm size. J. Bus. Finance Account. 27 (5–6), 555–574.
Brusa, J., Liu, P., Schulman, C., 2005. Weekend effect, 'reverse' weekend effect, and investor trading activities. J. Bus. Finance Account. 32 (7–8), 1495–1517.
Butler, M., Kazakov, D., 2012. Testing implications of the Adaptive Market Hypothesis via computational intelligence. Paper read at In: 2012 IEEE Conference on Computational Intelligence for Financial Engineering and Economics (CIFEr).
Campbell, J.Y., Lo, A.W.-C., MacKinlay, A.C., 1997. The Econometrics of Financial Markets. Princeton University press.
Chan, M.W.L., Khanthavit, A., Thomas, H., 1996. Seasonality and cultural influences on four Asian stock markets. Asia Pac. J. Manage. 13, 1–24.
Charles, A., Darné, O., Kim, J.H., 2012. Exchange-rate return predictability and the adaptive markets hypothesis: evidence from major foreign exchange rates. J. Int. Money Finance 31 (6), 1607–1626.
Chong, T.T.-L., Lam, T.-H., Yan, I.K.-M., 2012. Is the Chinese stock market really inefficient? China Econ. Rev. 23 (1), 122–137.
Connolly, R.A., 1989. An examination of the robustness of the weekend effect. J. Financ. Quant. Anal. 24 (2), 133–169.
Doyle, J.R., Chen, C.H., 2009. The wandering weekday effect in major stock markets. J. Bank. Finance 33 (8), 1388–1399.
Engle, R., 2001. GARCH 101: the use of ARCH/GARCH models in applied econometrics. J. Econ. Perspect. 15 (4), 157–168.
Fama, E.F., 1970. Efficient capital markets: a review of theory and empirical work. J. Finance 25 (2), 383–417.
Gao, L., Kling, G., 2005. Calendar Effects in Chinese Stock Market. Annals of Economics and Finance 6, 75–88.
Ghazani, M.M., Araghi, M.K., 2014. Evaluation of the Adaptive Market Hypothesis as an evolutionary perspective on market efficiency: evidence from the Tehran stock exchange. Res. Int. Bus. Finance 32, 50–59.
Gibbons, M.R., Hess, P., 1981. Day of the week effects and asset returns. J. Bus. 54 (4), 579–596.
Grossman, S.J., Stiglitz, J.E., 1980. On the impossibility of informationally efficient markets. Am. Econ. Rev. 70 (3), 393–408.
Gu, A.Y., 2003. The declining January effect: evidences from the U.S. equity markets. Q. Rev. Econ. Finance 43 (2), 395–404.
Hall, S., Foxon, T.J., Bolton, R., 2017. Investing in low-carbon transitions: energy finance as an adaptive market. Climate Policy 17 (3), 280–298.
Hiremath, G.S., Kumari, J., 2014. Stock returns predictability and the Adaptive Market Hypothesis in emerging markets: evidence from India. SpringerPlus 3 (1), 428.
Hiremath, G.S., Narayan, S., 2016. Testing the Adaptive Market Hypothesis and its determinants for the Indian stock markets. Finance Res. Lett. 19, 173–180.
Hull, M., McGroarty, F., 2014. Do emerging markets become more efficient as they develop? Long memory persistence in equity indices. Emerg. Markets Rev. 18, 45–61.
Kato, K., Schallheim, J.S., 1985. Seasonal and size anomalies in the Japanese stock market. J. Financ. Quant. Anal. 20 (2), 243–260.
Keim, D.B., 1983. Size-related anomalies and stock return seasonality: further empirical evidence. J. Financ. Econ. 12 (1), 13–32.
Kelly, F., 1930. Why You Win or Lose: The Psychology of Speculation. Houghton Mifflin, Boston.
Kim, J.H., Shamsuddin, A., Lim, K.-P., 2011. Stock return predictability and the adaptive markets hypothesis: evidence from century-long U.S. data. J. Empir. Finance 18 (5), 868–879.
Kohers, T., Kohli, R.K., 1991. The anomalous stock market behavior of large firms in January: the evidence from the S&P composite and component indexes. Q. J. Bus. Econ. 30 (3), 14–32.
Kunkel, R.A., Compton, W.S., Beyer, S., 2003. The turn-of-the-month effect still lives: the international evidence. Int. Rev. Financ. Anal. 12 (2), 207–221.
Lakonishok, J., Smidt, S., 1988. Are seasonal anomalies real? A ninety-year perspective. Rev. Financ. Stud. 1 (4), 403–425.
Lee, C.-C., Lee, J.-D., 2009. Energy prices, multiple structural breaks, and efficient market hypothesis. Appl. Energy 86 (4), 466–479.
Lo, A.W., 2004. The adaptive markets hypothesis. J. Portf. Manag. 30 (5), 15–29.
Lo, A.W., 2005. Reconciling efficient markets with behavioral finance: the Adaptive Markets Hypothesis. J. Invest. Consult. 31 (1), 21–44 Social Science Electronic Publishing.
Lo, A.W., 2007. Efficient markets hypothesis. The New Palgrave: A Dictionary of Economics, second ed. Palgrave McMillan, New York.
Maberly, E.D., 1995. Eureka! Eureka! Discovery of the Monday effect belongs to the ancient scribes. Financ. Anal. J. 51 (5), 10.
Manahov, V., Hudson, R., 2014. A note on the relationship between market efficiency and adaptability – New evidence from artificial stock markets. Expert Syst. Appl. 41 (16), 7436–7454.
Mehdian, S., Perry, M.J., 2002. Anomalies in US equity markets: a re-examination of the January effect. Appl. Financ. Econ. 12 (2), 141–145.
Neely, C.J., Weller, P.A., Ulrich, J.M., 2009. The adaptive markets hypothesis: evidence from the foreign exchange market. J. Financ. Quant. Anal. 44 (2), 467–488.
Noda, A. 2012. A test of the Adaptive Market Hypothesis using non-Bayesian time-varying AR model in Japan. Preprint arXiv 1207.
Noda, A., 2016. A test of the Adaptive Market Hypothesis using a time-varying AR model in Japan. Finance Res. Lett. 17, 66–71.
Rodriguez, E., Aguilar-Cornejo, M., Femat, R., Alvarez-Ramirez, J., 2014. US stock market efficiency over weekly, monthly, quarterly and yearly time scales. Physica A 413, 554–564.
Rozeff, M.S., Kinney Jr., W.R., 1976. Capital market seasonality: the case of stock returns. J. Financ. Econ. 3 (4), 379–402.
Siegel, J., 1998. Stocks For the Long Run. McGraw Hill, New York.
Sun, Q., Tong, W.H.S., 2010. Risk and the January effect. J. Bank. Finance 34 (5), 965–974.
Yuan, T., Gupta, R., 2014. Chinese Lunar New Year effect in Asian stock markets, 1999–2012. Q. Rev. Econ. Finance 54 (2014), 529–537.
Todea, A., Ulici, M., Silaghi, S., 2009. Adaptive markets hypothesis: evidence from Asia-Pacific financial markets. Rev. Finance Bank 1 (1), 007–013.
Urquhart, A., McGroarty, F., 2014. Calendar effects, market conditions and the Adaptive Market Hypothesis: evidence from long-run U.S. data. Int. Rev. Financ. Anal. 35, 154–166.
Urquhart, A., McGroarty, F., 2016. Are stock markets really efficient? Evidence of the Adaptive Market Hypothesis. Int. Rev. Financ. Anal. 47, 39–49.
Urquhart, A., Hudson, R., 2013. Efficient or adaptive markets? Evidence from major stock markets using very long run historic data. Int. Rev. Financ. Anal. 28, 130–142.
Wachtel, S.B., 1942. Certain observations on seasonal movements in stock prices. J. Bus. 15 (2), 184–193.
Wong, P.L., Neoh, S.K., Lee, K.H., Thong, T.S., 1990. Seasonality in the Malaysian stock market. Asia Pac. J. Manag. 7, 43–62.
Yen, H., Shyy, A.L., 1993. Chinese Lunar New Year effect in Asian stock market. Taiwan Natl. Univ. Manag. J. 4, 417–436.
Zhou, J., Lee, J.M., 2013. Adaptive Market Hypothesis: evidence from the REIT market. Appl. Financ. Econ. 23 (21), 1649–1662.