Testing Calendar Effects of International Equity and Real Estate Markets

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Abstract

There are a lot of previous studies on calendar effects. However, most of them use traditional methods like regression. Hui et al. Habitat International 48, 38–45, (2015b) incorporated Shiryaev-Zhou index with logistic regression to study the Halloween and January effects of eight securitized real estate markets, but they fixed the moving-window size to be 130 days. How the change in moving-window size affects the calendar effects cannot be seen. In this study, we also apply the Shiryaev-Zhou index, but we allow the moving-window size to vary. Furthermore, we incorporated Shiryaev-Zhou index with analysis of mean (ANOM) and logistic regression to examine calendar effects of general equity and securitized real estate indices of Hong Kong, Japan, US, UK, France and Germany during the period 1996 – 2014. The results show that our new methods can detect additional channels of significant calendar effects of which normal methods fail to show. Furthermore, the general equity indices show significant Halloween and January effects. However, for the securitized real estate indices, the Halloween and January effects are less significant or even go into reverse in some cases. This study has two main implications. Firstly, investors can formulate a better trading strategy to earn more profits. Secondly, trends and phenomena found in equity markets may not be applicable to real estate markets, so investment rules on equity markets may not work on real estate markets.

Keywords Halloween effect. January effect. Shiryaev-Zhouindex . Securitizedreal

Introduction

The Bbuy-and-hold^ strategy, supported by the efficient market hypothesis (EMH), which tells that stock prices reflect all available information wholly at any time (Malkiel and Fama 1970), is believed by many investors. A number of studies like

Malkiel and Fama (1970), Malkiel (2003, 2005), Barber and Odean (2000) supported the EMH. However, some other studies showed evidence contrary to EMH. For example, Hui et al. (2013) found informed trading in Hong Kong and mainlandbased real estate equities listed in Hong Kong, which provides evidence contrary to EMH. With the EMH is questionable, the Bbuy-and-hold^ strategy may fail. In fact, a number of previous works found monthly trends, called Bcalendar effects^, in stock price movement. The most common calendar effects are the Halloween and January effects. The Halloween effect comes from the old saying BSell in May and go away^, which refers to the belief that stock returns are significantly lower during May-October than during November-April. The effect was first found by Bouman and Jacobsen (2002), who discovered that during 1970 − 1998, the average returns from November to April were much greater than the average returns from May to October. The January effect states that stock prices increase in January by a significantly larger extent than in other months, and was first discovered by Wachtel (1942), who found that since 1925, the high-yields stocks had outperformed Dow-Jones Industrial Average (DJIA) in January.

There were a number of studies on calendar effects in the past. However, most of them use traditional methods like linear regression (see Section 2 for details). Hui and Chan (2015b) incorporated Shiryaev-Zhou index with logistic regression to investigate the Halloween and January effects of eight securitized real estate markets. However, they fixed the moving-window size (the number of days used to calculate the estimator of the Shiryaev-Zhou index) to be 130 days. Hence the resulting trading strategy, although outperforms the Bbuy-and-hold^ strategy in general, may not be optimal. How the change in moving-window size affects the calendar effects cannot be seen, too. In this study, we allow the moving-window size to vary as in Hui and Chan (2015a), thus giving rise to a generalized time-dependent strategy (see Hui and Chan (2015a)) of which if a suitable moving-window size is chosen, the resulting strategy beats Bbuyand-hold^ by an even larger extent. This helps investors formulate a better trading strategy to increase profits. We can also see how the pattern the calendar effects changes as the moving-window size varies. Furthermore, Hui and Chan (2015b) tested the Halloween and January effects only, but not the overall calendar effect. Moreover, Hui and Chan (2015b) did not compare their results with those using normal methods like regression. In this study, we incorporate Shiryaev-Zhou index with analysis of mean (ANOM) to investigate the overall calendar effect, including the January effect. We also incorporate Shiryaev-Zhou index with logistic regression to examine the Halloween effect. We compare the results with those using normal methods.

This study investigates the calendar effects of general equity and securitized real estate indices of six economies: Hong Kong, Japan, US, UK, France and Germany (for each economy, one general equity index and one securitized real estate index are chosen, so there are totally 12 stock indices), during the period 1996 − 2014. The paper proceeds as follows: Section 2 review previous literature on calendar effects. Section 3 shows the formula of the Shiryaev-Zhou index, its statistical estimation and the resulting trading strategy derived by Hui and Chan (2015a). Section 4 describes the data source. Section 5 explains the tests of calendar effects and displays the results. Finally, a conclusion is drawn in Section 6.

Literature Review

There were a lot of studies on calendar effects in the past. The most common calendar effects studied are the Halloween effect and the January effect. Tables 1 and 2 extracted from Hui and Chan (2015b) summarizes previous studies on Halloween and January effects.

Tables 1 and 2 show that previous works on Halloween and January effects produced mixed results. From Table 1, the majority of previous studies on Halloween effect showed significant Halloween effect, but some studies found that the Halloween effect was insignificant. Table 2 shows that the results of previous studies on January effect are even more diverged: the number of articles which found significant January effect is almost the same as the number of articles which found insignificant January effect. Most of the previous studies investigated equity markets. Only a few worked on real estate markets (Hardin et al. 2005; Almudhaf and Hansz 2011; Hui et al. 2014). Therefore, the real pattern of calendar effects of real estate markets is yet to be explored. Hence we investigate the calendar effects of six securitized real estate markets. VC Brokerage Limited (2015) found that in Hong Kong, the Hang Seng Property Index and the Centa-City Leading Index (CCL) exhibit some degree of positive correlation with the former running a few months ahead (see Fig. 1). This shows that securitized real estate indices can reflect the performance of the real estate markets. Furthermore, the majority of the previous works applied traditional methods like linear regression. None of them applied Shiryaev-Zhou index as their methodologies. Although Hui and Chan (2015b) incorporated Shiryaev-Zhou index with logistic regression to investigate the Halloween and January effects of eight securitized real estate markets, the movingwindow size was fixed to be 130 days in their studies. If the moving-window size varies, the pattern of calendar effects may change. In order to bridge these gaps, we modified Hui and Chan (2015b)′s method by allowing the moving-window size to vary as in Hui and Chan (2015a), giving rise to a generalized time-dependent strategy (see Hui and Chan 2015a) which outperforms the Bbuy-and-hold^ strategy in general. How the change in moving-window size affects the calendar effects can thus be seen.

The Shiryaev-Zhou Index, its Statistical Estimation and the Resulting Trading Strategy

This study applies the Shiryaev-Zhou index to investigate the calendar effects of 12 stock indices. The Shiryaev-Zhou index is motivated from the problem of minimizing the time between the selling and maximum prices of a stock, which was solved by Shiryaev et al. (2008), who derived the Bgoodness index^ to determine the optimal time to sell a stock to minimize the average relative error of selling price to maximum price. A probabilistic proof of the Bgoodness index^ was provided by Du Toit and Peskir (2008). Yam et al. (2009, 2012, 2012a) adopted the techniques in solving the secretary

Table1 ResultsofpreviousworksonHalloweenEffect

ArticleMethodCountriesAssettypesPeriodof				observation	Result significantor insignificant)
Sullivanetal.(2001)	Linearregression Bootstrap	U.S.	Equity1897	–	(Insignificant Significant(exceptforone
BoumanandJacobsen(2002)		Australia,Austria,Beligium,Canada,Denmark,France, Germany,HongKong,Italy,Japan,Netherlands,Norway, Singapore,Spain,Sweden,Switzerland,U.K.,U.S., Argentina,Brazil,Chile,Finland,Greece,Indonesia, Ireland,Jordan,Malaysia,Mexico,NewZealand, Philippines,Portugal,Russia,SouthAfrica,SouthKorea, Taiwan,Thailand,Turkey	Equity1970 1998	– 1996	country) Significant
LuceyandWhelan(2002)	Out-of-sampletestU.S.,U.K.,Ireland		Equity1934	–	Insignificant
MaberlyandPierce(2004)	Linearregression	U.S.	Equity1970	–	Significantfor5countries
BrounenandHamo(2009)	Linearregression	U.S.,Japan,HongKong,U.K.,Australia,France,Singapore, Canada,Netherlands,Austria,SouthAfrica	Equity1987	1999 – 1998	Significant
JacobsenandVisaltanachoti(2009	Linearregression	U.S.	Equity1926	–	Significant
Lean(2011)	GARCH(1,1)	HongKong,China,Japan,Singapore,Malaysia,IndiaEquity1991		–	Significant
Andradeetal.(2012))	Linearregression,out-of- sampletest	Australia,Austria,Beligium,Canada,Denmark,France, Germany,HongKong,Italy,Japan,Netherlands,Norway, Singapore,Spain,Sweden,Switzerland,U.K.,U.S., Argentina,Brazil,Chile,Finland,Greece,Indonesia, Ireland,Jordan,Malaysia,Mexico,NewZealand, Philippines,Portugal,Russia,SouthAfrica,SouthKorea, Taiwan,Thailand,Turkey	Equity1970 2007	2006 – 2008 2012	:
Huietal.(2014)	Linearregression,White's RealityCheckand Hansen'sSuperior PredictiveAbilitytests	Canada,U.S.,HongKong,Japan,Philippines,Singapore, Belgium,Finland,France,Germany,Italy,Netherlands, Sweden,Switzerland,U.K.,Australia	RealEstate including (REIT)	1984– 2011	Linearregression significantfortwo countriesonly. White'sRealityCheckand Hansen'sSuperior PredictiveAbilitytests: insignificant

Source:Huietal.(2015 b)

problem to resolve the same problem in the binomial tree setting. Thus the ShiryaevZhou index was derived and generalized over the corresponding framework. Hui et al. (2012) first put Shiryaev-Zhou index into practice to find the latest selling dates of each property stock listed in Hong Kong. Hui and Yam (2014) derived a trading strategy from the Shiryaev-Zhou index, and found that their strategy generally outperformed the "buy-and-hold" strategy on four European and North American securitized real estate indices. The same strategy was applied by Hui et al. (2014b) on six Asian securitized real estate indices. Their results also showed that their trading strategy yielded larger returns than the "buy-and-hold" strategy in general.

The formula of the Shiryaev-Zhou index is (Yam et al. 2009; 2012a, b; 2012a; Hui et al. 2012; Hui and Yam 2014):

$$\mu = \alpha - 0.5\sigma^2, \quad \mu/\sigma^2 = \alpha/\sigma^2 - 0.5; \qquad (3.1)$$

where α, σ are the annual drift and annual volatility of the stock respectively (α,σ are constants).

The trading rule is to buy a stock and hold it throughout the whole period if $\mu \geq 0$. Otherwise, sell the stock immediately (Yam et al. 2009; 2012a 2012a, b; 2012a; Hui et al. 2012).

In (3.1), α, σ are constants. However, in reality, these parameters always vary in time and we normally do not know their exact values. Therefore, as in Wong et al. (2012), we adopt the moving-window approach to estimate their values: for each day i ($i>n$), the starting day of the moving-window is day $i-n+1$, while the ending date is day i, so the moving-window size is n. We use the stock returns from day $i-n+1$ to day i to estimate the values of α and σ on that day, and hence obtain the estimated value of the Shiryaev-Zhou index on day i. Since the stock prices on both day $i-1$ and day i are required to calculate the stock return on day i, stock prices from day $i-1$ to day i are needed to estimate the values of α and σ on day i.

The estimatorof the Shiryaev-Zhou indexμ on day i ($i>n$) is (Hui and Chan (2015a)):

$$\hat{\mu}_i(n) = \frac{\hat{\alpha}_i(n)}{\hat{\sigma}_i^2(n)} - 0.5; \qquad (3.2)$$

where n is the moving-window size, $\hat{\alpha}_i(n)$ is the estimator of α on day i, and $\hat{\sigma}^2_i(n)$ is the estimator of σ^2 on day i. For details of derivation of the formula (3.2), please refer to Hui and Yam (2014) and Hui et al. (2014b). Unlike Hui and Chan (2015b) who fixed the moving-window size to be 130, this study allows the moving-window size n to vary. We select the six moving-window sizes chosen by Hui and Chan (2015a): 40, 80, 120, 160, 200, 240.

Hui and Chan (2015a) used the estimator of the Shiryaev-Zhou index to construct a trading strategy. The following two assumptions are made:

(1) The transaction price (buying and selling price) of a stock index is its closing price on that day.

Table 2 Results of previous works on January Effect

Article	Method	Countries	Asset types	Period of observation	Result significant or insignificant
Keim (1983)	Linear regression	U.S.	Equity	–	Significant
Agrawal and Tandon (1994)	Linear regression	Australia, Belgium, Brazil, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Luxembourg, Mexico, Netherlands, New Zealand, Singapore, Sweden, Switzerland, U.K., U.S.	Equity	1971–1979	Significant for 10 countries
Cheung and Coutts (1999)	Linear regression	Hong Kong	Equity	1985–1987	Insignificant
Fountas and Segredakis (2002)	Linear regression	Argentina, Chile, Colombia, Greece, India, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Portugal, Taiwan, Thailand, Turkey, Venezuela, Zimbabwe	Equity	1987–1997	Insignificant (except for Chile)
Gu (2003)	Power ratio method	U.S.	Equity	–	Declining (becoming less significant over time)
Hansen et al. (2005)	χ^2 test	Denmark, France, Germany, Hong Kong, Italy, Japan, Norway, Sweden, U.K., U.S.	Equity	1896–1995	Significant
Hardin et al. (2005)	Linear regression	U.S.	REIT	1994–2002	Insignificant for the REIT value-weighted index, but significant for the REIT equal-weighted index
Brounen and Hamo (2009)	Linear regression	U.S., Japan, Hong Kong, U.K., Australia, France, Singapore, Canada, The Netherlands, Austria, South Africa	Equity	1987–2000	Insignificant
Kang et al. (2010)	Linear regression	China	Equity	1996–2007	share: insignificant B-share: significant at 10% level, but insignificant at 5% level
Almudhaf and Hansz (2011)	Linear regression	Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, U.K.	Securitized real estate	2002–2007	Insignificant (except for Switzerland)
Hui et al. (2014) (2007)	Linear regression, White's Reality Check and Hansen's Superior Predictive Ability tests	Canada, U.S., Hong Kong, Japan, Philippines, Singapore, Belgium, Finland, France, Germany, Italy, Netherlands, Sweden, Switzerland, U.K., Australia	Real Estate (including REIT)	1984–2011	Insignificant

Source: Hui et al. (2015b)

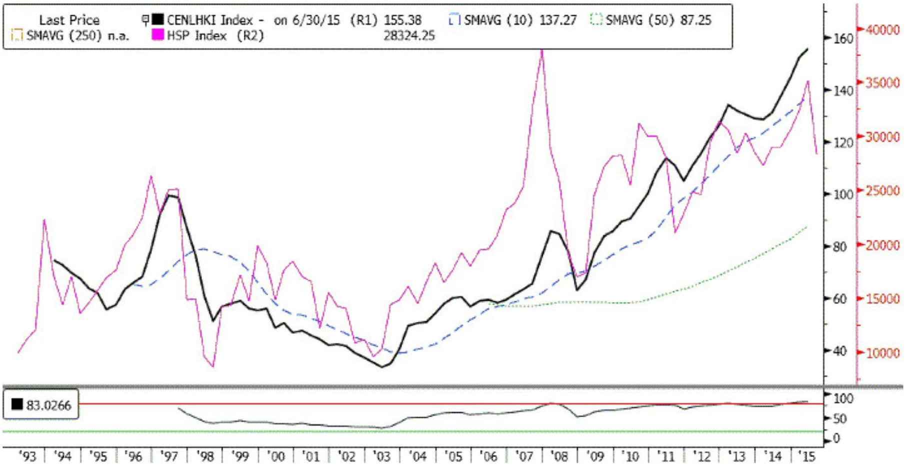

Fig. 1 Trends of the Hang Seng Property Index and the Centa-City Leading Index (CCL) since 1993. source: VC Brokerage Limited (2015)

(2) The amount of cash held at time t=0 is adequate to cover all transactions during the period.

Their trading strategy is as follows (Hui and Chan 2015a):

1. On Day 1, if $\hat{\mu}_1(n) \geq 0$, buy one unit of the stock index. Otherwise, take no action.
2. From Day 2 to the second last day of the period, trade the stock index according to the following rule:
   (a) if $\hat{\mu}_{i-1}(n) \geq 0$ and $\hat{\mu}_i(n) \geq 0$, take no action (keep holding one unit of the stock index).
   (b) if $\hat{\mu}_{i-1}(n) \geq 0$ and $\hat{\mu}_i(n) < 0$, sell the entire one unit of the stock index we hold.
   (c) if $\hat{\mu}_{i-1}(n) < 0$ and $\hat{\mu}_i(n) \geq 0$, Buy one unit of the stock index.
   (d) if $\hat{\mu}_{i-1}(n) < 0$ and $\hat{\mu}_i(n) < 0$, take no action (keep holding entire cash).
3. On the last day of the period, sell the entire one unit of the stock index if one is still holding the one unit of the stock index. Otherwise, do not take any action.

For example, for HSI index, $\hat{\mu}_i(n) = -4.06$ on November 21, 2014, but rises to 9.33 on the next trading day (November 24, 2014), so we buy one unit of HSI on November 24, 2014. For the same index, $\hat{\mu}_i(n) = 1.99$ on December 12, 2014, but falls to −0.96 on the next trading day (December 15, 2014), so we sell one unit of HSI on December 15, 2014.

Hui and Chan (2015a) found that their strategy outperformed the Bbuy-and-hold^ strategy in general.

Data

The period of observation is January 1, 1996 – December 31, 2014, a total of 4958 observations. As described in Section 3, since the largest moving-window size we choose is 240, the calculation of the estimated value of Shiryaev-Zhou index $\hat{\mu}_i(n)$ on day i using the moving-window size n=240 requires the stock price on day i−240 to be known. Hence we trace back the timeline by 240 days, i.e., back to January 28, 1995. For each of the 6 economies: Hong Kong, Japan, U.S., U.K., France and Germany, one general equity index and one securitized real estate index are selected, making up a total of 12 stock indices. We select the 12 stock indices chosen by Hui and Chan (2015a) as shown in Table 3. Note that the code in the bracket next to the index indicates the Bloomberg code of that index. The six general equity indices consist of the most frequently traded equities in the corresponding economies, and are widely accepted as benchmarks of performance of equity markets of the corresponding economies. Since most housing price indices are weekly or monthly indices, we use securitized indices, which are of daily frequency and can reflect the performance of the real estate markets. All of the six securitized real estate indices belong to the FTSE EPRA/ NAREIT Global Real Estate Index Series, which incorporates REITs and stocks of real estate holding and development companies, and is designed for the construction of index tracking funds, derivatives and as a performance benchmark. They consist of the most heavily traded real estate securities in the corresponding countries, and can reflect the performances of listed real estate companies (Hui and Chan 2014). Hence the selected securitized real estate indices can truly reflect the performance of the overall real estate market of the corresponding economies.

We mention in Section 2 that in Hong Kong, the Hang Seng Property Index and the Centa-City Leading Index (CCL) exhibit some degree of positive correlation with the former running a few months ahead (Fig. 1). However, we select the FTSE EPRA/NAREIT indices as the securitized real estate indices in this study to make the indices compatible. In fact, the correlation between the continuously compounded daily returns of the Hang Seng Property Index and the FTSE EPRA/NAREIT Hong Kong Index (ELHK) during the period January 1, 1996 – December 31, 2014 is very high at 0.94. Therefore, the ELHK Index also has some degree of positive correlation with the CCL Index. We expect that the other FTSE EPRA/NAREIT indices are positively correlated to the housing price indices of the corresponding economies as well.

Table 3 The stock indices we choose

Economy	General equity index	Securitized real estate index
Hong Kong	Hang Seng Index (HSI)	FTSE EPRA/NAREIT Hong Kong Index (ELHK)
Japan	Tokyo Stock Exchange Tokyo Price Index Topix (TPX)	FTSE EPRA/NAREIT Japan Index (ELJP)
U.S.	S&P 500 Index (SPX)	FTSE EPRA/NAREIT US Index (UNUS)
U.K.	FTSE 100 Index (UKX)	FTSE EPRA/NAREIT UK Index (ELUK)
France	CAC 40 Index (CAC)	FTSE EPRA/NAREIT France Index (EPFR)
Germany	DAX Index (DAX)	FTSE EPRA/NAREIT Germany Index (EPGR)

Tests of Calendar Effects

In this section, we investigate the calendar effects of the 12 stock indices during the whole period of observation. In particular, we examine whether the Halloween and January effects exist. We divide the whole timeline into 12 months of a year. For each stock index and each moving-window size n, we calculate the percentage of days of which $\hat{\mu}_i(n) \geq 0$ for each month during the period of observation. For each month, the percentage of days of which $\hat{\mu}_i(n) \geq 0$ denotes the percentage of days of which we should hold the securitized real estate index according to Hui and Chan (2015a)′s trading strategy in that month. Thus we can observe whether any calendar exists. Applying the Shiryaev-Zhou index, the Halloween and January effects in this paper are equivalent to the following hypotheses:

H_1(Halloween effect): the percentage of days of which $\hat{\mu}_i(n) \geq 0$ is significantly higher from November to April than from May to October.

J_1(January Effect): the percentage of days of which $\hat{\mu}_i(n) \geq 0$ in January is significantly above the average level.

The corresponding null hypotheses are defined as H_0 and J_0 respectively.

For each stock index and each moving-window size n, define a dummy variable R_i by R_i=1 when $\hat{\mu}_i(n) \geq 0$, and 0 otherwise. The mean of R_i in each month denotes the percentage of days of which $\hat{\mu}_i(n) \geq 0$ in that month, i.e., the percentage of days of which we should hold the stock index in that month according to Hui and Chan (2015a)′s strategy (see Section 3). We use the technique analysis of mean (ANOM) to investigate the overall calendar effect (and hence the January effect). ANOM is a graphical analog to ANOVA that tests the equality of population means. The graph displays each factor level mean, the overall mean, and the decision limits. If a point falls outside the decision limits, then evidence exists that the factor level mean represented by that point is significantly different from the overall mean. To test the overall calendar effect, we conduct a one-way ANOM of R_i with month as the factor.

normal method for comparison, we also use ANOM, but we replace R_i by the continuously compounded daily return $r_i = \log\frac{S_i}{S_{i-1}}$, where S_i is the stock index on day i. The following tables show the results performed by the software Minitab 17 (the significance level is set at 5 %):

For our method, since there are totally 12 stock indices and 6 different movingwindow sizes (40, 80, 120, 160, 200, 240), this makes up a total number of 72 cases. For the sake of convenience, we list out the results in Table 4. We only present the figure for HSI index with moving-window size 40 as an example (see Fig. 2).

In Tables 4 and 5, the entries highlighted in green indicate that those entries lie above the 95 % confidence interval, this means that the percentage of days of which $\hat{\mu}_i(n) \geq 0$ (i.e., the percentage of days of which we should hold the stock index according to Hui and Chan (2015a)'s strategy) in that month is significantly above average at 5 % significance level. Meanwhile, the entries highlighted in red indicate that those entries lie below the 95 % confidence interval, this means that the percentage of days of which $\hat{\mu}_i(n) \geq 0$ (i.e., the percentage of days of which we should hold the stock index according to Hui and Chan (2015a)'s strategy) in that month is significantly below average at 5 % significance level. In this way, our method can show the percentage of time we should (or should not) hold a stock index in a month according to Hui and Chan (2015a)'s strategy. All entries in Table 5 lie within the 95 % confidence interval. This implies that for all the 12 stock indices, no significant calendar effects for any months can be detected at 5 % significance level (hence the January effect is also insignificant). However, some entries in Table 4 lie outside the 95 % confidence interval, showing significant calendar effects at 5 % significance level. This shows that our method using Shiryaev-Zhou index can detect significant calendar effects of which normal methods fail to detect. Furthermore, when the moving-window size increases, the number of red/green entries in Table 4 generally decreases, indicating that the overall calendar effect becomes less significant as the moving-window size increases. The reason for this result is that when the movingwindow size n increases, a larger number of days is used to calculate $\hat{\mu}_i(n)$. This creates a smoothing effect, reducing the volatility of $\hat{\mu}_i(n)$ and hence R_i, so the mean of R_i in each month tends to concentrate to a value, reducing the chance that the mean of R_i in a month lies outside the 95 % confidence interval. Another phenomenon is that as the moving-window size increases, the red/green entries in Table 4 shift to the right, indicating that the overall calendar effect delays. This is because $\hat{\mu}_i(n)$ is calculated using stock prices from day $i-n$ to day i (see Section 3), so $\hat{\mu}_i(n)$ in fact lags behind the stock price. When the moving-window size increases, more past stock price data are used to calculate $\hat{\mu}_i(n)$, so $\hat{\mu}_i(n)$ lags behind the stock price even more, delaying the calendar effect.

To investigate the January effect, we look at the entries for the month January in Table 4. A green entry indicates that the percentage of days of which $\hat{\mu}_i(n) \geq 0$ (i.e., the percentage of days of which we should hold the stock index according to Hui and Chan (2015a)'s strategy) in January is significantly above average at 5 % significance level, so the January effect is significant. On the other hand, a red entry indicates that the percentage of days of which $\hat{\mu}_i(n) \geq 0$ (i.e., the percentage of days of which we should hold the stock index according to Hui and Chan (2015a)'s strategy) in January is significantly below average at 5 % significance level, so the January effect goes into reverse significantly. The result differs between general equity indices and securitized real estate indices. For the six general equity indices, there are totally 13 green entries and 3 red entries, indicating that there are some cases where the January effect is significant, while there are only a few cases where the January effect goes into reverse significantly. However, for the six securitized real estate indices, there are totally 7 green entries and 8 red entries. This indicates that the number of cases of significant January effect is nearly the same as the number of cases where the January effect goes into reverse significantly. The general equity indices show some signs of the January effect, but the securitized real estate indices behave differently.

For the Halloween effect, we have to apply regression. However, since the dependent variable R_i is a dummy variable which has a value of either 1 or 0, linear regression is inappropriate. We have to apply logistic regression instead. The following model is set up:

$$\text{logit}\,E(R_i|D_i) = \alpha + \beta D_i + \varepsilon_i; \qquad (5.1)$$

where $\text{logit}(p) = \ln\frac{p}{1-p}$; E denotes expectation, D_i is a dummy variable giving a value of 1 when day i lies within the period November – April, and 0 otherwise. To test for the Halloween effect (i.e., the hypothesis H_1), we apply logistic regression to (5.1), and

Table 4 The test results for the overall effect using our method

HSI

Moving-window size	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	95% confidence interval
40	0.554502	0.463542	0.399522	0.459658	0.610451	0.48642	0.591017	0.661098	0.587224	0.531915	0.659259	0.64455	(0.4895, 0.6202)
80	0.732227	0.598958	0.492823	0.442543	0.472684	0.4	0.477541	0.548926	0.641278	0.595745	0.602469	0.630332	(0.4879, 0.6181)
120	0.658768	0.625	0.638756	0.594132	0.482185	0.451852	0.489362	0.4812	0.616078	0.617021	0.696296	0.661137	(0.5193, 0.6489)
160	0.687204	0.65625	0.62201	0.674817	0.605701	0.550617	0.51773	0.563246	0.53317	0.56974	0.632099	0.632701	(0.5387, 0.6683)
200	0.637441	0.625	0.641148	0.669927	0.617577	0.585185	0.65721	0.646778	0.660934	0.588652	0.587654	0.623223	(0.5642, 0.6928)
240	0.540284	0.585938	0.578947	0.621027	0.653207	0.644444	0.593381	0.675418	0.685504	0.640662	0.612346	0.616114	(0.5562, 0.6851)

TPX

Moving-window size	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	95% confidence interval
40	0.597156	0.533854	0.526316	0.572127	0.565321	0.444444	0.567376	0.412888	0.390663	0.401891	0.409877	0.476303	(0.4258, 0.5576)
80	0.518957	0.554688	0.631579	0.594132	0.584323	0.575309	0.562648	0.315036	0.353808	0.283688	0.360494	0.395735	(0.4124, 0.5416)
120	0.490521	0.526042	0.607656	0.599022	0.562945	0.580247	0.574468	0.431981	0.383292	0.286052	0.325926	0.42654	(0.4176, 0.5477)
160	0.473934	0.455729	0.5	0.577017	0.510689	0.533333	0.579196	0.448687	0.425061	0.380615	0.291358	0.374408	(0.3971, 0.5282)
200	0.362559	0.408854	0.552632	0.459658	0.453682	0.474074	0.576832	0.534606	0.481572	0.347518	0.365432	0.334123	(0.3808, 0.5115)
240	0.485782	0.5	0.397129	0.435208	0.444181	0.451852	0.484634	0.463007	0.452088	0.484634	0.414815	0.42891	(0.3872, 0.5196)

SPX

Moving-window size	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	95% confidence interval
40	0.729858	0.588542	0.600478	0.665037	0.665083	0.540741	0.586288	0.470167	0.552856	0.579196	0.720988	0.755924	(0.5579, 0.6853)
80	0.800948	0.734375	0.717703	0.660147	0.684086	0.590123	0.605201	0.491647	0.587224	0.498818	0.604938	0.779621	(0.5836, 0.7084)
120	0.722749	0.731771	0.818182	0.753056	0.68171	0.664198	0.671395	0.634845	0.55774	0.55792	0.683951	0.687204	(0.6187, 0.7415)
160	0.691943	0.684896	0.732057	0.753056	0.807601	0.775309	0.744681	0.656325	0.707617	0.583924	0.639506	0.682464	(0.6447, 0.7652)
200	0.691943	0.677083	0.739234	0.726161	0.764846	0.77284	0.763593	0.756563	0.749386	0.643026	0.703704	0.744076	(0.6688, 0.7870)
240	0.680095	0.721354	0.741627	0.721271	0.724466	0.728395	0.775414	0.763723	0.781327	0.754137	0.735802	0.739336	(0.6806, 0.7974)

UKX

Moving-window size	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	95% confidence interval
40	0.734957	0.622396	0.566986	0.611247	0.648456	0.417284	0.49409	0.50358	0.560197	0.550827	0.701235	0.675355	(0.5261, 0.6550)
80	0.800948	0.708333	0.636364	0.660147	0.653207	0.488889	0.48227	0.393795	0.523342	0.524823	0.582716	0.708531	(0.5330, 0.6602)
120	0.684834	0.697917	0.789474	0.696822	0.667458	0.535802	0.56974	0.441527	0.501229	0.546099	0.575309	0.585308	(0.5435, 0.6711)
160	0.625592	0.601563	0.69378	0.731051	0.750594	0.664198	0.635934	0.539379	0.619165	0.543735	0.54231	0.561611	(0.5620, 0.6897)
200	0.616114	0.588542	0.691388	0.643032	0.68171	0.733333	0.737589	0.615752	0.710074	0.619385	0.624691	0.590047	(0.5915, 0.7175)
240	0.691943	0.632813	0.602871	0.606357	0.629454	0.65679	0.70922	0.687351	0.712531	0.661939	0.698765	0.680095	(0.6016, 0.7271)

CAC

Moving-window size	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	95% confidence interval
40	0.71564	0.661458	0.547847	0.674817	0.700713	0.528395	0.472813	0.436754	0.609337	0.65974	0.592593	0.64455	(0.5314, 0.6602)
80	0.772512	0.690104	0.727273	0.723716	0.643705	0.567801	0.539007	0.431981	0.542998	0.513002	0.538272	0.623223	(0.5454, 0.6728)
120	0.580569	0.705729	0.791866	0.745721	0.67696	0.565432	0.56947	0.520286	0.520885	0.510638	0.57037	0.540284	(0.5436, 0.6714)
160	0.606635	0.619792	0.662679	0.738386	0.724466	0.607407	0.652482	0.596659	0.65602	0.513002	0.516049	0.552133	(0.5564, 0.6844)
200	0.620853	0.627604	0.631579	0.633252	0.648456	0.654321	0.661939	0.625298	0.724816	0.664303	0.62963	0.604265	(0.5801, 0.7075)
240	0.675355	0.669271	0.641148	0.682152	0.662708	0.654321	0.631206	0.665871	0.702703	0.661939	0.711111	0.656398	(0.6049, 0.7303)

DAX

Moving-window size	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	95% confidence interval
40	0.781991	0.671875	0.566986	0.633252	0.698337	0.560494	0.548463	0.441527	0.501229	0.567376	0.661728	0.767773	(0.5534, 0.6802)
80	0.78673	0.760417	0.708134	0.689487	0.665083	0.580247	0.602837	0.441527	0.555283	0.508274	0.567901	0.696682	(0.5667, 0.6927)
120	0.618483	0.674479	0.779904	0.787286	0.76247	0.693827	0.652482	0.551313	0.572482	0.543735	0.604938	0.601896	(0.5908, 0.7157)
160	0.64218	0.630208	0.669856	0.738386	0.800475	0.753086	0.763593	0.627685	0.670762	0.586288	0.649383	0.677725	(0.6230, 0.7457)
200	0.663507	0.630208	0.636364	0.628362	0.667458	0.74321	0.808511	0.742243	0.761671	0.609929	0.669136	0.683834	(0.6261, 0.7486)
240	0.71564	0.679688	0.636364	0.628362	0.631829	0.634568	0.671395	0.701671	0.771499	0.728132	0.767901	0.729858	(0.6302, 0.7526)

Table 4 (continued)

ELHK

Moving-window size	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	95% confidence interval
40	0.623223	0.434896	0.42823	0.422893	0.567696	0.464198	0.572104	0.625298	0.601966	0.491276	0.555556	0.587678	(0.4665, 0.5980)
80	0.654028	0.598958	0.514354	0.498778	0.432304	0.328395	0.423168	0.52506	0.638821	0.659574	0.614185	0.57346	(0.4732, 0.6034)
120	0.661137	0.596354	0.590909	0.628362	0.574822	0.496296	0.44208	0.508353	0.621622	0.55792	0.683951	0.691943	(0.5227, 0.6524)
160	0.675355	0.664063	0.595694	0.545232	0.586698	0.501235	0.50591	0.584726	0.609337	0.598109	0.609877	0.64455	(0.5281, 0.6583)
200	0.594787	0.627604	0.655502	0.613692	0.586698	0.503704	0.503546	0.677566	0.641278	0.617201	0.604938	0.609005	(0.5292, 0.6596)
240	0.585308	0.606771	0.564593	0.662592	0.634204	0.577778	0.586288	0.661098	0.673219	0.650118	0.597531	0.623223	(0.5540, 0.6832)

ELJP

Moving-window size	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	95% confidence interval
40	0.518957	0.567708	0.607656	0.655257	0.56057	0.446914	0.56974	0.408115	0.457002	0.591017	0.471605	0.379147	(0.4537, 0.5850)
80	0.462085	0.447917	0.555024	0.625917	0.657957	0.590123	0.472813	0.391408	0.400491	0.399527	0.474074	0.409953	(0.4250, 0.5561)
120	0.417062	0.447917	0.502392	0.562347	0.591449	0.595062	0.664303	0.584726	0.422604	0.444444	0.454321	0.390995	(0.4412, 0.5725)
160	0.438389	0.390625	0.488038	0.547677	0.532067	0.528395	0.643026	0.656325	0.641278	0.591017	0.387654	0.402844	(0.4562, 0.5869)
200	0.407583	0.403646	0.476077	0.420538	0.551069	0.575309	0.550827	0.622912	0.579853	0.643026	0.664198	0.516588	(0.4694, 0.6004)
240	0.526066	0.502604	0.437799	0.420538	0.432304	0.45679	0.605201	0.582339	0.5086	0.612293	0.562963	0.521327	(0.4485, 0.5806)

UNUS

Moving-window size	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	95% confidence interval
40	0.751185	0.619792	0.619617	0.606357	0.643705	0.560494	0.583924	0.608592	0.547912	0.498818	0.491358	0.646919	(0.5339, 0.6633)
80	0.689573	0.6875	0.69378	0.731051	0.712589	0.708642	0.63357	0.591885	0.570025	0.510638	0.437037	0.563981	(0.5639, 0.6906)
120	0.604265	0.690104	0.720096	0.784841	0.793349	0.809877	0.732861	0.615752	0.621622	0.534279	0.57037	0.540284	(0.6061, 0.7291)
160	0.597156	0.596354	0.684211	0.743276	0.800475	0.807407	0.718676	0.651551	0.63145	0.598109	0.590123	0.590047	(0.6057, 0.7295)
200	0.632701	0.627604	0.681818	0.694377	0.774347	0.797531	0.758865	0.71599	0.668305	0.588652	0.587654	0.630332	(0.6186, 0.7416)
240	0.64218	0.679688	0.665072	0.652812	0.726841	0.698765	0.758865	0.661098	0.685504	0.676123	0.641975	0.611374	(0.6129, 0.7373)

ELUK

Moving-window size	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	95% confidence interval
40	0.654208	0.744792	0.61244	0.564792	0.665083	0.483951	0.475177	0.610979	0.624079	0.468085	0.560494	0.443128	(0.5096, 0.6393)
80	0.611374	0.622396	0.696172	0.669927	0.705643	0.602469	0.659574	0.599045	0.545455	0.58156	0.6	0.537915	(0.5551, 0.6837)
120	0.580569	0.539063	0.624402	0.640587	0.724466	0.745679	0.624113	0.565632	0.614251	0.567376	0.585185	0.632701	(0.5564, 0.6848)
160	0.606635	0.59375	0.617225	0.618582	0.693587	0.703704	0.72104	0.673031	0.636364	0.605201	0.585185	0.56872	(0.5717, 0.6994)
200	0.618483	0.627604	0.62201	0.682152	0.662708	0.683951	0.643026	0.687351	0.638821	0.591017	0.632099	0.623223	(0.5788, 0.7064)
240	0.632701	0.648438	0.629187	0.643032	0.686461	0.664198	0.567376	0.620525	0.577396	0.555556	0.597531	0.587678	(0.5526, 0.6818)

EPFR

Moving-window size	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	95% confidence interval
40	0.684834	0.705729	0.748804	0.630807	0.63658	0.530864	0.48227	0.508353	0.589681	0.567376	0.577778	0.533175	(0.5346, 0.6635)
80	0.689573	0.666667	0.727273	0.814181	0.793349	0.587654	0.539007	0.52506	0.503686	0.531915	0.57037	0.57346	(0.5637, 0.6896)
120	0.687204	0.721354	0.803828	0.767726	0.80285	0.720988	0.704492	0.613365	0.53317	0.465721	0.516049	0.597156	(0.5996, 0.7223)
160	0.575829	0.690104	0.717703	0.740831	0.760095	0.738272	0.742317	0.680191	0.65602	0.588652	0.62963	0.578199	(0.6126, 0.7363)
200	0.632701	0.614583	0.650718	0.669927	0.738717	0.745679	0.754137	0.73031	0.72973	0.680851	0.706173	0.689573	(0.6346, 0.7567)
240	0.748815	0.710938	0.712919	0.669927	0.738717	0.792593	0.808511	0.775656	0.808354	0.711584	0.775309	0.746445	(0.6927, 0.8075)

EPGR

Moving-window size	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	95% confidence interval
40	0.5	0.619792	0.509569	0.479218	0.674584	0.528395	0.397163	0.494033	0.542998	0.437352	0.530864	0.433649	(0.4454, 0.5772)
80	0.471564	0.434896	0.617225	0.586797	0.660333	0.558025	0.486998	0.498807	0.402948	0.460993	0.520998	0.447867	(0.4468, 0.5786)
120	0.485782	0.466146	0.550239	0.535452	0.67696	0.582716	0.527187	0.539379	0.501229	0.491726	0.501235	0.549763	(0.4684, 0.6006)
160	0.471564	0.510417	0.590909	0.515892	0.603325	0.562963	0.555556	0.508353	0.513514	0.588652	0.595062	0.521327	(0.4788, 0.6111)
200	0.511848	0.453125	0.535885	0.572127	0.586698	0.479012	0.463357	0.505967	0.484029	0.510638	0.548148	0.552133	(0.4510, 0.5837)
240	0.469194	0.552083	0.638756	0.520782	0.555819	0.54321	0.49401	0.431981	0.402948	0.527187	0.518519	0.495261	(0.4461, 0.5785)

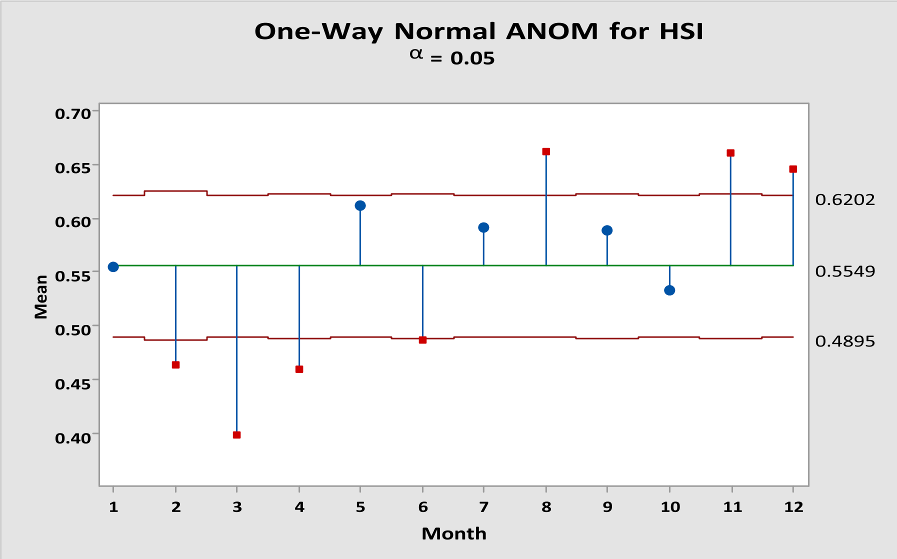

Fig. 2 The overall calendar effect of HSI index using our method with moving-window size 40

conductaone-tailedz-testto $\frac{\hat{\beta}}{\hat{\sigma}}$,whereβ^ istheestimatorofβ,andσ^ isthestandarderrorofβ^.

For the normal method for comparison, we use linear regression with the following model:

$$r_i = \gamma + \lambda D_i + \varepsilon_i; \qquad (5.2)$$

where r_i is the the continuously compounded daily return defined above and D_i is the dummy variable in (5.1). To test for the Halloween effect, we apply OLS regression to (5.2), and conduct a one-tailed z-test to $\frac{\hat{\lambda}}{\hat{\varphi}}$, where λ^ is the OLS estimatorof λ, and ϕ^ is the standard error of λ^.

The following tables show the results performed by Minitab 17:

Note that Bp-value^ in Tables 6 and 7 corresponds to the p-value obtained from conducting a two-tailed z-test by Minitab 17. However, since we conduct a one-tailed test here, for those stock indices with β^ < 0 (or λ^ < 0), we would treat the result as the

Halloween effect goes into reverse. Table 7 shows that λ^ < 0 for all 12 stock indices, but the statistics are significant at 5 % level for three indices only: TPX, CAC and DAX. This shows that by the normal method of linear regression, the Halloween effect exists in all 12 stock indices, but the effect is significant at 5 % level for the three indices only: TPX, CAC and DAX. For each economy, the p-value of the slop coefficient for the general equity index is smaller than that for the securitized real estate index, except for Hong Kong. In particular, all the three indices with significant Halloween effect at 5 % level (TPX, CAC and DAX) are general equity indices. The Halloween effect is more prevalent in the general equity markets than in the securitized real estate markets. However, Table 6 shows different results when using our method of logistic regression. Out of all 72 cases, there are 52 cases where the p-value is smaller

Table 5 The test results for the Halloween effect using the normal method

Index	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	95% confidence interval
HSI	−0.000771	0.000959	−0.000801	0.001112	−0.000370	0.000130	0.000996	−0.000816	−0.000158	0.000532	0.000876	0.000468	(−0.0020,0.0023)
TPX	−0.000149	0.000336	0.000681	0.000832	−0.000624	0.000793	−0.000712	−0.001013	−0.000246	−0.000969	0.000459	0.000441	(−0.0018,0.0018)
SPX	−0.000004	−0.000253	0.000746	0.000945	0.000097	−0.000124	0.000037	−0.000481	−0.000172	0.000707	0.000769	0.000621	(−0.0014,0.0019)
UKX	−0.000547	0.000408	0.000168	0.000964	−0.000335	−0.000685	0.000317	−0.000123	−0.000643	0.000633	0.000340	0.000896	(−0.0015,0.0017)
CAC	0.000229	0.000062	0.000647	0.001103	−0.000358	−0.000196	−0.000099	−0.000702	−0.000936	0.000735	0.000657	0.000838	(−0.0018,0.0021)
DAX	0.000167	0.000057	0.000466	0.001527	0.000096	0.000131	0.000278	−0.001433	−0.001083	0.000967	0.001259	0.001106	(−0.0017,0.0023)
Index	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	95% confidence interval
ELHK	−0.000015	0.000612	−0.000582	0.001148	−0.001003	−0.000445	0.001501	−0.000322	−0.001010	0.000484	0.001167	0.001158	(−0.0024,0.0028)
ELJP	0.000403	0.000654	0.001409	0.001184	−0.000329	0.000411	−0.000766	−0.000293	0.000414	−0.000065	−0.000733	−0.000352	(−0.0026,0.0029)
UNUS	−0.000097	−0.000453	0.000866	0.001409	0.000168	−0.000198	0.000487	0.000052	−0.000029	−0.000553	−0.000260	0.001210	(−0.0021,0.0025)
ELUK	−0.000500	0.000761	0.000044	0.001087	0.000181	−0.001262	0.000739	0.000569	−0.000604	−0.000161	−0.000296	0.000684	(−0.0016,0.0018)
EPFR	0.000569	0.001313	0.000754	0.000138	0.000347	−0.000717	0.000562	0.000308	0.000059	0.000147	−0.000122	0.000807	(−0.0013,0.0020)
EPGR	0.000617	0.000249	0.000015	0.000985	0.000376	−0.001658	0.000125	−0.000057	−0.001394	0.000676	−0.000913	0.000650	(−0.0022,0.0021)

than 0.05, indicating that the Halloween effect (or the reverse of the Halloween effect, for cases where $\hat{\beta} < 0$) is significant at 5 % level. The proportion of significant statistics is much larger than that using the normal method. This reaffirms that our new method can detect additional channels of significant calendar effects of which normal methods fail to show.

Comparing the result of Table 4 with that of Table 6, we can see the contribution of each month to the Halloween effect. For example, Table 6 shows that the Halloween effect is significant at 5 % level for the general equity indices, especially for smaller moving-window sizes. Table 4 shows that the January effect is generally significant for the general equity indices (13 green entries and 3 red entries), especially for movingwindow sizes of 120 and smaller, so the January effect has some contribution to the Halloween effect. On the other hand, for the six general equity indices, the month of October reports 18 red entries out of all 36 cases, indicating that the percentage of days of which $\hat{\mu}_i(n) \geq 0$ (i.e., the percentage of days of which we should hold the stock index according to Hui and Chan (2015a)'s strategy) in October is significantly below average at 5 % significance level. This is due to the October effect, which is also called the Mark Twain effect saying that stock returns in October are lower than in other months. We can see that the October effect has a major contribution to the Halloween effect, too.

Different results are shown for the general equity indices and the securitized real estate indices. For the six general equity indices, for smaller moving-window sizes (40, 80 and 120), $\hat{\beta} > 0$ for all cases except for HSI with moving-window size 40, and the p-value is smaller than 0.05 for all cases except for SPX with moving-window size 120. This reflects that for most cases, the Halloween effect exists and is significant at 5 % level (in fact, the Halloween effect is significant at 0.1 % level except for two cases: HSI with moving-window size 40, and SPX with moving-window size 120). However, for larger moving-window sizes (160, 200, 240), there are more cases where $\hat{\beta} < 0$ (13 out of 18), and there are 8 cases where the p-value is larger than 0.05, indicating that there are more cases where the Halloween effect goes into reverse, and the overall degree of significance is smaller than that using smaller moving-window sizes. This shows that for the six general equity indices, the Halloween effect is more significant when smaller moving-window sizes are used. When the moving-window size increases, the Halloween effect becomes less significant and even goes into reverse for some cases. In overall the Halloween effect exists rather goes into reverse for the majority of cases (22 out of 36).

The results for the six securitized real estate indices are, however, different. $\hat{\beta} < 0$ for slightly over half of the cases (19 of 36), indicating that the Halloween effect goes into reverse for the majority of cases. In particular, there are more cases of $\hat{\beta} < 0$ for larger moving-window sizes (160, 200 and 240) (13 out of 18). Meanwhile, the number of cases where the p-value is less than 0.05 for smaller moving-window sizes (40, 80, 120) (12 out of 18) is approximately the same as that for larger moving-window sizes (13 out of 18), showing that the moving-window size does not have an apparent effect on the significance of Halloween effect.

The results reveal that for both the overall calendar effect and the Halloween effect, our methods can detect additional channels of significant calendar effects of which normal methods cannot show. This is because normal methods use the stock return r_i of

Table 6 The test results for the Halloween effect using our method

HSI						
Moving-window size	40	80	120	160	200	240
β^	−0.1927	0.2468	0.5083	0.3942	0.0205	−0.2392
p-value	0.001	<0.001	<0.001	<0.001	0.727	<0.001
TPX						
Moving-window size	40	80	120	160	200	240
β^	0.5111	0.7243	0.5386	0.0048	−0.2503	−0.1063
p-value	<0.001	<0.001	<0.001	0.935	<0.001	0.077
SPX						
Moving-window size	40	80	120	160	200	240
β^	0.2208	0.2544	0.1056	−0.1370	−0.2601	−0.0827
p-value	<0.001	<0.001	0.063	0.016	<0.001	0.147
UKX						
Moving-window size	40	80	120	160	200	240
β^	0.3607	0.5934	0.3959	−0.0384	−0.1682	0.0425
p-value	<0.001	<0.001	<0.001	0.512	0.005	0.481
CAC						
Moving-window size	40	80	120	160	200	240
β^	0.4791	0.6234	0.4854	−0.0702	−0.1372	−0.1631
p-value	<0.001	<0.001	<0.001	0.259	0.032	0.012
DAX						
Moving-window size	40	80	120	160	200	240
β^	0.5460	0.6186	0.2137	−0.1476	−0.3235	0.0156
p-value	<0.001	<0.001	<0.001	0.016	<0.001	0.799
ELHK						
Moving-window size	40	80	120	160	200	240
β^	−0.1764	0.2984	0.4539	0.2403	0.1902	−0.1017
p-value	0.002	<0.001	<0.001	<0.001	0.001	0.082
ELJP						
Moving-window size	40	80	120	160	200	240
β^	0.1649	0.0283	−0.1636	−0.3192	−0.0730	0.0469
p-value	0.004	0.629	0.005	<0.001	0.218	0.422
UNUS						
Moving-window size	40	80	120	160	200	240
β^	0.1046	0.0430	−0.3556	−0.6294	−0.4259	−0.1542
p-value	0.066	0.449	<0.001	<0.001	<0.001	0.007
ELUK						
Moving-window size	40	80	120	160	200	240
β^	0.3925	0.3997	0.1877	−0.1809	−0.3259	−0.2382
p-value	<0.001	<0.001	0.002	0.003	<0.001	<0.001
EPFR						
Moving-window size	40	80	120	160	200	240

β^	0.2063	0.0549	−0.1503	−0.3036	−0.3425	−0.2419
p-value	<0.001	0.350	0.013	<0.001	<0.001	<0.001
EPGR						
Moving-window size	40	80	120	160	200	240
β^	−0.0058	0.0089	−0.1520	−0.0867	0.0980	0.1575
p-value	0.919	0.876	0.008	0.129	0.085	0.006

Table 7 The test results for the Halloween effect using the normal method

Index	HSI	TPX	SPX	UKX	CAC	DAX
λ^	0.000236	0.000904	0.000463	0.000500	0.000849	0.000936
p-value	0.614	0.017	0.183	0.135	0.039	0.029
Index	ELHK	ELJP	UNUS	ELUK	EPFR	EPGR
λ^	0.000699	0.000538	0.000470	0.000369	0.000449	0.000578
p-value	0.207	0.361	0.343	0.310	0.191	0.211

which the distribution is more converged to a point. However, our new method use the dummy variable R_i which depends on the sign of $\hat{\mu}_i$ð Þn , and has a value of either 0 or 1. Hence R_i has a more dispersed distribution than r_i. Therefore, when applying ANOM or regression to investigate the calendar effects, our methods would be more likely to result in significant statistics than the normal methods.

However, our methods show that the general equity indices and securitized real estate indices exhibit different patterns of calendar effects. The general equity indices show significant Halloween and January effects as found in some previous studies, but the results of the securitized real estate indices are less normal. A possible reason is that the majority the previous studies worked on equity markets. Only a few studies investigated calendar effects of real estate markets. Therefore, the calendar effects of real estate markets have not been fully explored yet. Furthermore, most of the wellknown calendar effects like the Halloween and January effects were discovered in equity markets initially. The real estate market is different from the equity market in nature. An important feature of real estate is that it has a much lower liquidity than equity. According to Hatemi-J and Roca (2010), real estate is non-tradeable. Furthermore, real estate can serve as a type of consumption goods as well as an investment tool (Hui and Zheng (2012)). Therefore, securitized real estate indices, which can reflect the performance of the real estate markets (see Sections 2 and 4), may exhibit patterns of calendar effects which are different from those of general equity indices. This also explains why the Halloween and January effects are found significant on the general equity indices, but less significant, or even goes into reverse on the securitized real estate indices in our results. Furthermore, Gu (2002) found that seasonality and predictability of the real estate market are different among states in the U.S. This is another difference between the trends of equity and real estate markets.

Conclusion

In this study, we incorporated the Shiryaev-Zhou index with ANOM and logistic regression to investigate the calendar effects of general equity and securitized real estate indices of six economies: Hong Kong, Japan, US, UK, France and Germany, during the period 1996 – 2014. The main results are as follows:

(1) Our new methods can detect additional channels of significant calendar effects of which normal methods fail to show.
(2) In general, the calendar effects diminish as the moving-window size increases, except for the Halloween effect of securitized real estate indices.
(3) Most of the general equity indices show significant Halloween and January effects. However, for the securitized real estate indices, the Halloween and January effects are less significant or even go into reverse in some cases.

A major advantage of our approach is that our methods can show the percentage of time we should (or should not) hold a stock index in a month according to Hui and Chan (2015a)'s strategy (see Section 5), which beats the Bbuy-and-hold^ strategy in general. Traditional methods cannot show the percentage of time we should hold a stock/stock index in a month. In this way, our method is superior. The results show that additional channels of significant calendar effects which cannot be shown by normal methods are discovered using our methods. From the results, we can know in which months, we should hold the stock indices for a significantly longer period of time than in other months, according to Hui and Chan (2015a)'s strategy. This can help investors to formulate a better trading strategy to earn more profits. Furthermore, different results are found between general equity indices and securitized real estate indices. Significant Halloween and January effects are found in the general equity indices, but these calendar effects go into reverse in some cases for the securitized real estate indices. This reflects the difference in nature between the equity and real estate markets as explained in Section 5. This has an implication to investors that trends and phenomena found in equity markets may not be applicable to real estate markets, so investment rules on equity markets may not work on real estate markets. A possible scope of future research is to apply our methodology to investigate calendar effects in markets of other financial assets and other calendar effects like the day-of-the-week effect.

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References

Agrawal, A., & Tandon, K. (1994). Anomalies or illusions? Evidence from stock markets in eighteen countries. Journal of International Money and Finance, 13(1), 83–106.
Almudhaf, F., & Hansz, J. (2011). Systematic equity return patterns in listed European property companies. International Real Estate Review, 14(1), 61–84.

Andrade, S., Chhaochharia, V., & Fuerst, M. (2012). BSell in May and Go Away^ Just Won't Go Away. Available at SSRN 2115197.

Barber, B. M., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. Journal of Finance, 55(2), 773–806.

Bouman, S., & Jacobsen, B. (2002). The Halloween Indicator, BSell in May and Go Away^: Another Puzzle. The American Economic Review, 92(5), 1618–1635.

VC Brokerage Limited (2015). Hong Kong/China Market. http://www.vcgroup.com.hk/Host/VC/UserFiles/ File/Research/2015/09/20150907_0071.pdf. Assessed 5 February 2016.

Brounen, D., & Ben-Hamo, Y. (2009). Calendar anomalies: the case of international property shares. Journal of Real Estate Finance and Economics, 38(2), 115–136.

Cheung, K. C., & Coutts, J. A. (1999). The January effect and monthly seasonality in the Hang Seng index: 1985–97. Applied Economics Letters, 6(2), 121–123.

DuToit,J.,&Peskir,G.(2008).Sellingastockattheultimatemaximum.TheAnnalsAppliedProbability,19,983–1014.

Fountas, S., & Segredakis, K. N. (2002). Emerging stock markets return seasonalities: the January effect and the tax-loss selling hypothesis. Applied Financial Economics, 12(4), 291–299.

Gu, A. Y. (2002). The predictability of house prices. Journal of Real Estate Research, 24(3), 213–234.

Gu, A. Y. (2003). The declining January effect: evidences from the US equity markets. The Quarterly Review of Economics and Finance, 43(2), 395–404.

Hansen, P. R., Lunde, A., & Nason, J. M. (2005). Testing the significance of Calendar Effects. Federal Reserve Bank of Atlanta Working Paper, (2005–02).

Hardin, W., III, Liano, K., & Huang, G. (2005). Real estate investment trusts and calendar anomalies: revisited. International Real Estate Review, 8(1), 83–94.

Hatemi-J, A. & Roca, E. (2010). The impact of the US real Estate market on other major markets during normal and crisis periods (No. finance: 201003). Griffith University, Department of Accounting, Finance and Economics.

Hui, E. C. M., & Chan, K. K. K. (2014). The global financial crisis: Is there any contagion between real estate and equity markets? Physica A: Statistical Mechanics and its Applications, 405, 216–225.

Hui, E. C. M., & Chan, K. K. K. (2015a). A new time-dependent trading strategy for securitized real estate and equity indices, forthcoming.

Hui, E. C. M., & Chan, K. K. K. (2015b). Testing calendar effects on global securitized real estate markets by Shiryaev-Zhou index. Habitat International, 48, 38–45.

Hui, E. C. M., & Yam, S. C. P. (2014). Can we beat the Bbuy-and-hold^ strategy? Analysis on European and American securitized real estate indices. International Journal of Strategic Property Management, 18(1), 28–37.

Hui, E. C. M., & Zheng, X. (2012). The dynamic correlation and volatility of real estate price and rental: an application of MSV model. Applied Economics, 44(23), 2985–2995.

Hui,E.C.M.,Yam,S.C.P.,&Chen,S.W.(2012).Shiryaev-Zhouindex–anobleapproachtobenchmarkingand analysis of real estate stocks. International Journal of Strategic Property Management, 16(2), 158–172.

Hui, E. C. M., Wang, Z., Yiu, C. K. F., & Wong, H. (2013). Inside information of real estate developers. Habitat International, 40, 244–257.

Hui, E. C. M., Wright, J. A., & Yam, S. C. P. (2014). Calendar effects and real estate securities. Journal of Real Estate Finance and Economics, 49(1), 91–115.

Jacobsen, B.,& Visaltanachoti, N. (2009).TheHalloweeneffectinUSsectors. Financial Review, 44(3),437–459.

Kang, S. H., Jiang, Z., Lee, Y., & Yoon, S. M. (2010). Weather effects on the returns and volatility of the Shanghai stock market. Physica A: Statistical Mechanics and its Applications, 389(1), 91–99.

Keim, D. B. (1983). Size-related anomalies and stock return seasonality: further empirical evidence. Journal of Financial Economics, 12(1), 13–32.

Lean, H. H. (2011). The Halloween puzzle in selected Asian stock markets. International Journal of Economics and Management, 5, 216–225.

Lucey, B. M., & Whelan, S. F. (2002). A promising timing strategy in equity markets. Journal of the Statistical and Social Inquiry Society of Ireland, 31, 74–110.

Maberly, E. D., & Pierce, R. (2004). Stock market efficiency withstands another challenge: Solving the Bsell in May/buy after Halloween^ puzzle. Econ Journal Watch, 1(1), 29–46.

Malkiel, B. G. (2003). The efficient market hypothesis and its critics. The Journal of Economic Perspectives, 17(1), 59–82.

Malkiel, B. G. (2005). Reflections on the efficient market hypothesis: 30 years later. Financial Review, 40(1), 1–9.

Malkiel, B. G., & Fama, E. F. (1970). Efficient capital markets: a review of theory and empirical work. Journal of Finance, 25(2), 383–417.

Shiryaev, A. N., Xu, Z., & Zhou, X. Y. (2008). Thou shalt buy and hold. Quantitative Finance, 8(8), 765–776.

Sullivan, R., Timmermann, A., & White, H. (2001). Dangers of data mining: the case of calendar effects in stock returns. Journal of Econometrics, 105(1), 249–286.

Wachtel, S. B. (1942). Certain observationson seasonal movements in stock prices. The Journal ofBusiness of the University of Chicago, 15(2), 184–193.

Wong, W. K., Wright, J. A., Yam, S. C. P., & Yung, S. P. (2012). Amixed Sharpe ratio.Risk and Decision Analysis, 3, 37–65.

Yam, S. C. P., Yung, S. P., & Zhou, W. (2009). Two rationales behind 'buy-and-hold or sell-at-once'. Journal of Applied Probabbility, 46, 651–668.

Yam, S. C. P., Yung, S. P., & Zhou, W. (2012a). A unified 'bang-bang' principle with respect to R-invariant performance benchmarks. Theory of Probability and Its Applications, 57(2), 405–414.

Yam, S. C. P., Yung, S. P., & Zhou, W. (2012b). Optimal selling time in stock market over a finite time horizon. Acta Mathematicae Applicatae Sinica, 28(3), 557–570.