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Dynamic lead–lag relationship between stock indices and their derivatives: A comparative study between Chinese mainland, Hong Kong and US stock markets

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HIGHLIGHTS

- Dynamic evolution of lead-lag relationship revealed by a non-parametric TOP method.
- Index future leads index in US and Hong Kong, but it's opposite in Chinese mainland.
- Index option leads the index in general, but it reverses when index collapses.

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ABSTRACT

As financial derivative products and systemic risk management tools, stock index futures and options have been greatly developed and widely issued in many countries. Taking the Shanghai Stock Exchange 50 (SSE 50) Index and its derivatives as the research objects, we first analyze the lead–lag relationship between stock index, index futures and index options in the Chinese mainland stock market based on a thermal optimal path (TOP) method whose essence is a non-parametric methodology, and compare the results with two mature markets, namely the Hong Kong and US stock markets. We find: (I) In US and Hong Kong stock markets, the index future leads the index. The index option leads the index future when the index remains stable or in an up-trend, but their lead–lag relation reverses when the index collapses; (II) In the Chinese mainland stock market, the index leads the index future, and the index option leads the index future in the whole period of our investigation; (III) In all three markets, the index option leads the index when the index remains stable or in an up-trend, but their lead–lag relation reverses when the index collapses. Our work gives new and strong evidence that the lead–lag relationship varies in different markets and with different market conditions, which has an important contribution to the reveal of the price discovery function of derivative products.

1. Introduction

In the 1970s, due to the collapse of the Bretton Woods system and the two oil crises, the US stock market experienced its worst crisis since World War II in 1973–1974. In order to avoid systematic risks, stock index futures and options were

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then launched. On February 24, 1982, the Kansas City Board of Trade (KCBT) promoted the world's first stock index futures contract, i.e., Value Line Composite Index Futures. Two months later, the Chicago Mercantile Exchange (CME) launched the S&P 500 Stock Index Futures. In March 1983, the Chicago Board Options Exchange (CBOE) launched the S&P 100 Stock Index Option, and in July the same year, the S&P 500 Stock Index Option was launched. Stock index futures and options have since developed rapidly as management tools of systematic risk since the 1980s. Stock index futures and options are currently issued in more than 130 financial markets in developed and developing countries, and the total transaction amount is more than 25 billion by the end of 2015.

Stock index futures and options are initially designed for hedging to avoid systematic risks in stock markets. The promotion of these derivative products are also conductive to strategy trading in portfolio investments for investors. The study of the lead–lag relationship between stock index and its derivatives, also known as the price discovery function, has practical value for both hedging and arbitrage trading, and it has attracted substantial attention in the past few decades.

The relationship between stock indices and stock index futures has been extensively studied, however the conclusions are inconsistent. The price movements of futures are found to lead the price movements of indices for a variety of stock indices in mature markets, such as S&P 500 [1–3], Nasdaq 100 [4], DAX [5], FTSE 100 [3,6,7] and HSI [8]. Similar phenomenon that the index futures affects the index is also observed in emerging markets, for instance, the markets in Mexico [9], Korea [10] and Thailand [11]. Other studies show the evidence that the index dominates the price discovery process [12–14]. In contrast to the one-way relationship, more recent studies indicate that there is a bidirectional relationship between spot and futures markets [15].

Much work has been devoted to the study of the relationship between stock indices and stock index options. The common view on their relationship is that the price movements of options lead the price movements of indices, which has been revealed in many studies [16–21]. The relation that the price movements of indices have impacts on the price movements of options has also been found [22,23]. Taking into account the trading cost, OConnor and Matthew [24] found that the return of the option lags the return of the index. Other studies found a bidirectional relationship between the return of the index and the return of the option [25].

There are also many studies focusing on the simultaneous relationship among stock indices, stock index futures and stock index options [5,26,27]. Diametrically conflicting conclusions are drawn for the studies in various markets over different time periods. Using daily data in the Hong Kong security market, the returns of the index and the index futures are found to lead the return of the index option, which may be due to the relatively small volume of transactions as the stock index option had just been launched [28]. An analysis of the Korean stock market indicates that the launch of the index option had an impact on the stock index and the index futures during the period of 1996–2001 [21]. Ryu [29] also studied the Korean stock market, but found the evidence that the index futures played a more important role in price discovery during the period of 2003–2006. Most of the studies based on intraday data show that the returns of both index options and index futures lead the return of the stock index [30–32]. The relationship between the index option and the index futures are controversial: Some studies found that the return of the option leads the return of the futures [28], but other studies found that the leading role of the futures is more significant [32].

As indicated in the above literature review, there are no consistent conclusions about the relationship between the stock index and its derivatives. One possible reason is that the time periods of the sample data analyzed in these studies are different. Therefore, it is important to analyze the dynamic evolution of the relationship over time. Wahab and Lashgari [33] proposed a co-integration method to study the dynamic relationship between S&P 500, FTSE 100 index and their associated futures, and found that the price movements of indices determined the price movements of index futures. Tse and Chan [34] used a threshold regression method to analyze the relationship between the S&P 500 index and its associated futures, and found that their relationship changed under different market conditions. Instead of the methods listed above [33,34], we here employ a thermal optimal path (TOP) method to study the dynamic evolution of the relationship between the stock index, the index futures and the index option.

Another possible reason which may lead to the different conclusions about the relationship between the stock index and its associated futures and option is that their interdependent analyses were carried out in different markets [9,15]. In emerging countries including Brazil and Hungary, the spot market is found to be more efficient than the futures market; however, the indices in mature markets like S&P 500, FTSE 100 and DAX 30 are found to lag the futures [35].

As the largest emerging market, the Chinese stock market has a large transaction value, accounting for more than one-third of the total value of global stock markets. It would be interesting to study the relationship between the stock index and its derivatives in China. There have been a few studies about the relationship between China Securities Index 300 (CSI300) and CSI 300 index futures, China's first index futures [8,36,37]. As a supplement of CSI 300 index futures, Shanghai Stock Exchange 50 (SSE 50) index futures was launched on April 16, 2015, and its underlying SSE 50 index includes 50 of the largest, high liquidity and most representative stocks listed in the Shanghai Stock Exchange. Almost at the same time, China unveiled its first equity option, i.e., SSE 50 ETF option, based on an exchange-traded fund (ETF) that tracks SSE 50 index. There are no options directly linked to the stock index in the Chinese mainland market. However, SSE 50 ETF option takes SSE 50 ETF as the subject, which treats the component stocks of SSE 50 index as investment targets. Therefore, we select SSE 50 ETF option as an alternative product of SSE 50 index option, and analyze the relationship between SSE 50 index and its derivatives, i.e., SSE 50 index futures and SSE 50 ETF option. To the best of our knowledge, this is the first time to study the simultaneous relationship between stock index and its associated futures and options in the Chinese equity market.

To compare with the results in mature markets, we also study the lead–lag relationship between stock indices and their associated derivatives in two representative mature markets. The US stock markets is generally considered as the world's most representative stock market, and commonly used as a benchmark for comparison with other stock markets. We choose S&P 500 index in the US stock market as one of our research objects, and study its relation with S&P 500 index futures and option. Another research object is HSI in the Hong Kong stock market, which is Asia's third largest stock market by market capitalization. We pay special attention on it, since it has much closer relationship with the Chinese mainland stock market after the launch of the Shanghai–Hong Kong and Shenzhen–Hong Kong Stock Connect program. The Hong Kong stock market is chosen as the closely related mature market in Asia, and we also study the relationship between HSI and its associated futures and options.

The remainder of this paper is organized as follows. Section 2 describes the data and the methods used in this paper. Section 3 presents the empirical results of our study. We first show the lead–lag relationship between SSE 50 index, SSE 50 index futures and SSE 50 ETF option, and then present the lead–lag relationship between HSI and S&P 500 indices and their associated derivatives for comparison. We summarize our findings in Section 4.

2. Data and methods

2.1. Data

Our sample data is retrieved from Bloomberg and Wind databases, see http://www.bloomberg.cn and http://www.wind.com.cn. The stock indices and their associated derivatives analyzed in our study include SSE 50 index, SSE 50 index futures and SSE 50 ETF option in the Chinese mainland stock market, HSI, HSI futures and HSI option in Hong Kong stock market, and S&P 500 index, S&P 500 index futures and S&P 500 index option in US stock market. The SSE 50 index futures and the SSE 50 ETF option have four types of contracts according to their delivery months: current month, next month, and two of the months from among March, June, September, and December following the current month. The HSI futures and the HSI option have four types of contracts the same as SSE 50 index futures and option. The S&P 500 index futures and the S&P 500 index option have eight contracts currently traded within a period of two years, and the delivery month of their contracts include March, June, September, and December. We collect the data of all the contracts, and filter out the data of the main contract, which has the largest trading volume among the currently traded contracts. The main contract generally corresponds to the current month contract, which is most actively traded and hence have the largest volume. If the main contract, generally the current month contract, reaches the delivery date, the next month contract will become the main contract, and this ensures the continuity of the data.

The daily closing prices are used in our study, and the sample period is selected as follows: The data of SSE 50 ETF options cover the period from its launch time, i.e., February 9, 2015, to June 30, 2016, and the data of SSE 50 index futures cover the period from its launch time, i.e., April 16, 2015, to June 30, 2016. To ensure that the index and the index option have the same length of data series in their relationship analysis, the sample period of SSE 50 index is from February 9, 2015 to June 30, 2016. In Hong Kong and US markets, index derivatives were launched earlier than those launched in the Chinese mainland market. In order to compare the results of these three different markets, the same period from February 9, 2015 to June 30, 2016 is chosen in the study of Hong Kong and US markets.

We denote $P(t)$ to be the price of the index or its derivatives at time t. The return $R(t)$ is defined as the difference between the logarithmic prices at t and $t-1$, following the formula

$$R(t) = \ln P(t) - \ln P(t-1). \tag{1}$$

The lead–lag relationship between the return series of the index, the index futures and the index options in three different markets are carefully analyzed in our study. It is worth to note that the order of magnitude of the return of the index option is much larger than those of the index and the index futures in some cases. To ensure that the two series, i.e., the index and the index option, the index futures and the index option, are comparable, both series are standardized.

2.2. Thermal optimal path method

The thermal optimal path (TOP) method is proposed by Sornette and Zhou [38,39]. By calculating the distance matrix between the two time series, the traditional economic problem can be solved by a classical probability transfer model in statistical physics. The lead–lag relationship is obtained by minimizing the total mismatch between the two series. The details of this method are introduced in the following context.

Suppose there are two normalized time series $\{X(t_1) : t_1 = 0, \ldots, N-1\}$ and $\{Y(t_2) : t_2 = 0, \ldots, N-1\}$. $\varepsilon(t_1, t_2)$ is the element of the distance matrix $E(X, Y)$, which is defined as the distance between $X(t_1)$ and $Y(t_2)$, and it is expressed as

$$\varepsilon(t_1, t_2) = [X(t_1) - Y(t_2)]^2. \tag{2}$$

For two series which have a steady lead–lag relationship as $Y(t) = X(t-k)$ with $k \neq 0$, it has a mapping $t_2 = t_1 + k = \phi(t_1)$ that makes $\varepsilon(t_1, t_2) = 0$. The lead–lag relationship between two time series is determined by searching for the mapping t_1

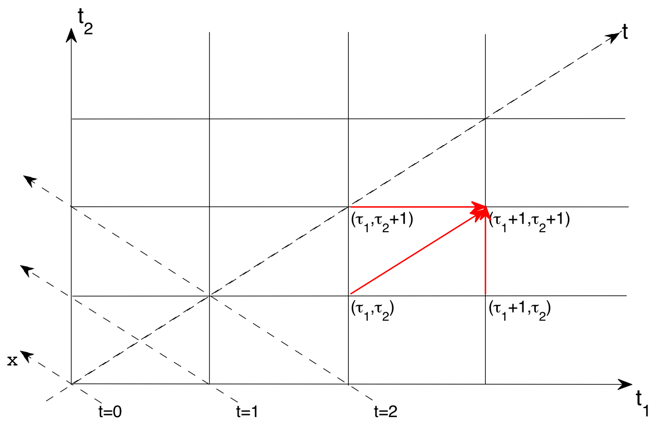

Fig. 1. (Color online.) Representation of the plane (t_1, t_2) and the rotated frame (x, t). The three red arrows depict the three possible paths from (τ_1, τ_2) to $(\tau_1 + 1, \tau_2 + 1)$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

$\to t_2$ by the following global minimization:

$$Min_{\{\phi(t_1), t_1=0,1,2,\ldots,N-1\}} \sum_{t_1=0}^{N-1} |X(t_1) - Y(t_2)|^2. \tag{3}$$

The distance matrix given by Eq. (2) can be interpreted as an energy landscape in the plane (t_1, t_2), and the distance is the energy associated with the node (t_1, t_2). Therefore, the global minimization of Eq. (3) can be transformed into searching for the configuration with minimal energy.

A transfer matrix method is proposed by [40], and is implemented as a useful and powerful method to solve the global optimization problem. In doing so, and the original coordinates are rotated as the following equation

$$\begin{aligned} x &= t_2 - t_1, \\ t &= t_1 + t_2. \end{aligned} \tag{4}$$

Fig. 1 shows the plane (t_1, t_2) with t_1 and t_2 as the horizontal and vertical coordinates. After the coordinate rotation according to Eq. (4), the original plane is transferred into a rotated frame (x, t) with coordinates x and t. The variable x quantifies the lead–lag relationship between the two series. If $x > 0$, $X(t_1)$ leads $Y(t_2)$, and else if $x < 0$, $Y(t_2)$ leads $X(t_1)$.

In reality, both $X(t_1)$ and $Y(t_2)$ can be expected to contain a significant amount of noise. Consequently, The distance matrix $E(X, Y)$ could also contain some noise. This problem may lead to the spurious interpretation of the relationship between the two time series. In order to make the results more robust and less sensitive to noise, the path configurations with energy slightly larger than the absolute minimal energy are allowed. The probability of a given path configuration with energy $\varepsilon(x, t)$ above the minimal energy to appear is specified by a Boltzmann factor $e^{-\varepsilon(x,t)/T}$, where the temperature T quantifies how much deviation from the minimal energy is allowed. For very large temperatures, too much useful information may be lost, and for very small temperatures, too much spurious noise may be extracted. Therefore, there is a compromise between too small and too large T.

To calculate the probability of a path to be at x at time t, a partition function $G(x, t)$ is introduced [38]. In Fig. 1, the three red arrows depict the three possible paths from (τ_1, τ_2) to $(\tau_1 + 1, \tau_2 + 1)$: either go horizontally by one step from (τ_1, τ_2) to $(\tau_1 + 1, \tau_2)$, vertically by one step from (τ_1, τ_2) to $(\tau_1, \tau_2 + 1)$; or along the diagonal from (τ_1, τ_2) to $(\tau_1 + 1, \tau_2 + 1)$. In the rotated frame (x, t), the recursive equation of the partition function $G(x, t)$ can be determined according to the following formula

$$G(x, t + 1) = [G(x - 1, t) + G(x + 1, t) + G(x, t - 1)]e^{-\varepsilon(x,t)/T}, \tag{5}$$

where $\varepsilon(x, t)$ is the element of the distance matrix defined in Eq. (2) and T is the temperature.

Using $G(x, t)$ in Eq. (5), the average position $\langle x(t)\rangle$ can be obtained by the following formula

$$\langle x(t)\rangle = \sum_x xG(x, t)/G(t), \tag{6}$$

where $G(t)$ is the sum of $G(x, t)$ over all paths from $(0, 0)$ to (x, t), and the ratio $G(x, t)/G(t)$ is the probability for a path to be at x at time t. $\langle x(t)\rangle$ represents the average lead–lag relationship of the two time series. A positive (negative) value of $\langle x(t)\rangle$ indicates that $X(t_1)$ leads (lags) $Y(t_2)$.

We here set the starting and end points to be within m units from the origin $(0, 0)$ and top-right point (N, N) respectively in the (t_1, t_2) plane. There are a total of $2m + 1$ possible positions for the starting points $(t_1 = 0, t_2 = 0)$, $(t_1 = 0, t_2 = j)$,

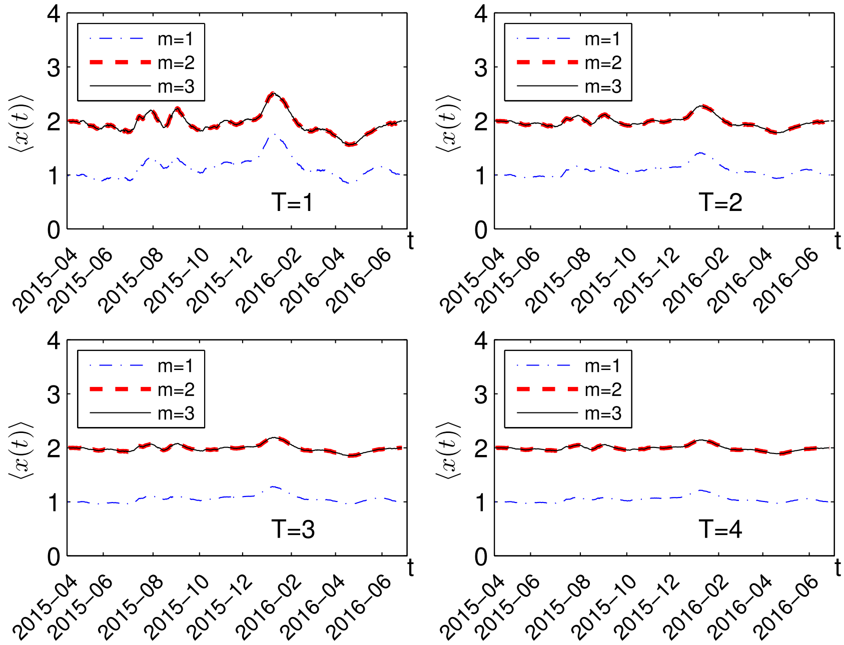

Fig. 2. (Color online) Lead–lag relationship between SSE 50 index and SSE 50 index futures with different values of parameters m and T. The four panels correspond to the average position $\langle x(t)\rangle$ for different values of the parameter T: 1 (upper left), 2 (upper right), 3 (lower left), and 4 (lower right). In each panel, m is set to be 1, 2, and 3 for a given value of T.

and $(t_1 = j, t_2 = 0)$ with $j = 1, 2, \ldots, m$, and end points $(t_1 = N, t_2 = N)$, $(t_1 = N, t_2 = N - j)$, and $(t_1 = N - j, t_2 = N)$ with $j = 1, 2, \ldots, m$. Consequently, there are $(2m + 1)^2$ possible pairs of starting and end points in total.

The starting and end points are determined by the energy of the thermal average path e_T, which can be calculated by the formula

$$e_T = \frac{1}{2N - |x_0| - |x_n| - 1} \sum_{t=|x_0|}^{2N-|x_n|-1} \sum_{x} \varepsilon(x, t)G(x, t)/G(t), \tag{7}$$

where x_0 and x_n are the values of coordinate x for the starting and ending positions respectively. The starting and ending positions with the minimum e_T are selected, and the average position $\langle x(t)\rangle$ under this pair of selected starting and end points is further calculated, which is used to quantify the lead–lag relationship between the two series.

In this paper, we will study the results with different values of parameters m and T, and search for the optimal values of these parameters for measuring the lead–lag relationship between the stock indices and their derivatives.

3. Empirical results

3.1. Chinese mainland stock market

We first analyze the relationship between SSE 50 index and SSE 50 index futures using the TOP method. We denote $R_i(t)$ and $R_f(t)$ as the returns of SSE 50 index and its futures respectively, and use the return series of SSE 50 index and its associated futures in their overlapping periods, i.e., from April 16, 2015 to June 30, 2016. Replacing the time series $X(t_1)$ and $Y(t_2)$ by $R_i(t)$ and $R_f(t)$, the thermal average position $\langle x(t)\rangle$ can be obtained by using the TOP method introduced in Section 2.2. If $\langle x(t)\rangle$ is positive (negative), the return of the index leads (lags) the return of the index futures.

We study the results of $\langle x(t)\rangle$ for different values of parameters m and T, and discuss the optimal estimation of the two parameters. Empirical studies have shown that the leading order of the index or its futures is generally smaller than 3 [8,41,42], therefore the parameter m is restricted to be m =1, 2, and 3.

Fig. 2 shows the lead–lag relationship between SSE 50 index and SSE 50 index futures with different values of parameters m and T. As we can see, $\langle x(t)\rangle$ shows a small fluctuation for different values of T, and the amplitude of the fluctuation decreases with increasing value of T, which indicates an information loss in $\langle x(t)\rangle$. Therefore, the optimal value of T is set to be $T = 1$. The selection of the parameter m can also affect the result of the lead–lag relationship. When $m = 1$, $\langle x(t)\rangle$ fluctuates around one day. When m is greater than or equal to 2, $\langle x(t)\rangle$ tends to approach a stable state. A further increase of m will not change the result of $\langle x(t)\rangle$, therefore, its optimal value is $m = 2$.

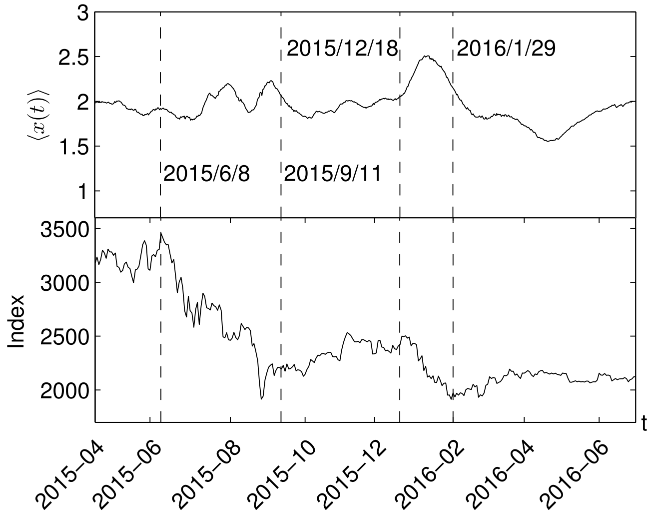

Fig. 3. (Color online) Lead–lag relationship between SSE 50 index and SSE 50 index futures obtained by the TOP method with the optimal parameters $m = 2$ and $T = 1$ (upper panel), and the evolution of SSE 50 index (lower panel).

The upper panel of Fig. 3 shows the lead–lag relationship between SSE 50 index and SSE 50 index futures obtained by the TOP method with the optimal setting values of parameters m and T. As we can see, the return of SSE 50 index leads the return of SSE 50 index futures by about two days during the whole period of our investigation.

The lower panel of Fig. 3 shows the evolution of SSE 50 index. According to the pattern of the index, we divide the whole sample period into five sub-periods. Considering that SSE 50 index reached its maximum on June 8, 2015, we take this as a dividing point. The index then experienced a period of decline. After that, the China Securities Regulatory Commission (CSRC) introduced a number of measures to limit futures trading in early September 2015, and the index returned to stability. We set September 11, 2015 as another dividing point. Due to the lifting of the ban in mid-December 2015 and the Circuit Breaker mechanism introduced in early 2016, the stock market has experienced another sharp decline. Later on, the index became stable after January 29, 2016. Therefore, we take December 20, 2015 and January 29, 2016 as two other dividing points. Using these dividing points, we split the entire sample period into five sub-periods: from April 16, 2015 to June 8, 2015, from June 9, 2015 to September 11, 2015, from September 12, 2015 to December 18, 2015, from December 19, 2015 to January 29, 2016, and from February 1, 2016 to June 30, 2016.

As we can see from the upper panel of Fig. 3, $\langle x(t)\rangle$ displays a large peak in the fourth sub-period, and two relatively small peaks in the second sub-period. In these two sub-periods, the SSE 50 index suffered a sharp decline as illustrated in the lower panel of Fig. 3. This may suggest that the leading role of the stock index strengthens when there is a sharp decline in the index.

We next analyze the relationship between SSE 50 index and SSE 50 ETF option. Since the contracts of SSE 50 ETF options were launched on February 9, 2015, we choose the sample period in this part of the analysis to be from February 9, 2015 to June 30, 2016. The thermal average position $\langle x(t)\rangle$ is calculated using the daily returns of SSE 50 index and SSE 50 ETF option, denoted by $R_i(t)$ and $R_o(t)$ respectively. If $\langle x(t)\rangle$ is positive (negative), the return of the index leads (lags) the return of the option.

Considering that SSE 50 ETF options are not traded as frequently as the underlying index and futures, the prices of the options contain more noise than the index and the futures. Therefore, we increase the value of T to 6, 8, 10 and 12. The maximum value of m remains to be 3.

Fig. 4 shows the lead–lag relationship between SSE 50 index and SSE 50 ETF option with different values of parameters $m = 1, 2,$ and 3 and $T = 6, 8, 10,$ and 12. The fluctuations of $\langle x(t)\rangle$ get smaller as T increases. For $T > 10$, $\langle x(t)\rangle$ has little change, and basically ranges within $[-5, 5]$. Furthermore, the curve for $m = 3$ coincides with the curve for $m = 2$. For $m > 3$, the coincidence with the curve for $m = 2$ remains. This indicates that $\langle x(t)\rangle$ approaches a stable state for $m \geq 2$. Therefore, the optimal parameters are selected as $T = 12$ and $m = 2$.

The upper panel of Fig. 5 shows the lead–lag relationship between SSE 50 index and SSE 50 ETF option obtained by the TOP method with the optimal setting values of parameters m and T. The lower panel of Fig. 5 shows the evolution of SSE 50 index. Using the same dividing date points shown in Fig. 3, which are determined by the pattern of the SSE 50 index, the whole sample period is also divided into five sub-periods as illustrated in the lower panel of Fig. 5. As we can see, $\langle x(t)\rangle$ varies drastically over time. In the first sub-period from February 9, 2015 to June 8, 2015, the return of the option leads the return of the index by 1–3 days. In the second sub-period from June 9, 2015 to September 11, 2015, $\langle x(t)\rangle$ displays two large peaks, and it fluctuates within the range of 0–4 days, which indicates that the index leads the option in this sub-period. In

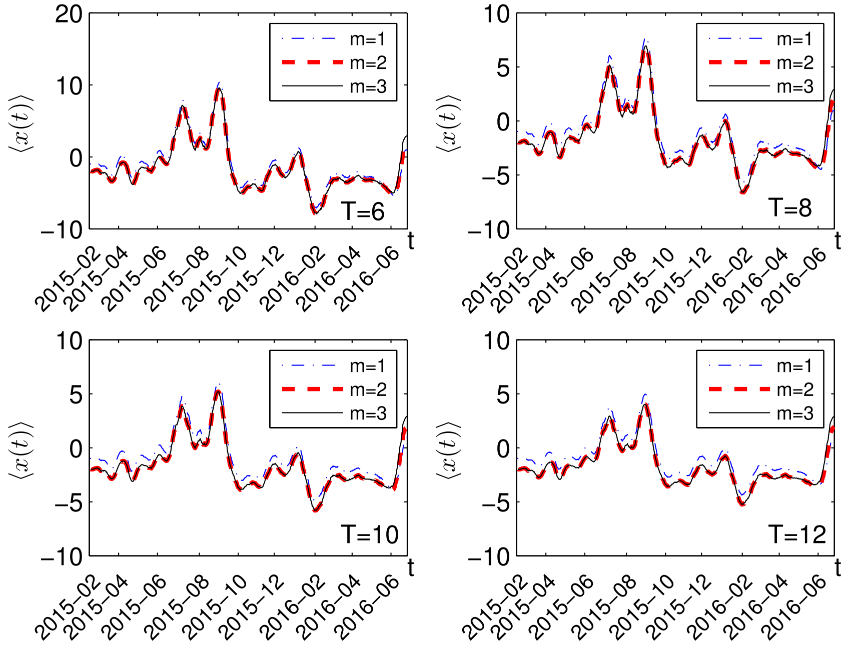

Fig. 4. (Color online) Lead–lag relationship between SSE 50 index and SSE 50 ETF option with different values of parameters m and T. The four panels correspond to the average position $\langle x(t)\rangle$ for different values of the parameter T: 6 (upper left), 8 (upper right), 10 (lower left), and 12 (lower right). In each panel, m is set to be 1, 2, and 3 for a given value of T.

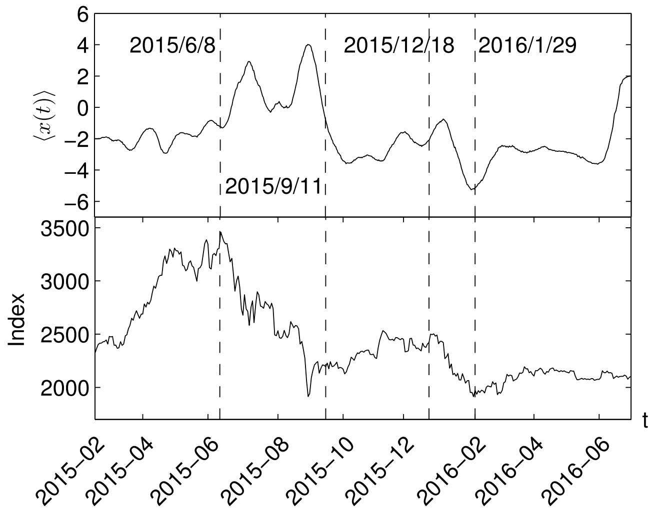

Fig. 5. (Color online) Lead–lag relationship between SSE 50 index and SSE 50 ETF option obtained by the TOP with the optimal parameters $m = 2$ and $T = 12$ (upper panel), and the evolution of SSE 50 index (lower panel).

the third sub-period from September 12, 2015 to December 18, 2015, the option leads the index by 2–4 days. In the fourth sub-period from December 19, 2015 to January 29, 2016, $\langle x(t)\rangle$ presents a peak, and the index lags the option by 1–5 days. On most of the trading days during the fifth period from February 1, 2016 to June 30, 2016, the option is three days ahead of the index.

In summary, $\langle x(t)\rangle$ displays two large peaks in the second sub-period and a relatively small peak in the fourth sub-period, in which the SSE 50 index suffered a sharp decline. This may suggest that the price discovery function of the option weakens when the index falls sharply. The index even has a leading impact on the option in the second sub-period. Notice that there is a sharp increase at the end of the curve of $\langle x(t)\rangle$. This phenomenon is due to the selection of the end point of the thermal average path, in which case the end of the curve returns to the end point that satisfies the condition $m = 2$.

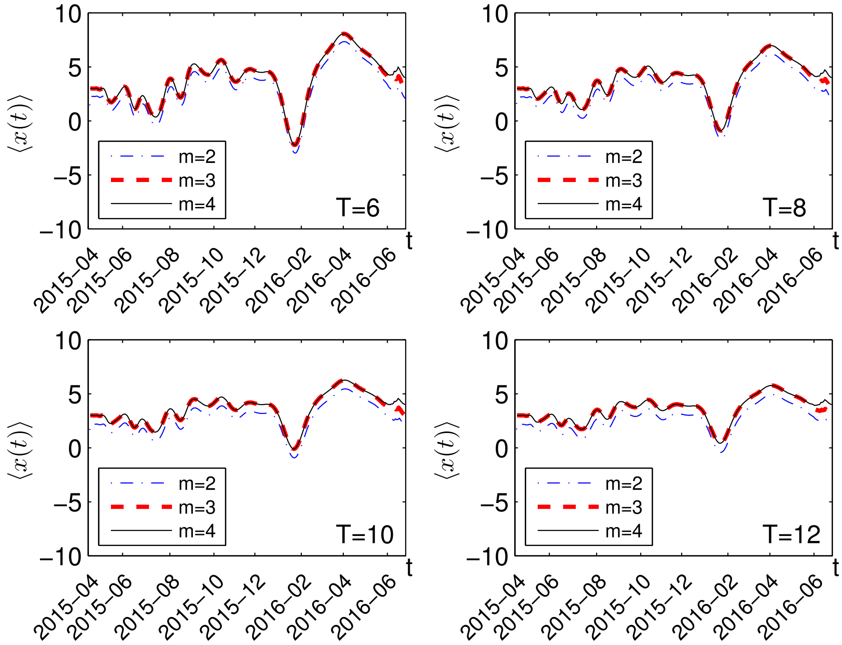

Fig. 6. (Color online) Lead–lag relationship between SSE 50 ETF option and SSE 50 index futures with different values of parameters m and T. The four panels correspond to the average position $\langle x(t)\rangle$ for different values of the parameter T: 6 (upper left), 8 (upper right), 10 (lower left), and 12 (lower right). In each panel, m is set to be 2, 3, and 4 for a given value of T.

We now analyze the relationship between SSE 50 ETF option and SSE 50 index futures. The returns of SSE 50 ETF option and SSE 50 index futures, denoted as $R_o(t)$ and $R_f(t)$ respectively, in their overlapping periods from April 16, 2015 to June 30, 2016 are used to calculate the thermal average position $\langle x(t)\rangle$ by the TOP method. If $\langle x(t)\rangle$ is positive (negative), the price movement of the option leads (lags) the price movement of the futures.

The results of the above analysis suggest that SSE 50 index leads SSE 50 index futures during the whole observation period and SSE 50 ETF option leads SSE 50 index on most of the trading days. A higher order lead–lag relationship may exist between the option and the futures. Therefore, we extend the maximum value of m to 4. Assuming that the noise contained in the return of the option is about the same as in the return of the futures, we set T to be 6, 8, 10 and 12. Fig. 6 shows the lead–lag relationship between SSE 50 ETF option and SSE 50 index futures with different values of parameters $m = 2$, 3, and 4 and $T = 6$, 8, 10, and 12. The amplitude of the fluctuation of $\langle x(t)\rangle$ decreases with increasing value of T, and the curve of $\langle x(t)\rangle$ collapses onto a single curve for $m \geq 3$. Following similar rules for the determination of optimal parameters used in the relationship analysis between the index and the index option, the optimal values of the parameters are selected to be $m = 3$ and $T = 12$.

The upper panel of Fig. 7 shows the lead–lag relationship between SSE 50 ETF option and SSE 50 index futures obtained by the TOP method with the optimal setting values of the parameters m and T. $\langle x(t)\rangle$ is positive in the whole sample period, indicating that the index option leads the index futures. According to the pattern of SSE 50 index shown in the lower panel of Fig. 7, the whole sample period is divided into the same five sub-periods as those in Figs. 3 and 5. In the first sub-period, the option leads the futures by about 3 days. In the second sub-period, the option leads the futures within a range of 2 to 4 days. In the third sub-period, the option is about 4 days ahead of the futures. In the fourth sub-period, the option leads the futures within a range of 0 to 4 days. In the fifth sub-period, the leading order of the option changes dramatically within a range of 1 to 6 days. It is clear that $\langle x(t)\rangle$ in the second and the fourth sub-periods is smaller than those in other sub-periods, and in these two sub-periods the SSE 50 index suffered sharp declines. This may suggest that the leading role of the option weakens when the index falls sharply. Again, the sharp drop at the end of $\langle x(t)\rangle$ is due to the artifact that the end of the curve should return to the end point that satisfies the condition $m = 3$.

Table 1 is a summary of the lead–lag relationships between the SSE 50 index and its derivatives. We find that when the index is relatively stable or in a rising trend, for instance, in the sub-periods from the starting point to June 8, 2015, from September 12, 2015 to December 18, 2015, and from March 1, 2016 to 30 June 2016, the option leads the index, and the index leads the futures. When the index falls sharply, as seen in the sub-periods from the mid-June 2015 to early September 2015 and from late December 2015 to the end of February 2016, the price discovery function of the option weakens. When the index collapses, individuals have the uncertain attitudes towards the stock market and its derivatives market, and they are more concerned about the changes of the spot market. Therefore, the lead–lag relationship reversed in the sub-period from the mid-June 2015 to early September 2015.

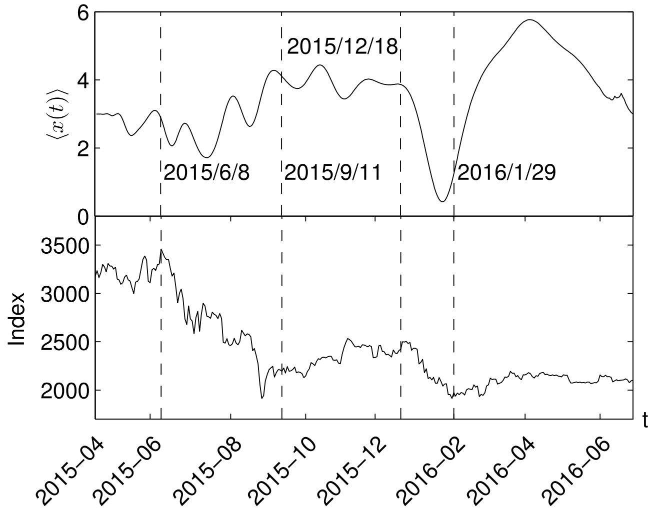

Fig. 7. (Color online) Lead–lag relationship between SSE 50 ETF option and SSE 50 index futures obtained by TOP method with the optimal parameters $m = 3$ and $T = 12$ (upper panel), and the evolution of SSE 50 index (lower panel).

Table 1
Summary of the relationship between the SSE 50 index and its derivatives.

Sub-periods	Index and future	Index and option	Option and future
Starting point-2015/6/8	R_i leads R_f 2 days	R_o leads R_i 1–3 days	R_o leads R_f 3 days
2015/6/9-2015/9/11	R_i leads R_f 2 days	R_i leads R_o 0–4 days	R_o leads R_f 2–4 days
2015/9/12-2015/12/18	R_i leads R_f 2 days	R_o leads R_i 2–4 days	R_o leads R_f 4 days
2015/12/19-2016/2/29	R_i leads R_f 2 days	R_o leads R_i 1–5 days	R_o leads R_f 0–3 days
2016/3/1-2016/6/30	R_i leads R_f 2 days	R_o leads R_i 3–5 days	R_o leads R_f 1–6 days

3.2. Hong Kong stock market

In this subsection, we analyze the lead–lag relationship between HSI, HSI futures and HSI option by the TOP method. The daily returns of HSI, HSI futures and HSI option denoted as $R_s(t)$, $R_f(t)$ and $R_o(t)$ in the period from February 9, 2015 to June 30, 2016 are used for analysis.

We first analyze the relationship between HSI futures and its underlying index. Using the returns of HSI and HSI futures, the thermal average position $\langle x(t)\rangle$ is calculated by the TOP method. If $\langle x(t)\rangle$ is positive (negative), the return of the index leads (lags) the return of the index futures. Following similar rules for the determination of optimal parameters introduced in Section 3.1, the optimal parameters are found to be $m = 1$ and $T = 1$.

The upper panel of Fig. 8 shows $\langle x(t)\rangle$ with the optimal parameters $m = 1$ and $T = 1$. Throughout the whole period of our investigation, $\langle x(t)\rangle$ is about one day and has relatively small fluctuations, indicating that the return of HSI futures leads the return of HSI by one day. This conclusion is diametrically opposite to that SSE 50 index leads SSE 50 index futures observed in the Chinese mainland market.

The lower panel of Fig. 8 shows the evolution of HSI. According to the pattern of HSI, the whole sample period is divided into five sub-periods. Taking into account the fact that HSI reached its maximum on April 28, 2015, we take it as a dividing point. The index then experienced a period of decline and reached a local minimum on September 30, 2015, which is picked as another dividing point. After that, the index became stable until December 14, 2015, followed by another sharp decline. Later on, the index returned to stability and rose after February 25, 2016. Therefore, we take December 14, 2015 and February 25, 2016 as two other dividing points. Using these dividing points, we split the entire sample period into five sub-periods: from 9 February, 2015 to April 28, 2015, from April 29, 2015 to September 30, 2015, from October 1, 2015 to December 14, 2015, from December 15, 2015 to February 25, 2016, and from February 26, 2016 to June 30, 2016. $\langle x(t)\rangle$ displays several peaks in the second sub-period and a single peak in the fourth sub-period. In these two sub-periods, the HSI experienced sharp declines. This suggests that the leading role of the futures weakens as the index collapses.

We next analyze the relationship between HSI and HSI option. The daily returns of HSI and HSI option are used to calculate $\langle x(t)\rangle$ by the TOP method. If $\langle x(t)\rangle$ is positive (negative), the index leads (lags) the index option. We find that $\langle x(t)\rangle$ reaches a stable state when m equals 2 and T equals 12.

The upper panel of Fig. 9 shows the lead–lag relationship between HSI and HSI option with the optimal parameters $m = 2$ and $T = 12$. The lower panel of Fig. 9 shows the evolution of HSI. Using the same dividing points shown in Fig. 8, the whole sample period is also divided into five sub-periods as illustrated in Fig. 9. In the first half sub-period from February 9, 2015

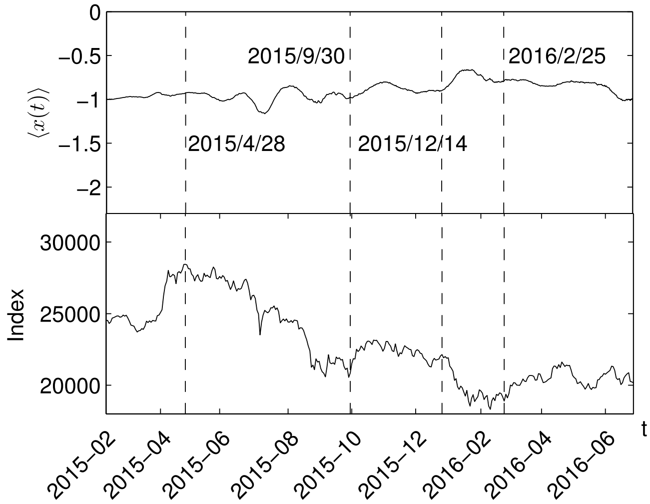

Fig. 8. (Color online) Lead–lag relationship between HSI and HSI futures obtained by the TOP method with the optimal parameters $m = 1$ and $T = 1$ (upper panel), and the evolution of HSI (lower panel).

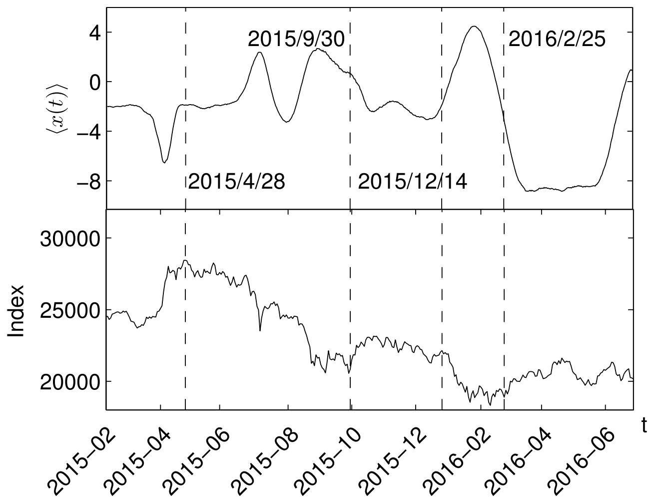

Fig. 9. (Color online) Lead–lag relationship between HSI and HSI option obtained by the TOP method with the optimal parameters $m = 2$ and $T = 12$ (upper panel), and the evolution of HSI (lower panel).

to April 28, 2015, the index option leads the index by two days, and $\langle x(t)\rangle$ displays a valley during the second half sub-period showing a minimum of -6. In the second sub-period from April 29, 2015 to September 30, 2015 $\langle x(t)\rangle$ displays two peaks, and the relationship between the index and the index option even reversed on the days close to the peak centers with the maximum order of three days. In the third sub-period from October 1, 2015 to December 14, 2015, the option is about two days ahead of the index. In the fourth sub-period from December 15, 2015 to February 25, 2016, $\langle x(t)\rangle$ displays a large peak, and fluctuates within the range from -2 to 4, in which the leading role of the index is quite evident. On most of the trading days during the fifth sub-period from February 26, 2016 to June 30, 2016, the option leads the index by about 8–9 days, and the price discovery function of the option strengthens. Due to the selection of the end point of the thermal average path, the end of the curve returns to the end point that satisfies the condition $m = 2$, which leads to a sharp increase at the end of $\langle x(t)\rangle$. The relationship between the index and the index options reverses when the market collapses, similar to their relationship observed in the Chinese mainland market.

The relationship between HSI option and HSI futures is further analyzed. The thermal average position $\langle x(t)\rangle$ is calculated using the daily returns of HSI option and HSI futures. If the thermal average position $\langle x(t)\rangle$ is positive (negative), the return of the index option (the index futures) has the leading impact on the return of the index futures (the index option). The optimal parameters for the detection of their relationship based on the TOP method are found to be $m = 1$ and $T = 12$.

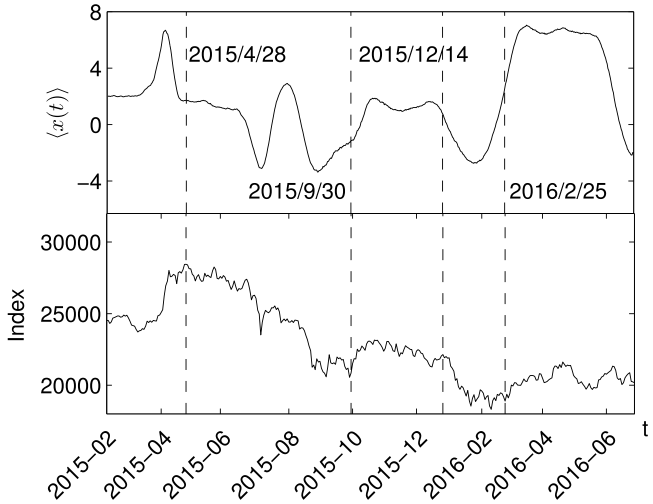

Fig. 10. (Color online) Lead–lag relationship between HSI option and HSI futures obtained by the TOP method with the optimal parameters $m = 1$ and $T = 12$ (upper panel), and the evolution of HSI (lower panel).

Table 2
Summary of the lead–lag relationship between HSI and its derivatives.

Sub-periods	Index and future	Index and option	Option and future
2015/2/9–2015/4/28	R_f leads R_i 1 day	R_o leads R_i [2,6] days	R_o leads R_f [2,6] days
2015/4/29–2015/9/30	R_f leads R_i 1 day	R_i leads R_o [−3,3] days	R_f leads R_o [−3,3] days
2015/10/1–2015/12/14	R_f leads R_i 1 day	R_o leads R_i 2 days	R_o leads R_f 2 days
2015/12/15–2016/2/25	R_f leads R_i 1 day	R_i leads R_o [0,4] days	R_f leads R_o [0,3] days
2016/2/26–2016/6/30	R_f leads R_i 1 day	R_o leads R_i [8,9] days	R_o leads R_f [6,7] days

The upper panel of Fig. 10 shows the lead–lag relationship between HSI option and HSI futures. The lower panel of Fig. 10 shows the evolution of HSI, and five sub-periods are divided with the same dividing points according to its pattern. In the first sub-period from February 9, 2015 to April 28, 2015, $\langle x(t) \rangle$ shows a sharp peak, and the option leads the futures by 2–6 days. In the second sub-period from April 29, 2015 to September 30, 2015, $\langle x(t) \rangle$ fluctuates within a range of −3 to 3, mainly showing two valleys. In the third sub-period from October 1, 2015 to December 14, 2015, the option is about two days ahead of the futures. In the fourth sub-period from December 15, 2015 to February 25, 2016, $\langle x(t) \rangle$ shows a valley, and the futures leads the options by 0–3 days. Ignoring the sharp decline at the end of $\langle x(t) \rangle$ caused by the setting of the end point, the option leads the futures by 6–7 days during the last sub-period from February 26, 2016 to June 30, 2016. The reversal of the relationship between the index option and index futures in declining sub-periods is also similar to that observed in the Chinese mainland market.

The lead–lag relationships between the stock index and its derivatives in the Hong Kong stock market detected by the TOP method are summarized in Table 2. We find that when the index is relatively stable or in an up-trend, for instance, in the sub-periods from February 9, 2015 to April 28, 2015, from October 1, 2015 to December 14, 2015, and from February 26, 2016 to June 30, 2016, the option leads the futures and the futures leads the index. When the index collapses, as seen in the sub-periods from April 29, 2015 to September 30, 2015 and from December 15, 2015 to February 25, 2016, the lead–lag relationships between the index and the option, the option and the futures reverse, indicating that the price discovery function of the option weakens.

3.3. US stock market

In this subsection, we analyze the relationship between S&P 500 index and its derivative futures and option. The daily returns of S&P 500 index, S&P 500 index futures, and S&P 500 index option, denoted as $R_f(t)$, $R_f(t)$, and $R_o(t)$ respectively, in the period from February 9, 2015 to June 30, 2016 are used for calculation.

We first analyze the relationship between S&P 500 index and S&P 500 index futures. Using the same approach as introduced previously, the optimal parameters are found to be $m = 1$ and $T = 1$, the same as those found in the Hong Kong market. $\langle x(t) \rangle$, using the optimal parameters, is plotted in the upper panel of Fig. 11. $\langle x(t) \rangle$ is relatively stable throughout the investigation period, and S&P 500 index futures is about one day ahead of S&P 500 index.

The lower panel of Fig. 11 shows the evolution of S&P 500 index. We also divide the whole sample period into five sub-periods according to the pattern of S&P 500 index. The S&P 500 index reached a local maximum on July 20, 2015, followed by a sharp decline impacted by the Chinese stock market crash and the global economic downturn. The index reached its local

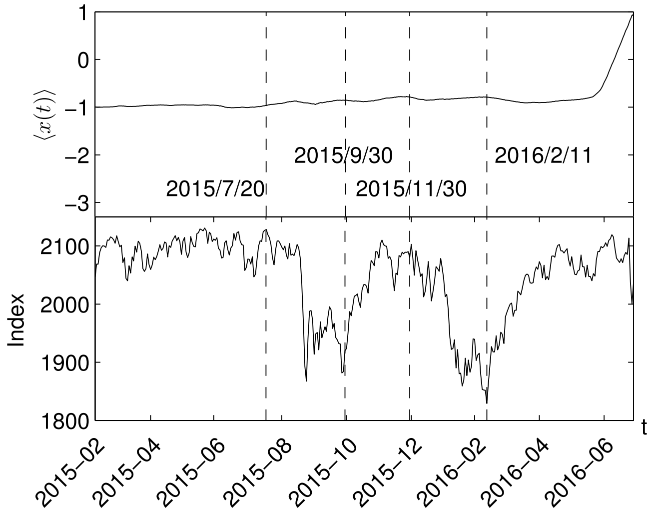

Fig. 11. (Color online) Lead–lag relationship between S&P 500 index and S&P 500 index futures obtained by the TOP method with the optimal parameters $m = 1$ and $T = 1$ (upper panel), and the evolution of S&P 500 index (lower panel).

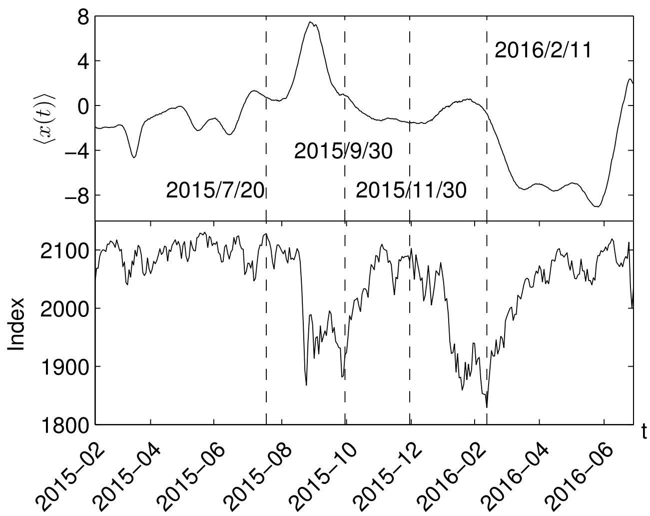

Fig. 12. (Color online) Lead–lag relationship between S&P500 index and S&P500 index option obtained by the TOP method with the optimal parameters $m = 2$ and $T = 12$ (upper panel), and the evolution of S&P500 index (lower panel).

minimum on September 30, 2015, and then recovered. From the beginning of December 2015 to February 2016, affected by the drop of the oil prices, the S&P 500 index fell sharply, and it reached a minimum value on February 11, 2016. The index was then in an up-trend. Accordingly, we split the entire sample period into five sub-periods: from February 9, 2015 to July 20, 2015, from July 21, 2015 to September 30, 2015, from October 1, 2015 to November 30, 2015, from December 1, 2015 to February 11, 2016, and from February 12, 2016 to June 30, 2016.

We next analyze the relationship between S&P 500 index and S&P 500 index option. The daily returns of the index and the index option are used to calculate $\langle x(t)\rangle$. If $\langle x(t)\rangle$ is positive (negative), the index (the index option) has an influence on the index option (the index). The optimal parameters are $m = 2$ and $T = 12$.

The upper panel of Fig. 12 shows the lead–lag relationship between S&P 500 index and S&P 500 index option with the optimal parameters. The lower panel of Fig. 12 shows the evolution of the S&P 500 index, and the whole sample period is divided into five sub-periods using the same dividing points shown in Fig. 11. In the first sub-period from February 9, 2015 to July 20, 2015, $\langle x(t)\rangle$ ranges within [-4,0], which means the return of the option is ahead of the return of the index on average. In the second sub-period from July 21, 2015 to September 30, 2015, the lead–lag relationship reverses, where the index leads the option by a maximum order of 8 days. In both sub-periods from October 1, 2015 to November 30, 2015 and from December 1, 2015 to February 11, 2016, the option leads the index by 0–2 days. However, $\langle x(t)\rangle$ in the latter sub-period

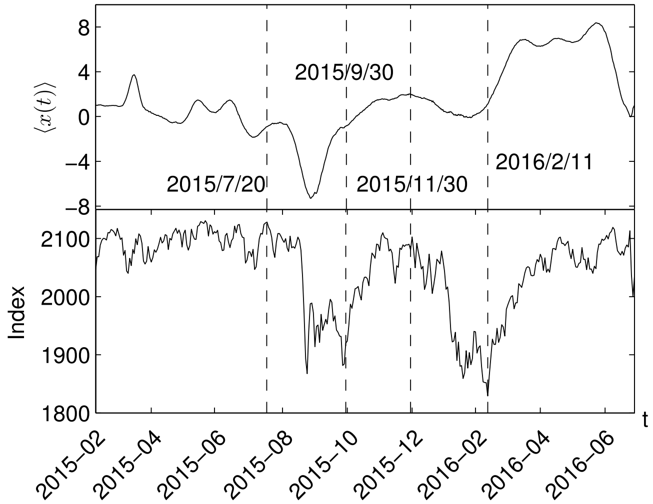

Fig. 13. (Color online) Lead–lag relationship between S&P500 index option and S&P500 index futures obtained by the TOP method with the optimal parameters $m = 1$ and $T = 12$ (upper panel), and the evolution of S&P500 index (lower panel).

Table 3
Summary of the lead–lag relationship between S&P 500 index and its derivatives.

Sub-periods	Index and future	Index and option	Option and future
2015/2/9–2015/7/20	R_f leads R_i 1 day	R_o leads R_i [0,4] days	R_o leads R_f [0,4] days
2015/7/21–2015/9/30	R_f leads R_i 1 day	R_i leads R_o [0,8] days	R_f leads R_o [1,7] days
2015/10/1–2015/11/31	R_f leads R_i 1 day	R_o leads R_i [0,2] days	R_o leads R_f [0,2] days
2015/12/1–2016/2/11	R_f leads R_i 1 day	R_o leads R_i [0,2] days	R_o leads R_f [0,2] days
2016/2/12–2016/6/30	R_f leads R_i 1 day	R_o leads R_i [7,9] days	R_o leads R_f [7,8] days

shows a relatively small peak, indicating that the leading role of the option weakens. In the fifth sub-period from February 12, 2016 to June 30, 2016, the option leads the index by about eight days, again ignoring the sharp decline at the end of $\langle x(t)\rangle$.

We finally analyze the lead–lag relationship between S&P 500 index option and S&P 500 index futures, and the daily returns of the option and the futures are used for calculation. If the thermal average position $\langle x(t)\rangle$ is positive (negative), the price movement of the option (the futures) is ahead of the price movement of the futures (the option). The optimal parameters are $m = 1$ and $T = 12$.

The upper panel of Fig. 13 shows the lead–lag relationship between S&P 500 index option and S&P 500 index futures with the optimal parameters. According to the pattern of S&P 500 index shown in the lower panel of Fig. 13, the whole sample period is divided into five sub-periods, the same as that illustrated in Figs. 11 and 12. In the first sub-period from February 9, 2015 to July 20, 2015, $\langle x(t)\rangle$ ranges within [0,4], and the option leads the futures by two days on average. In the second sub-period from July 21, 2015 to September 30, 2015, $\langle x(t)\rangle$ shows a deep valley below zero, indicating that the relationship between the option and the futures reverses. In the third sub-period from October 1, 2015 to November 30, 2015, the option leads futures by about 0–2 Days. Though the option also leads the futures by 0–2 days in the fourth sub-period from December 1, 2015 to February 11, 2016, $\langle x(t)\rangle$ shows a small valley which indicates that the leading role of the option weakens. On most of the trading days during the last sub-period from February 12, 2016 to June 30, 2016, the option leads the futures by 7–8 days.

To better reveal the lead–lag relationships between the stock index and its derivatives in the US stock market detected by the TOP method, we summarize the results in Table 3. We find that the results of the US stock market is very similar to those of the Hong Kong stock market, both of which are mature markets. When the index is relatively stable or in an up-trend, i.e., in the first, third and fifth sub-periods, the option leads the futures, and the futures leads the index. When the index falls sharply, i.e., in the second and fourth sub-periods, the leading role of the option weakens. The relationships between the index and the option, the option and the futures even reverse, in an extreme case of collapse in the second sub-period.

As a representative developing market, the Chinese stock market has lead–lag relationships dramatically different from those observed in the two mature markets, i.e., Hong Kong and US stock markets. In the Chinese mainland market, the SSE 50 index leads the SSE 50 index futures, which coincides with the relationship between the China Securities Index 300 (CSI 300) and its associated futures [8]. On the other hand, the HSI and S&P 500 index futures lead their underlying indices in the Hong Kong and US stock markets. In addition, the SSE 50 ETF option in the Chinese mainland market basically leads the SSE 50 futures in the whole period of our investigation, but the relationship between the options and the futures reverses in extreme cases in both mature markets. The differences in market structure and information efficiency between the Chinese mainland market and the two mature markets may cause the dramatically different relationships between the index, the index futures and the index option.

There are also similarities between the lead–lag relationships of the Chinese stock market and the two mature markets. For all three markets, the option leads the index when the stock market is stable or in an up-trend, and the leading role of the option weakens when the stock market drops. In the extreme case of collapse, their relationship even reverses. For the relationships between the option and the futures, though there are some differences between the Chinese stock market and the two mature markets, the leading role of the option weakens or even reverses when the stock market collapses. In the study of the relationship between the index and the futures, we find that the leading role of the index strengthens in the Chinese stock market when the index drops, which is consistent with the phenomenon that the leading role of the futures weakens in the Hong Kong stock market. Similar phenomena that the futures leadership is less evident or the spot market is more informationally efficient when the market is falling, suffers a structural change or under high variance conditions [35,43,44] provides sufficient evidence to support our results. When the stock market collapses, the market expectations underlying historical spot prices might be difficult to obtain, and the relevant information can not be efficiently reflected in the prices of futures or options. Since the price discovery function of the index derivatives fails, investors are more cautious and are inclined to focus on the current price changes of the spot market in derivatives trading. This may provide a qualitative explanation for the weakening role of the option or futures when the stock markets collapse.

4. Conclusion and discussion

Based on the results of the lead–lag relationship analysis, we summarize the differences between the three markets as follows: In the Chinese mainland stock market, the index leads the index futures, and the index option leads the index futures in the whole period of our investigation. In mature markets like the Hong Kong and US stock markets, the leading role of the option and the futures are more prominent, i.e., the index futures leads the index in the whole investigation period and the index option leads the index when the market remains stable or in an up-trend. The different performance of the price discovery function of the derivatives between the Chinese mainland stock market and the two mature markets might be attributed to their different market mechanisms. The mature markets usually have higher information efficiency, and therefore their derivatives have a stronger price discovery function.

There are also similarities between the relationships among the stock index, stock index futures and option in the three markets. When the market is stable or in an up-trend, the index option leads the index, and their relationship reverses in the extreme case of collapse. For the relationship between the index option and futures, the leading role of the option weakens or even reverses when the market drops. In the similar extreme case of collapse, the index plays a more important role in its relationship with the index futures. More specifically, the leading role of the index strengthens in the Chinese stock market, and the leading role of the index futures weakens in the Hong Kong stock market. The possible reason for the weakening role of the derivatives when the stock market drops may due to the decline of the information efficiency in the derivatives markets. When the spot market collapses, the relevant information cannot be efficiently reflected in the derivatives' prices, and the market expectations might be difficult to obtain from the derivatives markets, which will cause the investors' excessive attention on the stock index in order to adjust their investment strategies.

Acknowledgments

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