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Dynamics lead-lag relationship of jumps among Chinese stock index and futures market during the Covid-19 epidemic

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\textbf{ABSTRACT}

This paper introduces thermal optimal path method to investigate the dynamics lead-lag relationship of jumps among Chinese stock index and futures market under the background of the Covid-19 epidemic. Based on three representative stock indexes and their index futures in China, we find the lead-lag structure changes significantly before and after the outbreak of COVID-19. Before the epidemic, there is mutual effect between different markets jumps. However, CSI 300 futures and SSE 50 futures significantly lead other markets for the after-epidemic period. For the volatility forecasting based on cross-market jumps, the lagged jumps of CSI 300 and SSE 50 index futures have significantly impacts on the volatility forecast of other markets.

1. Introduction

With the global outbreak of the 2019 novel coronavirus (COVID-19), financial markets are experiencing drastic turbulence. Faced with numerous risk factors, the frequency and intensity of jump volatility in asset returns have increased. Jumps are known to have distinctly different implications for risk measurement and management, as well as valuation of derivative securities. It is often defined as the unexpected large and discontinuous changes, which is important to understand the magnitude of extreme risk for the financial markets (Bloom, 2009; Duffie et al., 2000; Merton, 1976).

Jump spillover is the extent to which jumps transmit across different markets. As the epidemic spreads, the vulnerability of the macro economy has increased. Such events have significantly intensified the jump spillover and affected the direction of spillover effects across a wide variety of assets. For example, Asgharian and Bengtsson (2006) study jump spillover effects between a number of equity indexes and find that jump spillover seems to be particularly large between countries that belong to the same regions. Li et al. (2017) investigate the jump spillover between oil prices and exchange rates, and find strong evidence of jump spillover effects. Schlossberg and Swanson (2019) observe that jumps have significant impact on excess returns during 2008–2009. Although the great achievement in the studies of jump spillover effects, however, to the best of our knowledge, there is no research that focuses on the dynamic lead-lag relationship of jumps between different markets, especially for the Chinese stock index and futures markets.

There are several convincing reasons for the study of the dynamic lead-lag relationships between different stock index and the related futures markets in China. First, it is often of interest to identify which market reacts to new information first. Theoretically, futures markets usually react new information more quickly than the spot markets due to its high leverage, low trading cost and lack of short sale restriction. Existing researches confirm that futures market contains more information than spot market (Chan, 2015; Easley

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et al., 1998; Fleming et al., 1996; Hasbrouck, 2003; Koutmos and Tucker, 1996; Stoll and Whaley, 1990). Therefore, once the extreme risk arises, it is interesting to know which market plays the dominate role in the risk transmission.

Second, the vulnerability of the macro economy has increased with the COVID-19 epidemic spreads. When the macro environment is extremely uncertain, the lead-lag relationships of jumps among different market change significantly. No previous infectious disease episode led to daily stock market swings that even remotely resemble the response in 2020 to COVID-19 developments. The COVID-19 period stands out for an extremely high frequency of large daily stock market moves. Changes in volatility are more sensitive to COVID-19 news than economic indicators. The COVID-19 crisis and its associated uncertainties have exacerbated the turbulence in financial market, thereby affected the global financial cycle (Baker et al., 2020; Chatjathumard Jindahra et al., 2021; Sadiq et al., 2021; Baek et al., 2020; Díaz et al., 2022). Moreover, there have been significant risk transfers among different markets. The COVID-19 pandemic has caused huge shocks to international financial markets, especially of those countries with severe pandemics, and the pandemic led to increased spillovers between financial markets. The impact of the COVID-19 pandemic on financial markets is uncertain in both the short and long terms (Youssef et al., 2021; Rai and Garg, 2021; Zhang and Hamori, 2021; Elgammal et al., 2021).

Third, compared with developed countries, the Chinese stock and futures markets have different characteristics. Retail investor of the Chinese capital market is predominant. According to the 2020 yearlybook of the Shanghai Stock Exchange, individual investors count for 52% of the total trading. To avoid over speculation of investors, the supervision organization established a higher barrier for investment in the Chinese index futures markets, but the speculative transactions dominated by private equity and individual investors still count for 50% of the market turnover, and the hedge and arbitrage only counts for about 25%. Disadvantage of the Chinese stock market of investor structure, makes the emotional fluctuation of medium and small investors to be an important factor of frequent and large fluctuations of stocks and the stock index futures. Markets dominated by small and medium investors are more likely to cause large market volatility when they encounter panic. Compared to that of the traditional and long-standing influenza index, exceptionally pronounced and persistent impacts of the coronavirus pandemic upon Chinese financial markets. There is an asymmetric effect during the COVID-19 period, and the asymmetric effect is time-varying and substantially intense during the COVID-19 period (Corbet et al., 2021; Shahzad et al., 2021). Overreactions are stronger for stocks with lower institutional ownership and, thus, retail investors have reacted more strongly to the COVID-19 outbreak (Huo and Qiu, 2020).

For the study of lead-lag relationships among financial markets variables, previous literatures usually use the linear vector auto-regression model (VAR), the vector error correlation model (VECM), the Granger causality test, as well as DY spillover index (Diebold and Yilmaz, 2009, 2012), quantifying how much of the total variance forecast is attributed to each other. Construction of the DY spillover index relies on forecast error variance decompositions, and is calculated as the proportion of the movement in a variable’s development over time due to its own shocks and that due to shocks in other variables in the VAR model. In contrast to these parametric methods, we employ the thermal optimal path (TOP) method to study the time-varying lead-lag relationships among these markets. The TOP model, initially proposed by Sornette and Zhou (2005) and Zhou and Sornette (2006), is a nonparametric estimation method applied to charactering the dynamic lead-lag relationship of complex sequences. One of the main advantages of the TOP methods is that they are able to identify the time-varying lead-lag structure between two time series, in contrast to the constant causality in the literature. More importantly, this non-parametric method does not require the stationarity of time series. This feature means that one does not need to differentiate the non-stationary series, thus preserve all the information of the original time series. The TOP approach has been widely employed to the studies of financial markets relationships (Guo et al., 2017; Shao et al., 2019; Yang and Shao, 2020; Yao and Li, 2020).

This article selects three representative stock indexes and their futures markets in China, the SSE 50 Index, the CSI 300 Index and the CSI 500 Index markets and their corresponding index futures. The SSE 50 Index selects the 50 most representative stocks with large scale and good liquidity in the Shanghai stock market, the CSI 300 Index samples contains the 300 most representative stocks in both Shanghai and Shenzhen securities markets, which cover about 60% of the total market value. Both of them have good market representation which can reflect the overall status of a group of high-quality large-cap companies in Chinese stock markets. The CSI 500 Index is composed of the top 500 stocks in terms of total market capitalization after excluding the constituent stocks of the CSI 300 Index and the top 300 stocks in total market value of A shares, which is used to reflect the performance of a group of small and medium-sized companies in the Chinese A-share market. Therefore, it is interesting to know which markets is the dominated one in terms of the lead-lag structure of jumps, especially during the Covid-19 epidemic.

We use the 5-minute intraday returns to calculate realized variance, and decompose the realized variance into continuous and jump components. We first employ the VAR models and the Granger Causality test to examine the static lead-lag relationships between different market jumps. Then the TOP method is used to check the dynamic lead-lag structure of jumps, especially the difference before and during the Covid-19 epidemic. Our empirical results show that the lead-lag relationships before and after the outbreak of COVID-19 change significantly, which is verified by both the parametric VAR model and nonparametric TOP method. Before the outbreak of COVID-19, the jumps of CSI 300 index and its futures markets have significant positive effects on other markets, which are opposite for the effects of SSES50 index and futures jumps. However, during the period with COVID-19, the jumps in CSI 300 index futures and SSE 50 index futures markets dominate the lead-lag relationships among the six markets.

Finally, for the application of the above analysis, we present the cross-market jumps spillover effects for realized volatility forecasting. Since volatility forecasting is of great interest to both academic and practitioners. The increase of jumps for some markets may lead to the corresponding increase of volatilities for other markets. Many literatures have studied the volatility prediction of cross markets (Chen et al., 2016; Lu et al., 2020; Zhang et al., 2020). Our motivation for this application is straightforward, we want to know whether the jumps of the dominant markets can improve the volatility forecasting of other markets. Our work is based on a simple but very successful econometric model, namely, the heterogeneous autoregressive model for realized variance (HAR-RV) pioneered by Corsi (2009). By adding the jumps of the six markets into the HAR-RV model, we conclude for the first time that forecasting of six
markets volatility depends on different factors. The lagged jumps of CSI 300 and SSE 50 index futures have significantly impact on the volatility forecast of other markets, and the adjusted $R^2$ of models adding jumps is higher than the standard HAR-RV model.

Our contributions to the previous studies lies in the following aspects. Firstly, we introduce the TOP method to analyze the lead-lag structure between different stock and futures markets jumps in China, which is time-varying. Secondly, we contribute to the studies about volatility forecasting based on cross-market jumps spillover effects, and confirm that the jumps of the dominant markets can improve the volatility forecasting of other markets. Thirdly and the most importantly, we check the different performances of jumps in the lead-lag structures before and during the Covid-19 epidemic periods, and find the significantly lead functions of the CSI 300 and SSE index futures market jumps.

The main body of the paper is organized as follows. First, the realized volatility, jump volatility and the TOP method are introduced in Section 2. Next, in Section 3, summary statistics and the empirical results are analyzed. In addition, the impact of cross-market jumps on volatility forecasting is also discussed. Finally, this paper concludes with a few remarks.

2. Methodology

2.1. Price jumps

Assume the logarithmic price of an asset $p_t$ follows the continuous-time jump diffusion process

$$dp_t = \mu_t dt + \sigma_t dW_t + \kappa_t dq_t,$$  \hspace{0.5cm} (1)

where $\mu_t$ is a continuous locally bounded variation process, the volatility process $\sigma_t$ is strictly positive, denotes a standard Brownian motion, $dq_t$ is a counting process with $dq_t = 1$ if there is a jump at time $t$ and 0 otherwise, and $\kappa_t$ refers to the size of the corresponding jumps.

The purpose of the jump test is to identify the jump component of the price series. There are many literatures suggest that quadratic variation consists of continuous volatility and jump volatility (Andersen et al., 2007; Barndorff-Nielsen and Shephard, 2005).

The relationship follows

$$QV_t = \int_{t-1}^{t} \sigma^2_t ds + \sum_{t-1 < j < t} \kappa^2_j .$$  \hspace{0.5cm} (2)

where $\int_{t-1}^{t} \sigma^2_t ds$ and $\sum_{t-1 < j < t} \kappa^2_j$ refers to the integrated variance from the continuous volatility and jump variance from the jump volatility.

Following Andersen and Bollerslev (1998), realized variance is the sum of squared return

$$RV_t = \sum_{i=1}^{M} |r_{i,j}|^2 \longrightarrow \alpha QV_t ,$$  \hspace{0.5cm} (3)

where $r_{i,j} = p_{i,t} - p_{i,t-j}$ is the return over the $i$-th interval on day $t$, and $M$ is the number of intervals. Realized variance converges uniformly in probability to quadratic variation.

In order to separate the jump variance, Barndorff-Nielsen and Shephard (2004) introduces realized bi-power variation, defined as follows

$$BPV_t = \mu_1^2 \left( \frac{M}{M-2} \right) \sum_{j=3}^{M} |r_{i,j-2}||r_{i,j}| \int_{t-1}^{t} \sigma^2_\kappa ds ,$$  \hspace{0.5cm} (4)

where $\mu_1 = \sqrt{2/\pi}$. As $M \to \infty$, the realized bi-power variation is a consistent estimate of the integrated variance in the presence of jumps.

Therefore, jump variance can be consistently measured by the difference between realized variance and realized bi-power variation

$$RV_t - BPV_t \longrightarrow \alpha \sum_{i-1 < j < t} \kappa^2_j .$$  \hspace{0.5cm} (5)

To identify the significant jumps in the price series, Barndorff-Nielsen and Shephard (2005) introduces a jump test statistics, which is identified according to

$$Z_t = \frac{(RV_t - BPV_t)/RV_t}{\sqrt{\left( \frac{1}{\alpha^2} + \pi - 5 \right) \max \left(1, \frac{\kappa^2}{\alpha^2} \right)}} > \Phi_\alpha ,$$  \hspace{0.5cm} (6)

Where $RTQ_t = M_\kappa^{2/3} \left( \frac{M}{M-2} \right) \sum_{j-3}^{M} |r_{i,j-4}||r_{i,j-2}|^{4/3}|r_{i,j}|^{4/3}$ is the four-power variation, $\mu_4 = E(|Z|^4), Z \sim N(0,1). \Phi_\alpha$ is the $\alpha$ quantile of the standard normal distribution, where $\alpha = 0.99$ in our study.

Therefore, the significant jump can be expressed as

$$J_t = (RV_t - BPV_t)I(Z_t > \Phi_\alpha) .$$  \hspace{0.5cm} (7)
where $I(\cdot)$ is an indicator function which is equal to 1 if $\Phi > \Phi_0$ and 0 otherwise.

2.2. Thermal optimal path (TOP) method

The TOP method is initially proposed by Sornette and Zhou (2005) and Zhou and Sornette (2006). This model transforms the classical economic problem into probability transmission model by introducing distance matrix of two time series, and use the partition function to obtain the dynamic relationship. The detailed implementation of this method is introduced in the following context.

Firstly, assume there are two normalized time series $x(t_1) : t_1 = 1, 2, ..., T_1$ and $y(t_2) : t_2 = 1, 2, ..., T_2$. To simplify, we suppose the lengths of the two time series is equal to $T$. The distance between $x(t_1)$ and $y(t_2)$ is defined as

$$d(t_1, t_2) = |x(t_1) - y(t_2)|.$$  

(8)

The purpose of the TOP method is to find a mapping relation between $t_1$ and $t_2$, that is, $t_2 = \phi(t_1)$, which can make distance matrix as small as possible

$$\phi^*(t_1) = \arg \min_{\phi(t_1)} \min_{\theta(t)} \sum_{t_1=1}^{T} |x(t_1) - y(\phi(t_1))|,$$

(9)

where $E$ is the sum of distances between two time series on path $\phi(t_1)$. To ensure the continuity of the path, the additional constraint is imposed on the mapping relation: $0 \leq \phi(t_1 + 1) - \phi(t_1) \leq 1$.

In order to facilitate the use of the TOP method to solve the above optimization problems, we first transform the coordinates $(t_1, t_2)$ into $(t, l)$

$$\begin{cases} 
    t = t_1 + t_2 \\
    l = t_2 - t_1,
\end{cases}$$

(10)

where $t$ is in the main diagonal direction of the $(t_1, t_2)$ coordinate system and $l$ is perpendicular to $t$. Then, $l(t)$ quantifies the dynamic lead-lag relation between two series, and a positive (negative) $l(t)$ means that first time series $x(t_1)$ leads (lags) the second time series $y(t_2)$. Therefore, we can obtain the optimal thermal path $\hat{I}(t)$ by

$$\hat{I}(t) = \sum_l l \frac{w(t, l)}{w(t)}.$$  

(11)

where partition function $w(t, l)$ is the sum of Boltzmann factors over all paths arriving at $(t, l)$ and $w(t) = \sum_l w(t, l)$. Then, $w(t, l) \frac{w(t)}{w(t)}$ can be interpreted as the probability for a path to be at position $l$ at time $t$. A positive $\hat{I}(t)$ implies the first time series $x(t_1)$ lead the second time series $y(t_2)$, and vice versa.

To maintain the direction of time required by causality, a feasible path arriving at $(t, l)$ can come from $(t - 1, l - 1)$ vertically, $(t - 1, l + 1)$ horizontally, or $(t - 2, l)$ diagonally. Therefore, $w(t, l)$ can be determined in a recursive manner as follow

$$w(t, l) = (w(t - 1, l - 1) + w(t - 1, l + 1) + w(t - 2, l))e^{-\beta(w(t) - w(t, l))},$$

(12)

where $\beta$ is a temperature parameter controlling the impact of noise.

2.3. VAR and HAR-RV-J models

We first apply the VAR models to study the static relationship between different markets jumps, and the regression models are as follows.

2.4. The VAR model

$$\begin{align*}
J_{x,t} &= C_x + \sum_{i=1}^{p} \alpha_{iJx} J_{x,t-i} + \sum_{i=1}^{p} \alpha_{2iJx} J_{x,t-i} + \sum_{i=1}^{p} \beta_{1Jx} J_{x,t-i} + \sum_{i=1}^{p} \beta_{2Jx} J_{x,t-i} + \varepsilon_t \\
J_{y,t} &= C_y + \sum_{i=1}^{p} \alpha_{iJy} J_{y,t-i} + \sum_{i=1}^{p} \alpha_{2iJy} J_{y,t-i} + \sum_{i=1}^{p} \beta_{1Jy} J_{y,t-i} + \sum_{i=1}^{p} \beta_{2Jy} J_{y,t-i} + \varepsilon_t \\
J_{r,t} &= C_r + \sum_{i=1}^{p} \alpha_{iJr} J_{r,t-i} + \sum_{i=1}^{p} \alpha_{2iJr} J_{r,t-i} + \sum_{i=1}^{p} \beta_{1Jr} J_{r,t-i} + \sum_{i=1}^{p} \beta_{2Jr} J_{r,t-i} + \varepsilon_t
\end{align*}$$  

(13)

where $p$ denotes maximum number of lag periods. $J_{x,t}$, $J_{y,t}$ and $J_{r,t}$ represent the jumps of CSI 300 index, SSE 50 index and CSI 500
index markets, respectively. $J_f^\alpha$, $J_f^\beta$ and $J_f^\gamma$ are the jumps in the three related index futures markets.

Further, we extend the standard logarithmic HAR-RV model by adding jumps of different markets, aiming to investigate the cross-market impacts of jumps on other market volatility. To simplify, we only report the results of models by adding jumps of CSI 300 and SSE 50 index futures markets. The extended model is called the HAR-RV-J model. Taking the realized volatility of CSI 300 index and futures for example, the regression models follow

$$\begin{align*}
\log(RV_{s,d}^{\alpha}) &= \lambda_{s,0}^\alpha + \lambda_{s,d}^\alpha \log(RV_{s,d-1}^{\alpha}) + \lambda_{s,w}^\alpha \log(RV_{s,w}^{\alpha}) + \lambda_{s,m}^\alpha \log(RV_{s,m}^{\alpha}) \\
&+ \sum_{i=1}^{p} (\omega_{s,i}^\alpha \ln(1 + J_{f,i}^\alpha) + \mu_{s,i}^\alpha \ln(1 + J_{f,i}^\beta)) + \epsilon_t \\
\ln(RV_{f,d}^{\alpha}) &= \lambda_{f,0}^\alpha + \lambda_{f,d}^\alpha \ln(RV_{f,d-1}^{\alpha}) + \lambda_{f,w}^\alpha \ln(RV_{f,w}^{\alpha}) + \lambda_{f,m}^\alpha \ln(RV_{f,m}^{\alpha}) \\
&+ \sum_{i=1}^{p} (\omega_{f,i}^\alpha \ln(1 + J_{f,i}^\alpha) + \mu_{f,i}^\alpha \ln(1 + J_{f,i}^\beta)) + \epsilon_t
\end{align*}\tag{14}$$

where $\ln(RV_{s,d-1}^{\alpha}), \ln(RV_{s,w}^{\alpha})$ and $\ln(RV_{s,m}^{\alpha})$ represent daily, weekly and monthly logarithm realized volatility of CSI 300 index, respectively. $J_{f,i}^\alpha$ and $J_{f,i}^\beta$ are the jumps of CSI 300 and SSE 50 index futures markets. The realized volatility regression models for the other two markets are settled in the similar way.

![Fig. 1. Jump volatility for CSI 300, SSE 50, CSI 500 index and index futures markets.](image-url)
Summary statistics of jump for six markets.

Table 1

| Market                  | N  | Mean  | Min  | Max  | Std.  | Skew  | Kurt    |
|-------------------------|----|-------|------|------|-------|-------|---------|
| CSI 300 Index           | 184| 1.757 | 0.075| 71.495| 5.697 | 10.435| 124.768 |
| CSI 300 Index Futures   | 174| 1.912 | 0.053| 61.763| 5.493 | 8.687 | 88.539  |
| SSE 50 Index            | 199| 1.454 | 0.063| 54.139| 4.300 | 10.026| 117.707 |
| SSE 50 Index Futures    | 189| 1.700 | 0.068| 57.936| 5.025 | 8.963 | 93.002  |
| CSI 500 Index           | 130| 2.257 | 0.070| 83.281| 7.594 | 9.622 | 101.718 |
| CSI 500 Index Futures   | 137| 2.597 | 0.138| 84.513| 7.742 | 9.078 | 93.963  |

3. Empirical analysis

3.1. Summary statistics

The intraday one-minute high-frequency data for CSI 300 index, SSE50 index, CSI 500 index and their corresponding index futures markets are downloaded from WIND database, which is widely used financial database in mainland China. There are four index futures traded on the March cycle, the contract ends on the third Friday of its delivery month. The time series of futures prices is formed from underlying index market. The SSE 50 Index and its futures have the largest number of jumps, 199 and 189 respectively. The CSI 500 Index Futures has higher mean value than other markets.

We use the five-minute intraday returns to calculate daily realized variance, then decompose the realized variance into continuous and jump components. The significance level of 1% is used to test jump (where equal to 0.99). Fig. 1 presents the jump volatility for the sample period is from October 16, 2017 to October 15, 2020. The index and index futures trade from 9:30 AM to 11:30 AM and from 13:00–15:00 PM. We choose five-minute frequency to avoid noise as most previous studies have done (Andersen et al., 2011; Seo and Kim, 2015). In total, the sample covers 729 trading days and contains 177,108 five-minute prices.

Table 1 provides the summary statistics of jump volatility. It can be seen that the volatility of the futures market is higher than its underlying index market. The SSE 50 Index and its futures have the largest number of jumps, 199 and 189 respectively. The CSI 500 Index and its futures have the least number of jumps, but the CSI 500 index futures has higher mean value than other markets.

In order to illustrate the synchronization of jumps, we calculate the co-jump of different markets (Lahaye et al., 2011)

$$\text{cof}_{m} = \prod_{m=1}^{M} I(J_{m}^{n}),$$

where $M$ represents the number of markets that have jumps simultaneously, $J_{m}^{n}$ refers to the significant jumps of the $m$-th market. $I(J_{m}^{n})$ is the indicator function which is equal to 1 if $J_{m}^{n} > 0$, and 0 otherwise.

Table 2 reports the number of days with co-jumps in two or more markets, which further illustrates the high correlation between jumps in the six markets. In particular, the co-jump among six markets accounts for 6.58% of all trading day.

3.2. Empirical results of VAR models

In this section, the stationary of jump sequences in different markets are first investigated by the Augmented Dickey-Fuller test method. Table 3 reveals that all market jumps are stationary series at 1% significant level.

According to the AIC criterion and the comprehensive evaluation of the model, lag period of the VAR model is selected as 4 and the corresponding regression results are reported in Table 4. For brevity, we only keep the significant explanatory variables in the obtaining results. In the stock index market, lagged jumps in the CSI 300 and SSE 50 index markets have positive impacts on other markets, which is contrary to the index futures markets. In other words, the jumps in the index market may increase the volatility of other markets, while the index futures market jumps, especially the CSI 300 index futures market, have a weaker effect. In addition, it is worth noting that the lag fourth-order of jumps in SSE 50 index futures has a positive impact on other markets. As an index of small
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and medium-sized stocks, the CSI 500 index market and its index futures market have no significant impact on other markets. Further, we carry out analysis of the causal relationship between any two markets jumps through Granger Causality test, and the obtaining results are shown in Table 5. Except for CSI 500 index and its futures market, there is bi-directional Granger Causality relationship between remaining four markets. However, jumps in the CSI 300 index futures and SSE 50 index futures market show a stronger guiding relationship for the relation stock markets and the cross-markets jumps. It can be seen that the results before and after the epidemic are significantly different. Market uncertainty increased due to the outbreak. When market volatility increases, most stock index markets leading functions become weaker. After the epidemic, the CSI 300 index futures and SSE 50 index futures market guide each other, which indicates that these two index futures markets may play an important role in risk transmission. However, there are some differences between the results of the Granger Causality test and the VAR results.

3.3. Empirical results of TOP

3.3.1. Numerical simulation and verification

In order to verify the effectiveness of the TOP method, we manually generate two time series for simulation. Firstly, the time series $x(t)$ is generated from an AR process:

$$x(t) = 0.7x(t-1) + \xi,$$  (16)

Table 2
The number of days of co-jump.

| M  | 2   | 3   | 4   | 5   | 6   |
|----|-----|-----|-----|-----|-----|
| Frequency | 8.93% | 6.31% | 6.31% | 4.53% | 6.58% |

Statistics of different numbers of markets co-jump. There are a total of 729 trading days, and the frequency are reported in bottom of table.

Table 3
ADF stationary test of jump volatility.

| Variable | Jump | log (Jump) |
|----------|------|------------|
|          | ADF Value | 1% Critical value | ADF Value | 1% Critical value |
| $J^*_s$  | -26.18 | -3.430 | ln $J^*_s$ | -24.724 | -3.430 |
| $J^*_f$  | -23.584 | -3.430 | ln $J^*_f$ | -23.584 | -3.430 |
| $J^*_s$  | -26.791 | -3.430 | ln $J^*_s$ | -25.793 | -3.430 |
| $J^*_f$  | -23.246 | -3.430 | ln $J^*_f$ | -24.873 | -3.430 |
| $J^*_s$  | -27.083 | -3.430 | ln $J^*_s$ | -25.542 | -3.430 |
| $J^*_f$  | -26.664 | -3.430 | ln $J^*_f$ | -25.542 | -3.430 |

Stationary test of jump for six markets.

Table 4
Jump volatility regressions under VAR models for six markets.

|          | $J^*_s$ | $J^*_f$ | $J^*_s$ | $J^*_f$ | $J^*_s$ | $J^*_f$ |
|----------|---------|---------|---------|---------|---------|---------|
| $\alpha_s$ | 0.556** | 0.552*** | 0.452*** | 0.586*** | 0.622** | 0.633** |
|          | (2.51)  | (2.71)  | (2.60)  | (3.04)  | (2.50)  | (2.42)  |
| $\alpha_f$ | -0.877*** | -1.318*** | -0.821*** | -1.216*** | -0.908*** | -1.167*** |
|          | (-3.08) | (-5.04) | (-3.68) | (-4.91) | (-2.85) | (-3.48) |
| $\gamma_s$ | 0.589** | 0.752*** | 0.583*** | 0.790*** | 0.605* | 0.722** |
|          | (2.08) | (2.89) | (2.62) | (3.20) | (1.90) | (2.16) |
| $\gamma_f$ | -0.426* | -0.401* | -0.458** | -0.354* | -0.375 | -0.436 |
|          | (-1.76) | (-1.80) | (-2.41) | (-1.68) | (-1.38) | (-1.53) |
| $\beta_s$ | 0.584** | 0.949*** | 0.544*** | 0.813*** | 0.638* | 0.844*** |
|          | (2.49) | (4.40) | (2.95) | (3.98) | (2.42) | (3.05) |
| $\beta_f$ | 0.364*** | 0.322*** | 0.312*** | 0.301*** | 0.319** | 0.400*** |
|          | (2.97) | (2.85) | (3.25) | (2.82) | (2.32) | (2.77) |
| $C$      | 0.036   | 0.093   | 0.050   | 0.097   | 0.033   | 0.043   |
| $R^2$    | 727     | 727     | 727     | 727     | 727     | 727     |

All regressions are estimated by OLS using Newey-West standard errors, yielding autocorrelation consistent results. Number of observations and adjusted $R^2$ are reported in the bottom of each table, and t-statistics are given in parenthesis below the estimated coefficients. ***, ** and * represent the 1%, 5% and 10% significant level, respectively.

and medium-sized stocks, the CSI 500 index market and its index futures market have no significant impact on other markets.

Further, we carry out analysis of the causal relationship between any two markets jumps through Granger Causality test, and the obtaining results are shown in Table 5. Except for CSI 500 index and its futures market, there is bi-directional Granger Causality relationship between remaining four markets. However, jumps in the CSI 300 index futures and SSE 50 index futures market show a stronger guiding relationship for the relation stock markets and the cross-markets jumps. It can be seen that the results before and after the epidemic are significantly different. Market uncertainty increased due to the outbreak. When market volatility increases, most stock index markets leading functions become weaker. After the epidemic, the CSI 300 index futures and SSE 50 index futures market guide each other, which indicates that these two index futures markets may play an important role in risk transmission. However, there are some differences between the results of the Granger Causality test and the VAR results.

3.3. Empirical results of TOP

3.3.1. Numerical simulation and verification

In order to verify the effectiveness of the TOP method, we manually generate two time series for simulation. Firstly, the time series $x(t)$ is generated from an AR process:

$$x(t) = 0.7x(t-1) + \xi,$$  (16)
where \( x(0) = 0 \) and \( \xi \sim N(0, 0.1) \).

In addition, we construct \( y(t) \) from \( x(t) \) as follows:

\[
y(t) = \begin{cases} 
0.8x(t-2) + \eta, & 2 < t \leq 100 \\
0.8x(t-4) + \eta, & 100 < t \leq 200 \\
0.8x(t+2) + \eta, & 200 < t \leq 298, 
\end{cases}
\]  

(17)

where \( \eta \sim N(0, 0.02) \).

The distance matrix between two time series is shown in Fig. 2. Due to the existence of noise, the landscape of the distance matrix is complex and it is difficult to extract the lead-lag structure directly.

The lead-lag structure of two simulated time series are divided into three parts. In the first two parts, the time series \( x(t) \) leads the time series \( y(t) \) by 2 order and 4 order, respectively. However, the lagging orders of time series \( x(t) \) reaches 2 in the last parts. The empirical evidence presented in Fig. 3 suggests that TOP method is able to accurately identify the lead-lag relationship of the three components from the complex distance matrix.

Based on the TOP method, Guo et al. (2017) study the dynamic relationship between the investor sentiment and stock market price, where sentiment lead over price only when the investor attention is high. In addition, Shao et al. (2019) research the time-dependent lead-lag relationship between the crude oil spot and futures markets, and the results show that the lead-lag relationship exists only before or after the outbreak of COVID-19.

Table 5: Granger Causality test among six markets.

| Year                  | \( J_s \)  | \( J_f \)  | \( J_s \)  | \( J_f \)  | \( J_s \)  | \( J_f \)  |
|-----------------------|----------|----------|----------|----------|----------|----------|
| Whole Sample          | \( \alpha \) | 0.100 | 0.127 | 0.046 | 0.153 | 0.183 |
|                       | \( \beta \) | 0.020 | 0.002 | 0.000 | 0.051 | 0.007 |
|                       | \( \gamma \) | 0.264 | 0.067 | – | 0.029 | 0.339 |
|                       | \( \delta \) | 0.054 | 0.000 | 0.006 | – | 0.097 | 0.018 |
|                       | \( \epsilon \) | 0.485 | 0.701 | 0.310 | 0.523 | – | 0.641 |
|                       | \( \zeta \) | 0.603 | 0.546 | 0.554 | 0.775 | 0.520 | – |

| Before outbreak of COVID-19 | \( J_s \)  | \( J_f \)  | \( J_s \)  | \( J_f \)  | \( J_s \)  | \( J_f \)  |
|-----------------------------|----------|----------|----------|----------|----------|----------|
| \( \alpha \)               | – | 0.380 | 0.593 | 0.058 | 0.014 | 0.197 |
| \( \beta \)                | 0.067 | – | 0.005 | 0.974 | 0.365 | 0.033 |
| \( \gamma \)               | 0.006 | 0.005 | – | 0.029 | 0.000 | 0.001 |
| \( \delta \)               | 0.025 | 0.108 | 0.002 | – | 0.046 | 0.026 |
| \( \epsilon \)             | 0.178 | 0.700 | 0.461 | 0.406 | – | 0.416 |
| \( \zeta \)                | 0.004 | 0.135 | 0.176 | 0.412 | 0.000 | – |

| After outbreak of COVID-19  | \( J_s \)  | \( J_f \)  | \( J_s \)  | \( J_f \)  | \( J_s \)  | \( J_f \)  |
|-----------------------------|----------|----------|----------|----------|----------|----------|
| \( \alpha \)               | – | 0.813 | 0.774 | 0.735 | 0.816 | 0.842 |
| \( \beta \)                | 0.427 | – | 0.218 | 0.029 | 0.578 | 0.367 |
| \( \gamma \)               | 0.909 | 0.563 | – | 0.542 | 0.933 | 0.823 |
| \( \delta \)               | 0.570 | 0.098 | 0.348 | – | 0.687 | 0.475 |
| \( \epsilon \)             | 0.983 | 0.974 | 0.951 | 0.955 | – | 0.954 |
| \( \zeta \)                | 0.936 | 0.810 | 0.916 | 0.863 | 0.898 | – |

Granger Causality test are adopted to analyze the relationship between different market jumps. The corresponding p-values are given in this table, where null hypothesis is that row variables do not Granger cause column variables.
temporarily. Similarly, Yang and Shao (2020) also adopt TOP method to examine the dynamic interaction patterns between the VIX and VIX futures markets, where VIX futures have been increasingly more important in the price discovery since the launch of several VIX ETPs.

3.3.2. Empirical analysis

In this section, we employ the TOP method to investigate the dynamic lead-lag structure of the six markets jumps. Fig. 4 depicts the average optimal thermal path $\hat{l}(t)$ between any two markets jumps. A positive $\hat{l}(t)$ indicates that the jump in current market leads other markets, and vice versa. The gray vertical line divides the whole sample into two parts, and the corresponding time is February 3, 2020 which is the first trading day after the end of the 2020 Lunar New Year. In China, the announcement of the COVID-19 pandemic lockdown which happened during the 2020 Chinese New Year holiday, was a significant shock for the Chinese stock market. Due to the extended Spring Festival holiday of China, the stock market was closed for a longer period than usual. For this reason, we study how the Chinese stock market reacted to the announcement of the pandemic lockdown by choosing the end of Chinese Spring Festival holiday in 2020 as the event window (Huo and Qiu, 2020). Affected by the epidemic, the CSI 300 index, SSE50 index, CSI 500 index and their index futures crashed simultaneously that day.

The empirical evidence provided in Fig. 4 suggests that the lead-lag relationship between different markets changes dynamically over time. Especially after the epidemic, the lead-lag structure among the six markets has changed significantly. Before outbreak of COVID-19, the jumps of CSI 300 index futures and SSE 50 index futures markets lead the jumps of the stock markets and the CSI 500 index futures market, the leading orders are around 2. However, the lead-lag structures change drastically after the outbreak of epidemic, the leading functions of jumps in CSI 300 index futures and SSE 50 index futures markets become much stronger with the leading order reaches about 4. In addition, the jumps of CSI 300 index and SSE 50 index guide the futures markets jumps sometimes before the outbreak of COVID-19, but they are far behind the jumps of index futures markets after the outbreak of COVID-19. A large body of literatures have confirmed that price discovery takes place in the futures market (Hasbrouck, 2003; Easley et al., 1998; Fleming et al., 1996; Stoll and Whaley, 1990). They point out that the most important point for the asymmetric lead-lag relation is because futures market is less costly for informed information, informed traders prefer to trade on the futures market, then making futures market contains more information than spot market. Futures market usually reacts new information more quickly than spot markets due to its high leverage, low trading cost and lack of short sale restriction. The SSE 50 Index selects the 50 most representative stocks with large scale and good liquidity in the Shanghai stock market, the CSI 300 Index samples contains the 300 most representative stocks in both Shanghai and Shenzhen securities markets, which cover about 60% of the total market value. Therefore, these two major markets are more important, and the information discovery function of the two futures markets is stronger than that of other markets. Investor panic is more likely to spread when bad news happens. Hence when uncertainty increases the dominant market has a bigger and longer-lasting impact on other markets.

In order to further verify the differences before and after the outbreak of epidemic obtained by the above TOP method, we carry out the regression analysis for the two subperiods, respectively. Panel A of Table 6 indicates that the lag second-order of CSI 300 index and its index futures markets jumps have significant positive spillover effects on most other markets before outbreak of COVID-19, while the lag second-order of SSE 50 index and its index futures markets jumps have negative impacts. The bi-directional lead-lag relationship is consistent with the results of TOP method. Panel B of Table 6 also shows the significant changes in lead-lag relationship after the outbreak of COVID-19. The lag forth-order of CSI 300 index futures markets jump has negative effect on other markets, while the lag forth-order of SSE 50 index futures jumps have positive impact on other markets, which are consistent with the results obtained by TOP method. Therefore, TOP method could find the time-varying lead-lag relationship between different markets jumps, which is better than traditional static analysis methods, such as Granger Causality test.

To explicitly assess the lead-lag relationship among different markets, we conduct further analysis using histogram of average TOP
Fig. 4. Lead-lag structure of different markets jump. Apply TOP method to analysis the dynamic lead-lag structure of the six markets. The location of gray vertical line dividing the whole sample into two sets is February 3, 2020 which is the first trading day after the end of the 2020 Lunar New Year. The curve above the black dotted line indicates that the current market guides other markets, and vice versa.
The jumps in different markets have mutual spillover effects, especially for the jumps in CSI 300 and SSE 50 index futures markets. The impact of jumps in these two markets for improving the volatility forecasting of other markets is significant. The above analysis reveals that the jumps in different markets have mutual interest to both academic and practitioners. The increase of jumps for some markets may lead to the corresponding increase of volatility for other markets.

3.4. Volatility forecasting by HAR-RV-J model

This part presents the cross-market jumps spillover effects for realized volatility forecasting. Since volatility forecasting is of great interest to both academic and practitioners. The increase of jumps for some markets may lead to the corresponding increase of volatilities for other markets. Our motivation for this application that we want to know whether the jumps of the dominant markets can improve the volatility forecasting of other markets. The above analysis reveals that the jumps in different markets have mutual spillover effects, especially for the jumps in CSI 300 index futures market and other three markets before and after epidemic, respectively. We can observe that there are bi-directional lead-lag relationships between CSI 300 index futures jump and other three markets jumps before the epidemic. The leading effect of CSI 300 index futures jump is stronger due to the fact that the histogram is centered on the right of zero. The similar results can be seen from Fig. 5.

Table 6
Jump volatility regressions under VAR models for six markets.

|        | \( \hat{\alpha}_f \) | \( \hat{\beta}_s \) | \( \hat{\gamma}_f \) | \( R^2 \) |
|--------|-----------------|-----------------|-----------------|--------|
| Panel A: Jump volatility regressions before outbreak of COVID-19 |
| \( \hat{\alpha}_f \) | 0.568** | 0.483** | 0.341 | 0.554*** |
| \( \hat{\beta}_s \) | 0.344** | 0.393*** | 0.437*** | 0.007 |
| \( \hat{\gamma}_f \) | -0.513*** | -0.686*** | -0.364*** | 0.007 |
| \( \hat{r}_2 \) | (2.34) | (2.34) | (2.34) | (2.34) |
| \( \hat{t}_2 \) | (2.96) | (3.84) | (2.18) | (2.18) |
| \( \hat{z}_2 \) | (3.24) | (1.96) | (3.99) | (3.99) |
| \( \hat{a}_2 \) | -0.213* | -0.079 | -0.135 | -0.135 |
| \( \hat{b}_2 \) | 0.117 | 0.056 | 0.085 | 0.085 |
| \( \hat{c}_2 \) | (1.47) | (0.68) | (1.11) | (1.11) |
| \( \hat{d}_2 \) | 0.279*** | 0.309*** | 0.281*** | 0.281*** |
| \( \hat{e}_2 \) | 0.352**** | 0.352**** | 0.352**** | 0.352**** |
| \( \hat{f}_2 \) | 0.562 | 0.562 | 0.562 | 0.562 |
| \( \hat{g}_2 \) | 0.701 | 0.701 | 0.701 | 0.701 |
| \( \hat{r}_2 \) | 0.071 | 0.063 | 0.063 | 0.063 |
| \( \hat{t}_2 \) | 0.062 | 0.163 | 0.086 | 0.086 |
| \( \hat{z}_2 \) | 0.175 | 0.175 | 0.175 | 0.175 |
| \( \hat{a}_2 \) | 0.054 | 0.054 | 0.054 | 0.054 |
| \( \hat{b}_2 \) | 0.061 | 0.061 | 0.061 | 0.061 |
| \( \hat{c}_2 \) | 0.069 | 0.069 | 0.069 | 0.069 |
| \( \hat{d}_2 \) | 0.076 | 0.076 | 0.076 | 0.076 |

All regressions are estimated by OLS using Newey-West standard errors, yielding autocorrelation consistent results. The sample before the epidemic is from October 16, 2017 to February 3, 2020 and the sample after the epidemic is from February 3, 2020 to October 15, 2020. Number of observations N and adjusted R² are reported in the bottom of each panel, and t-statistics are given in parenthesis below the estimated coefficients. ***, ** and * represent the 1%, 5% and 10% significant level, respectively.
Fig. 5. Histogram of average $\hat{\text{TOP}}(t)$. Except for CSI 500 index market and its futures market, the remaining four markets are taken into consideration. The upper and third panels are the average TOP between CSI 300 index futures market and other three markets (CSI 300 index, SEE 50 index and SEE 50 index futures) before and after the epidemic, respectively. The second and lower panels are related to the average TOP between SSE 50 index futures market and other three markets before and after epidemic, respectively.
Table 7

Logarithm realized volatility regressions under HAR models for six markets (Whole sample).

|                | CSI 300 Index | CGI 300 Index Futures | SSE 50 Index | SSE 50 Index Futures | CSI 500 Index | CSI 500 Index Futures |
|----------------|---------------|-----------------------|--------------|----------------------|---------------|-----------------------|
|                | HAR-RV        | HAR-RV-J              | HAR-RV       | HAR-RV-J             | HAR-RV        | HAR-RV-J              |
|                | (5.89)        | (5.40)                | (5.58)       | (5.58)               | (7.94)        | (7.94)                |
|                | (1.19)        | (1.19)                | (0.91)       | (0.91)               | (1.75)        | (1.75)                |
|                | (2.60)        | (2.60)                | (2.61)       | (2.61)               | (1.99)        | (1.99)                |
|                | (3.01)        | (3.01)                | (2.81)       | (2.81)               | (3.01)        | (3.01)                |
|                | (2.67)        | (2.67)                | (2.67)       | (2.67)               | (2.67)        | (2.67)                |
|                | (1.16)        | (1.16)                | (1.16)       | (1.16)               | (1.16)        | (1.16)                |
|                | (1.58)        | (1.58)                | (1.58)       | (1.58)               | (1.58)        | (1.58)                |
|                | (1.80)        | (1.80)                | (1.80)       | (1.80)               | (1.80)        | (1.80)                |
|                | (1.45)        | (1.45)                | (1.45)       | (1.45)               | (1.45)        | (1.45)                |
|                | (1.23)        | (1.23)                | (1.23)       | (1.23)               | (1.23)        | (1.23)                |
|                | (2.95)        | (2.95)                | (2.95)       | (2.95)               | (2.95)        | (2.95)                |
|                | (2.84)        | (2.84)                | (2.84)       | (2.84)               | (2.84)        | (2.84)                |

Logarithm realized volatility regressions under HAR models for six markets. The constant coefficients logarithm realized volatility regressions for six markets. In each panel, Number of observations and adjusted $R^2$ are reported in the bottom of each table, and t-statistics are given in parenthesis below the estimated coefficients. ***, ** and * represent the 1%, 5% and 10% significant level, respectively.
Table 8
Logarithm realized volatility regressions under HAR models for six markets for subsample.

| Panel A Before outbreak of COVID-19 | CSI 300 Index | CSI 300 Index Futures | SSE 50 Index | SSE 50 Index Futures | CSI 500 Index | CSI 500 Index Futures |
|-----------------------------------|----------------|----------------------|------------|---------------------|--------------|----------------------|
| Panel A Before outbreak of COVID-19 |                |                      |            |                     |              |                      |
| H(t)                             | 0.166***       | 0.300***             | 0.190***   | 0.295***            | 0.124***     | 0.226***            |
| H(t)                             | (3.98)         | (4.46)               | (3.80)     | (4.73)              | (2.33)       | (3.42)              |
| λ(t)                             | 0.432***       | 0.461***             | 0.346***   | 0.424***            | 0.498***     | 0.552***            |
| λ(t)                             | (5.47)         | (4.98)               | (4.23)     | (4.50)              | (5.06)       | (5.81)              |
| α(t)                             | 0.133*         | 0.096                 | 0.183***   | 0.131***            | 0.119        | 0.084               |
| α(t)                             | (1.79)         | (1.32)                | (2.32)     | (1.68)              | (1.51)       | (1.10)              |
| λ(t)                             | -0.430***      | -0.343***            | -0.557***  | -0.062              | -0.304**     | -0.324**            |
| λ(t)                             | (-2.32)        | (-2.99)               | (-3.97)    | (-0.47)             | (-2.29)      | (-2.30)             |
| α(t)                             | -0.333**       | -0.332**             | -0.359**   | -0.088              | -0.405***    | -0.284**            |
| α(t)                             | (-2.43)        | (-2.34)               | (-2.58)    | (-2.78)             | (-2.78)      | (-1.92)             |
| λ(t)                             | 0.330***       | 0.464***             | 0.303**    | 0.239               | 0.400***     | 0.386***            |
| λ(t)                             | (2.40)         | (3.25)                | (2.17)     | (1.63)              | (2.92)       | (2.96)              |
| C                                | -0.113***      | -0.065*              | -0.109***  | -0.019              | -0.094***    | -0.019             |
| C                                | (-3.64)        | (1.13)                | (-1.84)    | (1.06)              | (-2.67)      | (0.46)              |
| R²                               | 0.390          | 0.290                 | 0.350      | 0.314               | 0.367        | 0.356               |
| R²                               | 0.334          | 0.428                 | 0.363      | 0.441               | 0.364        | 0.453               |

Observations and adjusted $R^2$ are reported in the bottom of each table, and $t$-statistics are given in parenthesis below the estimated coefficients. ***, ** and * represent the 1%, 5% and 10% significant level, respectively.
4. Conclusions

Price jumps play an important role in the financial market. A lot of literatures have investigated the effect of single market jumps, however, few works focus on the cross-market dynamic relationship of different markets jumps. This article studies the time-varying lead-lag relationship between the jumps of SSE 50 index, the CSI 300 index and the CSI 500 index markets and their corresponding stock index futures markets jumps by means of the TOP meth.

The empirical results show that the relation before and after the outbreak of COVID-19 has changed significantly, which is consistent with the regression results of VAR model. The lag second-order of CSI 300 index and its index futures markets jumps have a significant positive spillover effect on most other markets before outbreak of COVID-19, while the lag second-order of SSE 50 index and its index futures markets jumps have negative impact on other markets. The lead-lag structure has changed significantly after the outbreak of COVID-19. The jumps of CSI 300 index futures and SSE 50 index futures dominate the markets. The lag forth-order of CSI 300 index futures jumps has negative effect on other markets, while the lag forth-order of SSE 50 index futures jumps has positive impact on other markets.

Finally, we study the impact of two dominant index markets jumps on volatility. The main impact of jumps in CSI 300 index futures market is negative, which is opposite to SSE 50 index futures market jumps. The performance of extended HAR-RV-J model has improved compared to the standard HAR-RV model.

CRediT authorship contribution statement

Wenwen Liu: Organization, Writing – review & editing. Yiming Gui: Conceptualization, Writing – review & editing. Gaoxiu Qiao: Writing – review & editing.

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