Information Sciences Letters
An International Journal

http://dx.doi.org/10.18576/isl/120752

Multiscale Spillover Transmission in China's Investment Preferences Using Dynamic Stochastic Volatility Framework

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Received: 21 Feb. 2023, Revised: 22 Mar. 2023, Accepted: 24 Mar. 2023.
Published online: 1 Jul. 2023.

Abstract: This paper aims to understand how volatility spreads in the financial system and affects security markets and financial crises. The researchers introduced a new approach using a multivariate stochastic volatility model with dynamic correlation and maximum overlap discrete wavelet. The approach can distinguish investment types and describe nonlinear volatility dynamics. Empirical analysis showed significant volatility spillovers between financial time series at different wavelet scales. Short-term investments had higher volatility spillovers than long-term investments, suggesting an interactive relationship between retail investors and long-term institutions and a shift from technology operations to value simulation.

Keywords: Volatility spillovers; Investment preference; Wavelet; Dynamic correlation; Value simulation.

1 Introduction

Volatility spillovers, which widely present in financial markets such as stocks and futures, mean that the fluctuation of financial market prices could be transmitted between different investment preferences [1,2]. Investors trading in the stock market could be generally separated into two categories: one is of short-term preference, mainly retail investors; the other is of long-term preference, mainly institutions [3,4]. According to the actual situation of China's stock market, there is a trend of polarization between retail investors and institutions gradually over the past decades. In terms of trading volume, retail investors account for nearly 90% of domestic trading volume, while investment institutions account for only about 10% [5–7]. While from the perspective of financial assets, the capitalization held by retail investors is further less than that of investment institutions, only reaching about 25% of the total. It supports that institutions still occupy the dominant position of investors in China’s stock market at present [8]. Nevertheless, if many retail investors prefer short-term investment trade frequently and intensively, it might lead to large fluctuations of market prices in a short period of time, and eventually affects the long-term investment of institutions through volatility spillovers [9,10]. The institutions with sufficient capital and information resources prefer long-term investment and their strategies are relatively stable in general, which would mainly affect the long-term trend of the stock market and guide retail investors preferring short-term trading towards effective value simulation [11,12]. Consequently, the volatility spillovers between various investment preferences would have a significant impact on the whole financial market [13–15]. Most of the existing studies focus on the interaction of stock returns between different markets or the correlation of different financial products [16,17], while few scholars explore the volatility spillovers between different investment preferences of the same stock returns in the same market [18].

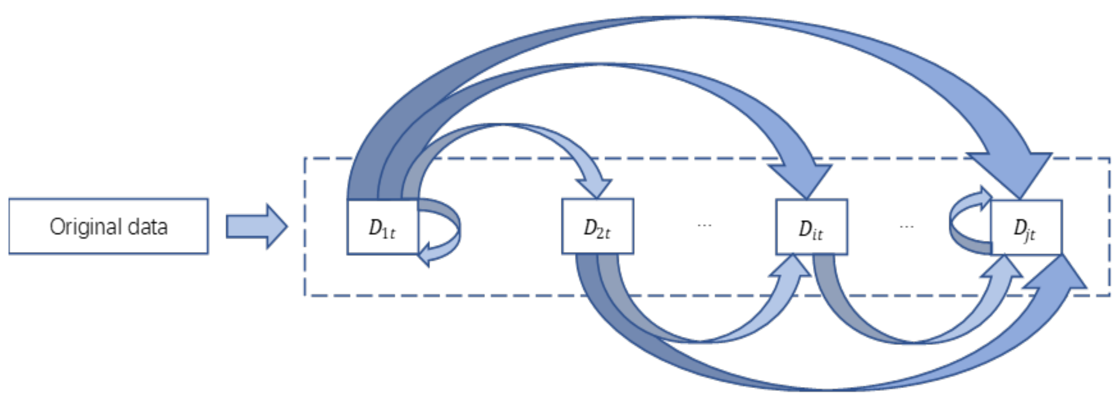

Fig. 1: Volatility Spillovers of different wavelet scales (investment preferences) in the same market.

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Fig. 1 shows that the introduction of wavelet breaks this limitation [19]. Compared with traditional methods, wavelet multiresolution analysis extracts the detail coefficients at different scales even better, which are not easy to be observed in the financial time series and has a strong ability to capture the multiscale features of mean and volatility spillovers of the complex market characteristics from both time and frequency dimensions in particular [20,21]. Therefore, different wavelet scales in the same market correspond to different investment preferences, and further correspond to different types of investors. A new approach is proposed based on the existing literature that we investigate the volatility spillovers of different wavelet scales in the same market to reflect the dynamic correlation between retail investors and institutions comprehensively in both time and frequency domains.

As the investment preferences affect stock markets, the relationship between multiple investment portfolios corresponding to investment preferences has attracted the attention of several economists over the past decade. They focus on the risk measurement and management of financial assets and operate the combination of stocks and futures for hedging [22–24]. Numerous studies have confirmed that short-term investments are mainly composed of speculative individual investments, which happen to be the primary factors causing stock price turbulence [25,26].

In the past years, several scholars have extensively conducted research on volatility spillovers and risk hedging in the financial market, especially in the stock market. Dutt (2013) confirms that low volatility stocks with higher operating profits generally earn higher returns than high volatility stocks in emerging markets and developed markets outside of North America, and highlights the connection between price volatility, operating performance, and stock returns [27]. Weng (2018) investigates how the information platforms providing insights pertaining to firms' financial performance capture the collective interest of traders through search trends, etc., and develops a financial expert system which incorporates investment preferences to predict short-term stock prices [28]. Alfreedi (2019) employs a multivariate volatility model to examine the spillover of returns in the stock markets of developed countries and evidence shows the volatility of returns results in conditional variance-covariance, indicating that spillover (return, shock and volatility) affects the stock market [29].

Although these results are important for both stock investment and financial supervision, few scholars have quantitatively analyzed the volatility spillovers between different investment preferences in the same market. Macroscopic regulating and controlling of China's stock market have been gradually improved in recent years, which provides more options, might cause volatility spillovers between different investments. For instance, the Shanghai-Hong Kong Stock Connect program and Shenzhen-Hong Kong Stock Connect program were implemented in 2014 and 2016 respectively, and further improve the openness of China's stock market, contributing to investment preference diversification. Sci-Tech innovation board (STAR Market) piloted in 2018 serves as a major reform of capital market which enhances the ability of service technology, enterprises innovation and market function. Likewise, it reflects the government's guidance on market balance and investment option. In 2019, the China Administration of Foreign Exchange announced the cancellation of the QFII quota, indicating that the Chinese stock market has further increased its globalization and continues to attract foreign investment into the financial market. China's stock market becomes mature gradually and the great charm of capital market has attracted a steady stream of investors [30]. Consequently, we can infer that the volatility spillovers between different investment preferences in China's stock market may also be stronger and it is necessary to pay more attention to the volatility spillovers across various investment terms in the same market [31].

In the context of China's stock market, this paper assesses whether the sensitive interaction between short-term investment of retail investors and long-term investment of institutions restricts each other in development. Different time scales correspond to investors of different investment preferences in China's stock market, and the volatility spillovers between different investment preferences have been studied intensively. The sample consists of Shanghai (Securities) Composite Index’s daily data from January 2010 to March 2020. The Shanghai Composite Index, which takes the calculation of all the listed stocks on the Shanghai Stock Exchange, contains several complete cycles and is the representative of China's stock market. We integrate multivariate stochastic volatility (MSV) model and maximum overlapping discrete wavelet and propose a new approach, wavelet-based DGC-t-MSV model, to study the volatility spillovers between retail investors of short-term investment and institutions of long-term investment in the same market. Wavelet transform is employed to decompose the original data of the Shanghai Composite Index into different scales and extract the detail (wavelet) coefficients of high-frequency signals to describe investment preferences, which reflect the mean and volatility spillovers between retail investors and institutions. The research findings can not only effectively assist in assessing market trends, but also provide objective references for investors to develop investment strategies and serve as a theoretical basis for financial regulation.

We contribute to providing new insights to investigate the multiscale features of volatility spillovers between different preferences composed of short-term investment and long-term investment in China’s stock market based on wavelet multiresolution analysis. In fact, the various ideas and judgments of stock investors lead to different investment terms and frequency domains. It is obvious that the research in single time dimension cannot reflect the correlation between financial series with the characteristics of time and frequency domains. Wavelet multiresolution analysis is used to distinguish different types of investors with different investment preferences, which extends the current studies evaluating the volatility spillovers in stock market and conducting the comprehensive analysis of financial series in time and frequency domains. This study explores the volatility spillovers between different investment preferences, and this is the first time, to the best of our knowledge, to address the issue directly, which is of critical importance as such volatility spillovers might affect stock market stability. In particular, the existence of volatility spillovers between stock returns of short-term and long-term investment is investigated to evaluate the potential transmission, which breaks through the limitation of the existing literature.

We also contribute to quantitatively assessing the volatility spillovers by examining the direction and intensity of which between short-term investment of retail investors and long-term investment of institutions through Granger causality. According to the analysis of different wavelet scales of stock returns, which represents investment preferences, this paper studies the volatility spillovers of retail investors and institutions, and quantifies the link between different types of investors, especially the interaction between retail investors and institutions. The comparison of estimation results reflects that volatility-related parameters vary within a certain range, and the responses of short-term investment volatility to a shock in the volatility of long-term investment are significant, meanwhile, a standard positive shock in the volatility of long-term investment has a positive impact on the volatility of short-term investment. These empirical results are robust for the research on alternative models of volatility transmission.

This paper provides detailed empirical evidence of the mechanism that investment institutions affect retail investors and makes reasonable suggestions for China's management of the stock market. We emphasize that investment institutions play a potential role as a stable driving factor for the overall stock market through the study of the volatility spillovers between long-term investment and short-term investment. Venture capital institutions funded by government are of great significance in guiding retail investors to transform from technology investment focusing on the single fluctuations of stock prices to the value simulation estimating enterprise capitalization. At the same time, we consider that institutional investment might encourage retail investors preferring short-term investment to invest in projects with high valuation by sharing the risks of retail investors to improve the efficiency of social investment and maintain the stability of stock prices.

The rest of the paper is structured as follows: Section 2 presents a brief review of the previous literature. Section 3 describes the data and outlines the framework of empirical research. Section 4 discusses the estimation results. Section 5 provides the concluding remark.

2 Literature Review

As the transmission of information between different financial markets, the volatility spillovers represent a significant concern within the field of financial economics [32]. It connects spillovers with risks transferred from various markets, which has significant implications for option pricing, asset allocation, and risk management [20,33,34]. Previously, some studies has analyzed different aspects of this relationship between markets. Diebold, FX (2009) finds that volatility spillovers display obvious bursts associated with financial crisis because of the gradually increasing financial integration of the last fifteen years, which could contribute to the larger risks caused by the financial crisis [35]. Nishimura (2018) suggests that volatility spillovers intensify as the openness of the stock market gradually increases, which are mainly caused by stock investors' transactions between different international markets, it means the spillover effects are more significant in accessible markets than in inaccessible markets [36]. Liu (2020) notes that most of the volatility spillovers are generated in the long-term trading and are sensitive to extreme financial events, which explains the further transmission of the financial crisis from the directional spillover effects [37]. Some researchers indicate that spillovers were particularly high during the Covid-19 and Russia-Ukraine wars as health and geopolitical risks considerably impact the return and volatility system [33,38,39]. Most of the existing literature documents the existence of spillover effects between financial markets, while we focus on the stock market itself, especially the volatility spillovers between different investment preferences based on different wavelet scales and emphasize the important role that institutions preferring long-term investment might play in maintaining the stability of the stock market.

In terms of methods, some previous studies adopt observational-driven models that extend the widely-used univariate GARCH-type formulations [40–42]. Liu (2017) investigates the evolution of volatility spillovers especially in the context of the financial crisis by employing BEKK-GARCH model and demonstrates there are contagions between stock markets in the global financial crisis period according to an intensification of volatility spillovers observed among different sectors [43]. Some researchers further conduct the studies based on a bivariate VAR-BEKK-GARCH model that the volatility linkages affect both markets directly and indirectly through spillovers, the results of which are of vital importance for policymakers and investors as well [38,44]. However, the improvement of GARCH model has not fundamentally solved the problem of the structure itself, especially the limitations of random error determined completely in GARCH models.

Multivariate stochastic volatility (MSV) model, therefore, is widely employed by increasing lines of research to analyze the dynamics of volatility in financial markets, which defines the random error term of a sequence as its own stochastic process [45–47]. Asai (2006) summarizes the evolution of MSV models with various categories and recommends Markov chain Monte Carlo (MCMC) methods, which are widely employed in substantial literature compared with alternative methods of estimation, based on the results of diagnostic checking [48]. Tian (2016) investigates the mechanism of financial spillovers between four US markets using SVAR-MSV model, and finds volatility spillovers have the characteristics of time delay and the dynamics of that vary tremendously with time [49]. Wu (2020) conducts the study to examine the transmission of volatility spillovers between main sectors including stocks and exchange rates using DGC-MSV model [50]. They demonstrate there is a persistence of dynamic correlation among the CER futures prices and other factors which could not be characterized through GARCH models.

This paper employs the research framework of MSV model. To explore the volatility spillovers between different investment preferences in stock market, however, we also need to decompose the original high-frequency data based on wavelet analysis. Rua (2009) assesses the spillovers among international stock markets at sectoral level by resorting to wavelet analysis, which means decomposition of the financial data, to measure the comovement in both time and frequency domains simultaneously and supports the existence of the volatility spillovers of stock returns in different wavelet scales [51]. Liu (2017) indicates that the features of spillover effects vary frequently across wavelet scales in terms of strength and direction during different periods, and the obvious interaction of which is demonstrated at multiple scales, which means that spillover spillovers could spread from one scale to another in frequency dimension [43]. The wavelet analysis is important in exploring the multiscale volatility spillovers of financial data, therefore, we integrate multivariate stochastic volatility (MSV) model and maximum overlapping discrete wavelet and propose a new approach, wavelet-based DGC-t-MSV model, to study the volatility spillovers between retail investors of short-term investment and institutions of long-term investment in the same market.

Due to the frequent occurrence of bull and bear stock markets in China during the past decade, the volatility spillovers of the Shanghai Composite Index's different wavelet scales get more obvious. Therefore, it is of great significance to study the correlation between long-term investment of institutions and short-term investment of retail investors. In fact, the volatility spillovers between retail investors preferring short-term investment and institutions preferring long-term investment in China's stock market have not been studied before. The present work contributes to extending the current studies evaluating the volatility spillovers of the same stock returns in the same market and conducting the comprehensive analysis of financial series in time and frequency domains. In addition, it is the first time that the correlation dynamics and volatility spillovers of different investment preferences in the same market, reflected from extracted coefficients, are analyzed through a multivariate DGC-t-MSV model in this context.

3 Methodology and data

In this study, we combine the DGC-t-MSV model with wavelet multiresolution analysis to capture the volatility spillovers between retail investors of short-term investment and institutions of long-term investment [52]. It allows us to characterize the feature of the mean and volatility transfer as well as the dynamic correlation between the two series [53,54].

3.1 Wavelet decomposition of the original series

Maximum overlap discrete wavelet (MODWT) proposed by Percival and Walden in 2000 is a highly redundant nonorthogonal transform compared with discrete wavelet (DWT), which has the following advantages: (1) Any number of samples can be analyzed; (2) No special provision for the starting point of data selection; (3) The amount of data in each scale after decomposition is constant; (4) It has translation invariance; (5) The wavelet coefficients are time-varying; (6) Decompose more information of low-frequency part by improving resolution. Therefore, this paper selects MODWT to process the sequence data of Shanghai Complex Index.

Let $\{\tilde{h}_l\}$ be the transform filter of MODWT and $\{\tilde{g}_l\}$ be the scale filter of MODWT. Equations (1) - (3) describe the properties of the filters above.

$$\sum_{l=0}^{L-1} \tilde{h}_l = 0, \sum_{l=0}^{L-1} \tilde{h}_l^2 = \frac{1}{2}, \sum_{l=0}^{L-1} \tilde{h}_l \tilde{h}_{l+2n} = 0 \tag{1}$$

$$\sum_{l=0}^{L-1} \tilde{g}_l = 1, \sum_{l=0}^{L-1} \tilde{g}_l^2 = \frac{1}{2}, \sum_{l=-\infty}^{\infty} \tilde{g}_l \tilde{g}_{l+2n} = 0 \tag{2}$$

$$\sum_{l=-\infty}^{\infty} \tilde{g}_l \tilde{h}_{l+2n} = 0 \tag{3}$$

$X = \{X_t; t = 0, \dots, N-1\}$ is the original time series data, $\widetilde{W}_{1,t}$ and $\tilde{V}_{1,t}$ respectively represent the detail (wavelet) coefficients and scaling coefficients of the maximum discrete overlapped wavelet transform at 1^{th} decomposition, which can be defined as follows:

$$\widetilde{W}_{1,t} = \sum_{l=0}^{L-1} \tilde{h}_{1,l} X_{t-l \bmod N}\,,\ \tilde{V}_{1,t} = \sum_{l=0}^{L-1} \tilde{g}_{1,l} X_{t-l \bmod N}, t = 0, \dots, N-1 \tag{4}$$

More generally, the wavelet coefficients and scale coefficients of the MODWT transform at j^{th} decomposition are given by:

$$\widetilde{W}_{j,t} == \sum_{l=0}^{L-1} \tilde{h}_{j,l} X_{t-l \bmod N}, \tilde{V}_{j,t} = \sum_{l=0}^{L-1} \tilde{g}_{j,l} X_{t-l \bmod N}, t = 0, \dots, N-1 \tag{5}$$

The wavelet filters and the scale filters of MODWT are $\tilde{h}_{j,l} = \frac{h_{j,l}}{2^{\frac{j}{2}}}$ and $\tilde{g}_{j,l} = \frac{g_{j,l}}{2^{\frac{j}{2}}}$, and the width can be expressed as:

$L_j = (2^j - 1)(L-1) + 1.$

The decomposition equations of MODWT transform can be defined as:

$$\|X\|^2 = \sum_{j=1}^{J_0} \left\|\widetilde{W}_j\right\|^2 + \left\|\tilde{V}_{J_0}\right\|^2, X = \sum_{j=1}^{J_0} \widetilde{D}_j + \tilde{S}_{J_0} \tag{6}$$

$\tilde{d}_j = \widetilde{w}_j{}'\widetilde{W}_j$ $(j = 1,2,\dots,J)$ are detail coefficients and $\tilde{s}_J = \tilde{v}_J{}'\tilde{V}_J$ are scale coefficients at j^{th} decomposition. According to the previous literature, the MODWT decomposition must reach the requirements: $J < log_2(\frac{N}{L-1} + 1)$, where L represents the width of the filters. With the frequency range $\left[\frac{1}{2^{j+1}}, \frac{1}{2^j}\right]$ of the filters, the corresponding transaction cycle can be matched to the time scale. This study takes the daily returns of Shanghai Composite Index; therefore, the time interval of the sequence is one day.

As for the selection of wavelet functions, we employ Symlet wavelet with the width of eight which is the improved version of Daubechies wavelet, according to the method of Dajcman (2013) [55]. Symlet wavelet is nearly symmetric, tightly supported, regular and smooth, and has the better performance of noise reduction, which is one of the best tools for orthogonal wavelet decomposition and reconstruction of financial time series with limited length.

3.2 Multivariate model of volatility: DGC-t-MSV

To explore the volatility spillovers between retail investors and institutions with different investment preferences, we use a Dynamic Granger Causality Multivariate Stochastic Volatility model based on the student's T distribution (DGC-t-MSV) in this research, as proposed by Yu (2006) [56]. The version of the DGC-t-MSV model is defined as follows:

$$y_t = diag(exp(\tfrac{h_t}{2}))\varepsilon_t \tag{7}$$

$$h_t = \mu + \Phi(h_{t-1} - \mu) + \eta_t, \eta_t \overset{i.i.d}{\sim} N(0, diag(\sigma_{\eta_1}^2, \sigma_{\eta_2}^2)) \tag{8}$$

$$q_t = \psi_0 + \psi(q_{t-1} - \psi_0) + \tau z_t, z_t \overset{i.i.d}{\sim} N(0,1) \tag{9}$$

$y_t = (y_{1t}, y_{2t})'$ is a (2x1) vector of returns for short-term returns and long-term returns of Shanghai Complex Index at time t. $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ is a (2x1) vector of random error terms such as $\varepsilon_t \overset{i.i.d}{\sim} t(0, \sum_{\varepsilon,t}, \upsilon)$, and $\Sigma_{\varepsilon,t}$ is a (2x2) time-vary correlation matrix describing the dynamic mean spillovers, where $\sum_{\varepsilon,t} = \begin{vmatrix} 1 & \rho_t \\ \rho_t & 1 \end{vmatrix}$.

$h_t = (h_{1t}, h_{2t})'$ be the (2x1) vector obtained by the logarithmic series of y_t at time t, for which $h_0 = \mu$. $\Phi = \begin{pmatrix} \varphi_{11} & \varphi_{12} \\ \varphi_{21} & \varphi_{22} \end{pmatrix}$ contains the parameters of volatility persistence and spillovers.

The coefficient ρ_t of time-varying correlation, for which $\rho_t = \frac{exp(q_t)-1}{exp(q_t)+1}$, is given by q_t. ψ represents the persistence parameter of dynamic correlation, and $q_0 = \psi_0$. The duration of correlation between different scales lasts longer when ψ approaches 1.

The volatility is transmitted across the different scales in the equations above. The parameters of Granger causality, φ_{12} and φ_{21}, account for the volatility spillovers between different wavelet scales of Shanghai Composite Index respectively, more specifically, from short term to long term and the other way round. φ_{11} and φ_{22} measure the impact of volatility persistence from the past volatility to the current series in the same wavelet scales.

We use the MCMC method with Gibbs sampling to estimate all the parameters [57]. The stationary distribution of Markov chain composed of parameter posterior distribution is obtained by the assignment of parameter prior distribution, and the sampling iteration is repeated before all the parameters reach the stationary state. Consequently, the DGC-t-MSV model combined with MODWT allows to capture the volatility spillovers between a series of different investment terms according to wavelet multiresolution analysis and take the persistence of volatility into account.

3.3 Convergence check and Granger causality

The convergence of MSV model family is mainly reflected in Gelman-Rubin statistic, which is defined:

$$\hat{R} = \frac{\hat{V}}{WSS} = \frac{T'-1}{T'} + \frac{\frac{BSS}{T'}}{WSS} * \frac{k+1}{k} \tag{10}$$

with: $\hat{R}$ is the regression value and approach to 1 when the sample iterations are sufficient, $\hat{V}$ is the total posterior variance of sample data and k is the number of Markov chains.

The coefficient significance of Granger causality is used to determine whether the sample series of different wavelet scales have volatility spillovers. The t statistic equation is:

$$t = \frac{\varphi_{ij}}{S_{\hat{\varphi}_{ij}}},\ S_{\hat{\varphi}_{ij}} = \sqrt{var\left(\frac{\sum_{i=m+1}^{n}\varphi_{ij}}{n-m}\right)}\ \ (i \neq j) \tag{11}$$

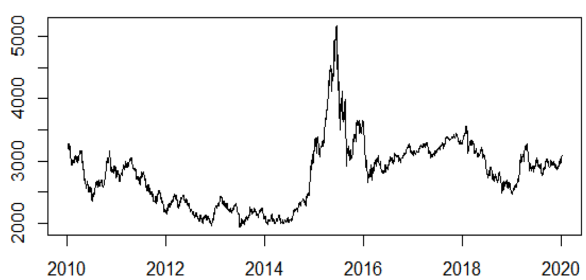
Where φ_{ij} is the parameter of volatility spillovers and the estimation of which is $\hat{\varphi}_{ij}$, $S_{\hat{\varphi}_{ij}} \sim \chi^2(n)$ is the standard deviation.

The comparison between t statistic and critical value determines whether the volatility spillover is significant.

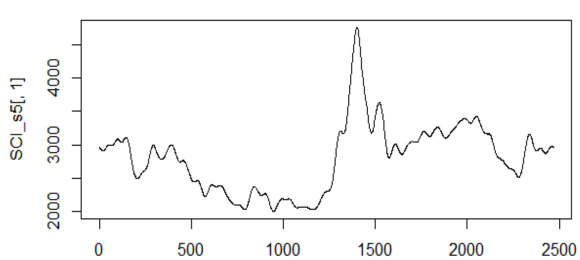
3.4 Data

Our data set used in this study consists of the Shanghai Complex Index’s daily returns of different wavelet scales over the period from January 4, 2010, to March 2, 2020, with 2468 observations. It is essential that the period covers representative economic events, including the Global Financial Crisis, the Sino-US trade disputes, and the improvement of China's stock market such as Shanghai-Hong Kong Stock Connect program, Sci-Tech innovation board (STAR Market) and the cancellation of the QFII quota, which have a significant influence on the volatility spillovers between different investment preferences of retail investors and institutions. The selected sample data of Shanghai Composite Index is decomposed into five scales by using the Sym8 wavelet, and the constraint conditions $5 < log_2(\frac{2468}{5} + 1) = 8.9501$ are satisfied.

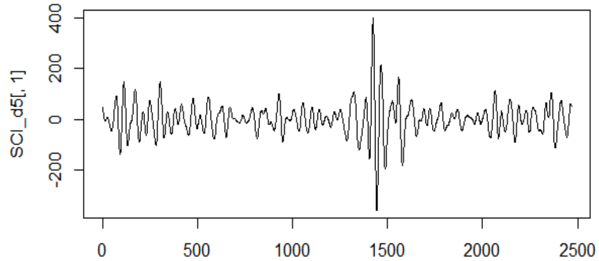
Original Data



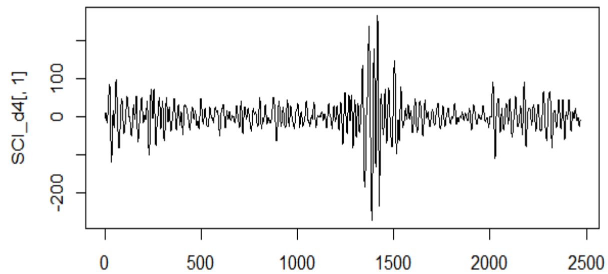
S5 Low-frequency Decomposition



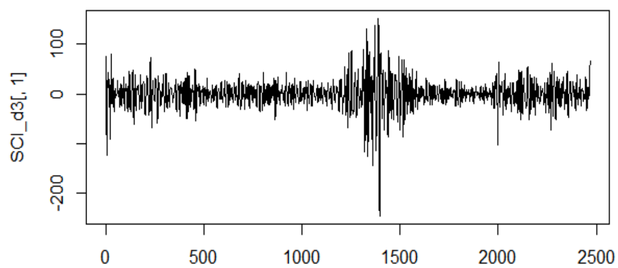
D5 High-frequency Decomposition



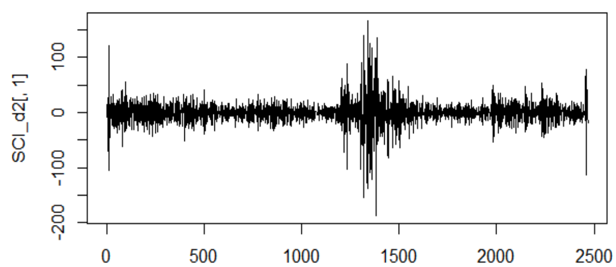
D4 High-frequency Decomposition



D3 High-frequency Decomposition



D2 High-frequency Decomposition



D1 High-frequency Decomposition

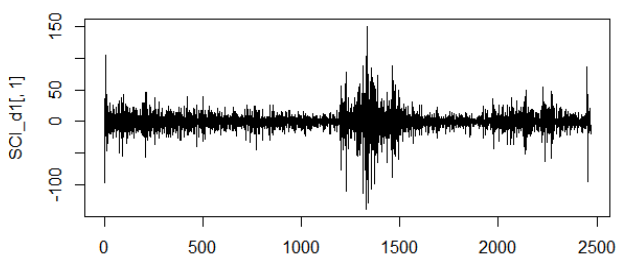


Fig. 2: MODWT decompositions of Shanghai Complex Index's daily returns.

Source: Author's calculations.

Fig. 2 illustrates the MODWT decompositions of the Shanghai Composite Index's daily returns. The original data sourced from Wind data allows us to measure the skewness and the extra excess kurtosis. S5 is the low-frequency scaling coefficient at 5^{th} decomposition, it demonstrates that China's stock has a slowdown during the period from 2010 to 2014 and a rapid growth after the third quarter of 2015, mainly caused by the cuts in interest rates as well as the increase in valuation of Hong Kong shares. After 2016, the stock price is relatively stable according to S5 low-frequency scaling coefficients. D1 to D5 scales represent high-frequency detail (wavelet) coefficients from 1^{th} to 5^{th} decompositions respectively and correspond to short-term investment of 2^1 days around as well as long-term investment of 2^5 days (more than a month). Compared to different high-frequency decompositions, the volatility is mainly concentrated in D1 scale and weakens gradually with the increase of decomposition level.

Table 1: Descriptive statistics of different wavelet decompositions.

Wavelet level	**Time**	**Mean.10^{-9}**	**Std.Dev**	**Skew.**	**Kurt.**	**J-B Prob.**	**Q (15)**	**ADF**
D1	2^1	-4.22	17.3149	0.0184	11.6862	0.000***	1084.6***	-82.953***
D2	2^2	-4.21	21.1135	0.0898	15.6914	0.000***	2439.2***	-30.008***
D3	2^3	-4.26	27.2369	0.2090	10.5019	0.000***	5945.2***	-14.267***
D4	2^4	-4.07	40.2582	-0.1609	11.4582	0.000***	12527.0***	7.116***
D5	2^5	-4.26	61.9652	-0.1598	11.3739	0.000***	13447.0***	-3.974***

Note: This table reports the descriptive statistics of different wavelet decompositions of Shanghai Complex Index's daily returns, including mean (Mean.10^{-9}), standard deviations (Std.Dev), skewness (Skew.), and kurtosis (Kurt.). J-B Prob. are the p-values of the Jarque-Bera test based on skewness and excess kurtosis. Q (15) are the empirical statistics of the Ljung-Box tests for autocorrelations of order 15 applied to data. ADF (Augmented Dickey and Fuller) are the unit root tests. $***$ indicate the rejection of the null hypothesis of associated statistical tests at the 1% level.

The dataset used in this study consists of wavelet coefficients from D1 to D5 scale. Table 1 reports the descriptive statistics of the MODWT decompositions of the sample data (Shanghai Complex Index's daily returns). The mean and standard deviations are reported below. The skewness statistics suggest that all the wavelet decomposition series tend to be skewed right except for D4 and D5 scales, which are skewed left. The kurtosis statistics, more than three, indicate that all the return series of detail coefficients at different scales follow the leptokurtic distribution with the character of fat tail. ADF test statistic is used to examine whether the wavelet coefficients are stable, the results of which reject the null hypothesis of a unit root at the 1% level of significance. The Jarque-Bera test statistics (p-value) determine that all the return series of detail coefficients at different scales reject the assumption of normality. The Ljung-Box test statistics reject the null hypothesis of absence of autocorrelation at the 1% level of significance. Therefore, it is confirmed that the decomposition results of return series are stationary, and the econometric models employed in this paper are without the spurious regression problem, which justify the use of the DGC-t-MSV process with the MODWT for the implementation of the empirical research.

We mainly concentrate on the volatility spillovers between D1 and D5 wavelet decompositions, which represent the short-term investment as well as the long-term investment in China's stock market. The retail investors and institutions mentioned in this paper are the two main forms of stock traders with the characters of short-term investment preference and long-term investment preference respectively. As a major part of investors in China, retail investors generally tend to short-term investment and the high-frequency occurrence of short-term factors, such as economic emergencies and speculative psychology, is easy to affect their trading behavior. It makes retail investors reappraise the market conditions and trade frequently and leads to the great volatility aggregation of high-frequency detail coefficients at D1 wavelet scale. However, institutions are characterized by long-term investment preference, and the volatility of high-frequency detail coefficients at D5 wavelet scale is weaker than that at D1 wavelet scale because of the limited impact of short-term volatility spillovers on the long-term investment.

4 Empirical Results

The estimations of DGC-t-MSV model are run by the MCMC method with Gibbs sampler to ensure the accuracy of the results [58]. We employ the software WinBUGS for posterior computation in multivariate stochastic volatility model, which provides an efficient approach to the Gibbs sampler and a specific implementation of the MCMC technique. The parameters φ_{12}, φ_{21}, φ_{11} and φ_{22} related to the volatility spillovers between short-term investment and long-term investment of D1 and D5 scales are concerned, and the iteration and convergence are as follows:

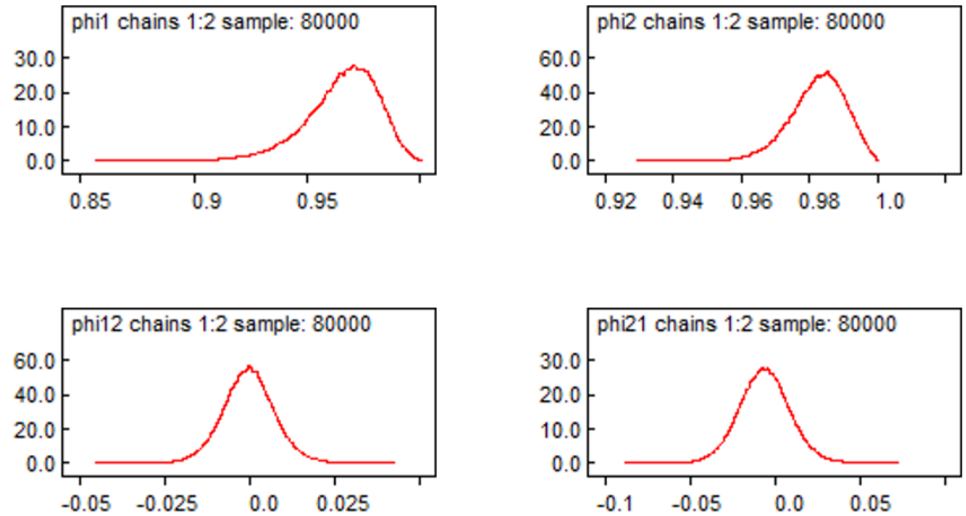


Fig. 3: The density estimations of the marginal distribution of volatility-related parameters.

Source: Author's calculations from WinBUGS.

Fig. 3 reports that the posterior density curves of the parameters related to the volatility spillovers between short-term and long-term investment of Shanghai Composite Index respectively. It tends to asymptotic normality with the iterations of sample data increasing and the curves are relatively smooth, which verified its effectiveness of approach with good convergence.

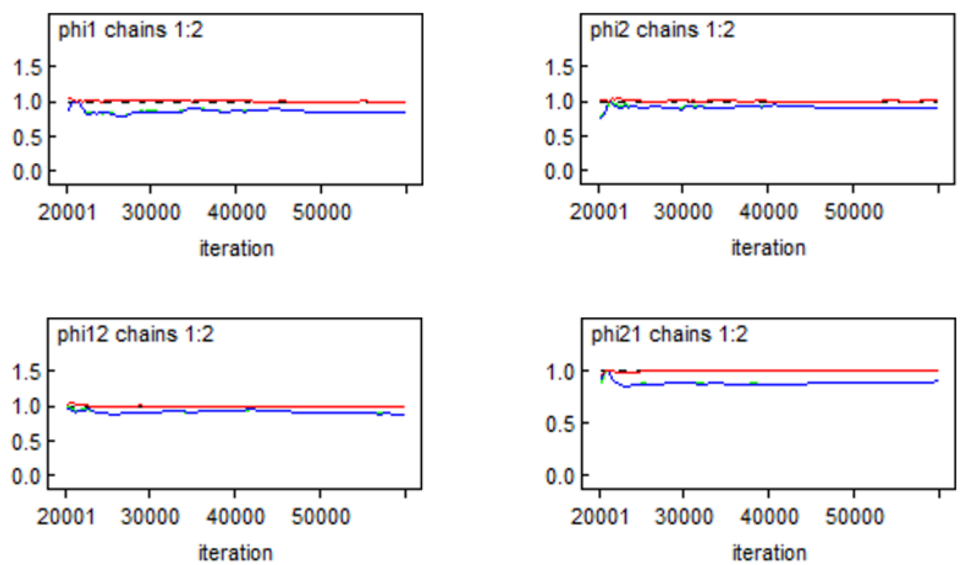


Fig. 4: Gelman-Rubin diagnostic of volatility spillovers parameters.

Source: Author's calculations from WinBUGS.

As demonstrated in **Fig. 4**, all the Markov chains of parameters approach 1 rapidly, which means the MCMC method based on Gibbs sampler fits the marginal posterior distribution. Consequently, it shows that DGC-t-MSV model is appropriate to characterize the short-term and long-term volatility spillovers of Shanghai Composite Index in China's stock market [59].

B. Description: The scale consists of (33) items distributed to (5) domains. The items (1-6) represent the domain of sign in the system, the items (7-13) represent the domain of interaction with courses and learning using the system, the items (14-20) denote the domain of communication skills, the items (21-26) represent the domain of the skills of attending lectures, and the items (27-33) represent the domain of e-evaluation skills.

4.1 Dynamic correlation

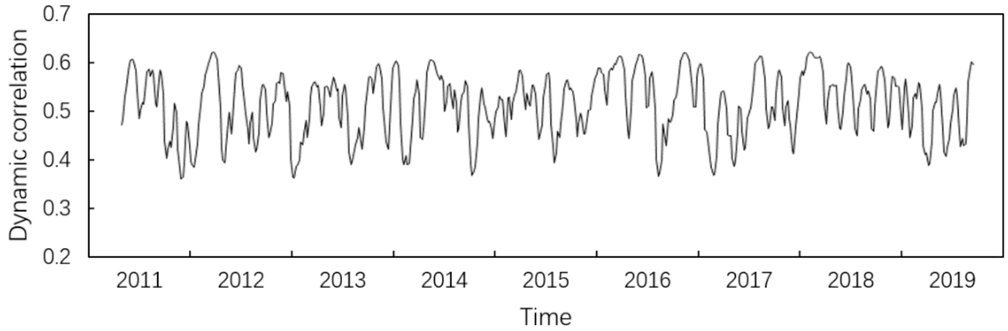


Fig. 5: Time-varying correlation coefficients, from January 2010 to March 2020.

We report the dynamic correlations, which are demonstrated in **Fig. 5**, between short-term and long-term investment preferences in China's stock market. Time-varying correlation coefficients are characterized by frequent fluctuations during the whole period and change in the certain range from 0.353 to 0.648 with the average value of 0.472. It indicates the significance of positive correlations between D1 and D5 scales. The characteristics of time-varying correlation between short-term and long-term investment demonstrate the volatilities correspond to the strong implication of institutions during a period of rapid changes in stock prices [60].

4.2 Estimation results

Table 2: Estimation results of DGC-T-MSV model.

Coefficient	Prior distribution	Scale	Mean	Std.Dev	MC error	Distribution interval
ψ	Beta (20, 1.5)	D1-D2	0.8413	0.1214	0.0057	(0.5047, 0.9919)
		D1-D3	0.8040	0.1046	0.0054	(0.5267, 0.9555)
		D1-D4	0.7211	0.0853	0.0033	(0.5620, 0.9124)
		D1-D5	**0.6424**	**0.0372**	**0.0018**	**(0.6078, 0.8389)**
		D2-D3	0.7930	0.0906	0.0048	(0.5405, 0.9417)
		D2-D4	0.6915	0.0394	0.0027	(0.5799, 0.8947)
μ_1	N (0, 25)	D1-D2	0.5709	0.1384	0.0068	(0.3012, 0.8363)
		D1-D3	0.9430	0.1250	0.0051	(0.7002, 1.1920)
		D1-D4	1.0550	0.2904	0.0113	(0.3962, 1.4680)
		D1-D5	**0.5966**	**0.1916**	**0.0025**	**(0.2179, 0.9701)**
		D2-D3	0.4477	0.1235	0.0052	(0.1945, 0.6803)
		D2-D4	0.6416	0.1319	0.0019	(0.3774, 0.8951)
μ_2	N (0, 25)	D1-D2	-0.0555	0.1409	0.0069	(-0.3389, 0.2245)
		D1-D3	-0.4970	0.1413	0.0054	(-0.7740, -0.2227)
		D1-D4	-0.5917	0.2618	0.0093	(-1.0140, -0.0216)
		D1-D5	**0.5046**	**0.1930**	**0.0019**	**(0.1289, 0.8804)**
		D2-D3	-0.2722	0.1455	0.0060	(-0.5687, -0.0029)
		D2-D4	-0.4991	0.1814	0.0026	(-0.8458, -0.1339)
$\delta_{\eta 1}^2$	Inverse-Gamma (2.5, 0.025)	D1-D2	0.4195	0.0568	0.0026	(0.3080, 0.5325)
		D1-D3	0.3823	0.0497	0.0022	(0.2938, 0.4849)
		D1-D4	0.3034	0.0634	0.0028	(0.2003, 0.4487)
		D1-D5	**0.3802**	**0.0489**	**0.0019**	**(0.2828, 0.4772)**
		D2-D3	0.3823	0.0497	0.0022	(0.2938, 0.4849)
		D2-D4	0.4780	0.0767	0.0032	(0.3290, 0.6322)
$\delta_{\eta 2}^2$	Inverse-Gamma (2.5, 0.025)	D1-D2	0.1062	0.0281	0.0013	(0.0598, 0.1665)
		D1-D3	0.1147	0.0376	0.0018	(0.0624, 0.2085)
		D1-D4	0.2789	0.1225	0.0060	(0.0663, 0.4445)
		D1-D5	**0.3291**	**0.0583**	**0.0025**	**(0.2282, 0.4489)**
		D2-D3	0.1147	0.0376	0.0018	(0.0624, 0.2085)
		D2-D4	0.3381	0.0474	0.0019	(0.2438, 0.4313)

Note: There are partial estimations of the parameters in the DGC-t-MSV model run by MCMC method with Gibbs sampler. Each parameter between different wavelet scales consists of a total of 2468 observations, respectively.

The estimation results of DGC-t-MSV model for the full 2010-2020 period of Shanghai Composite Index original data are reported in **Table 2**. It includes six pairwise combinations of the MODWT decompositions. We mainly investigate the dynamics of the mean and volatility spillovers between wavelet decompositions D1 and D5, which represent the short-term investment of retail investors as well as the long-term investment of institutions respectively in Shanghai Composite Index's daily return. Additional estimations at the remaining decomposition scales are shown only for reference.

The Monte Carlo (MC) error of all the parameters is far less than the standard deviations. It is possible to conclude that the DGC-t-MSV model is valid and adequate for the MODWT decompositions of different investment preferences, especially between the short-term investment at D1 scale and the long-term investment at D5 scale.

The time-varying coefficients ψ are the persistence of correlation dynamics for all sectors. In **Table 2**, it reports the average values as well as the standard deviations of ψ, which decrease from the low decomposition scale of pairwise combinations to the high level gradually. In the D1-D5 scale, the correlation persistence ranges from 0.6078 to 0.8389, verifying that short-term return has a positive linkage with long-term return in terms of dynamic correlation.

Table 2 reports the mean μ_1 and μ_2 of the detail coefficients with the average values and the standard deviations. It shows that μ_1 is basically higher than μ_2 at the same decomposition scale. Especially, the estimation results in the D1-D5 scale indicate the average return on the short-term investment is higher than that of the long-term investment in China's stock market. The results partially accord with those of Zhong (2017) in daily stock market return forecasting [61].

The conditional variances $\delta_{\eta 1}^2$ and $\delta_{\eta 2}^2$ of the detail coefficients at different wavelet scales are reported in **Table 2**. As for the low wavelet decomposition, the conditional variances have the characters of high average values and standard deviations especially in the D1-D2 scale and decrease gradually. Indeed, the higher value of $\delta_{\eta 1}^2$ reflects the deviation from the standard value in the short-term investment is larger than that in the long-term investment. It is basically consistent with the situation in China's stock market. Most of the stocks suitable for short-term operation have the characteristics of large trading volume, high yield and high risks [62].

4.3 Mean spillovers

Table 3: Estimation results of mean spillovers.

Mean spillovers			Mean	Std.Dev	MC error	Distribution interval
φ_{11}	Beta (20, 1.5)	D1-D2	0.8850	0.0716	0.0028	(0.7156, 0.9877)
		D1-D3	0.9145	0.0602	0.0023	(0.7700, 0.9925)
		D1-D4	0.9277	0.0490	0.0018	(0.8029, 0.9897)
		D1-D5	**0.9618**	**0.0079**	**0.0003**	**(0.9452, 0.9764)**
		D2-D3	0.9352	0.0440	0.0014	(0.8285, 0.9940)
		D2-D4	0.8553	0.0459	0.0015	(0.7582, 0.9376)
φ_{22}	Beta (20, 1.5)	D1-D2	0.4608	0.0814	0.0042	(0.2902, 0.6091)
		D1-D3	0.6887	0.0642	0.0032	(0.5463, 0.8019)
		D1-D4	0.8747	0.1074	0.0053	(0.6258, 0.9848)
		D1-D5	**0.9677**	**0.0063**	**0.0002**	**(0.9549, 0.9795)**
		D2-D3	0.6896	0.0436	0.0020	(0.5914, 0.7655)
		D2-D4	0.9185	0.0258	0.0008	(0.8620, 0.9635)

Note: The table 3 provides the estimations of the mean spillover parameters ϕ_{11} and ϕ_{22} in the DGC-t-MSV model with the posterior distribution run on the whole periods of daily returns. Each parameter is estimated by MCMC method with Gibbs sampler and consists of a total of 2468 observations.

The mean spillovers are captured by the φ_{11} and φ_{22} coefficients in **Table 3**. The estimations show that there are time-dependent mean spillovers for each pairwise combination series, which increase gradually from low scale of wavelet decomposition to high scale. It can be explained by the high degree of volatility persistence. For instance, the Nymex WTI futures slumped to a historical negative price in April 2020, and caused the economic decline transmitting from the short-term investment to the long-term investment in China's shock market. This increasing influence of volatility persistence leads to the great volatility aggregation between detail coefficients of different wavelet scales in that period. Meanwhile, the results demonstrate the MODWT decompositions of Shanghai Complex Index's daily return at different scales significantly depend on their lagged values. It is concluded the lagged values affect significantly and continuously stock return series, and the features of volatility persistence make it difficult for stock prices to return stability. Results in Table 3 also reveal that the time-dependent mean spillovers in the short-term investment of D1 scale and the long-term investment of D5 scale are significantly positive and far above the other decompositions. Therefore, the previous information of decomposition D1 and D5 scales is more important in terms of conditional return prediction than the other information is.

4.4 Volatility spillovers

Table 4: Estimation results of volatility spillovers.

volatility spillovers		Mean	Std.Dev	MC error	Distribution interval	t-ratio
ϕ_{12}	D1-D2	0.4885	0.0681	0.0028	(0.3746, 0.5224)	7.1733***
	D1-D3	0.2592	0.1563	0.0045	(-0.1207, 0.3402)	1.6583*
	D1-D4	0.0814	0.0977	0.0017	(-0.0624, 0.0941)	0.8332
	D1-D5	**-0.0967**	**0.0311**	**0.0045**	**(-0.1018, -0.0405)**	**-3.1093*** **
	D2-D3	0.1592	0.0681	0.0010	(0.1150, 0.1951)	2.3377**
	D2-D4	0.0861	0.0965	0.0098	(-0.0373, 0.1021)	0.8922
ϕ_{21}	D1-D2	0.0797	0.0240	0.0002	(0.0446, 0.0824)	3.3208***
	D1-D3	0.0612	0.0311	0.0001	(0.0125, 0.0702)	1.9678**
	D1-D4	0.0374	0.0205	0.0012	(-0.0007, 0.0419)	1.8244
	D1-D5	**-0.0215**	**0.0078**	**0.0028**	**(-0.0358, -0.0151)**	**-2.7564*** **
	D2-D3	0.0037	0.0375	0.0008	(-0.0164, 0.0551)	0.0987
	D2-D4	0.0557	0.0242	0.0015	(0.0023, 0.0801)	2.3017**

Note: The table 4 provides the estimations of the volatility spillover parameters ϕ_{12} and ϕ_{21} in the DGC-t-MSV model with the posterior distribution run on the whole periods of daily returns, which are based on the prior distribution N (0, 10) according to previous literature. Each parameter is estimated by MCMC method with Gibbs sampler and consists of a total of 2468 observations. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Estimations in **Table 4** reflect that the volatility spillover effects are captured by the φ_{12} and φ_{21} coefficients, and the means of which vary within a certain range in all the sectors. It shows that the sensitivities to the pairwise combination series are highly significant at the low decomposition scales. The marginal volatility of Shanghai Complex Index's daily returns is more likely to transfer gradually from the low wavelet scale of the short-term investment to the high MODWT decomposition scales. A comparison between the detail coefficients at different wavelet scales indicates that the impact of short-term marginal volatility in D1 and long-term marginal volatility in D5 is relatively higher than in most of the remaining scales. The findings reveal in D1-D5 scale time-varying bidirectional volatility spillovers between short-term investment and long-term investment are significant and negative at the 1% level of significance. The responses of long-term investment volatility to a shock in the volatility of short-term investment are significant, meanwhile, a standard positive shock in the volatility of short-term investment has a negative impact on the volatility of long-term investment instead. The volatility spillover effects of short-term investment preference are more significant than those of long-term input.

The robust t statistic displays the volatility spillovers from the D1 decomposition scale to the D5 decomposition scale as indicated by the significance at the 1% level of the coefficients φ_{12}. It suggests that the short-term investment is the Granger causality of the long-term investment and introduces an additional source of disturbance, which can be explained by the technology investment mainly forecasting the stock price fluctuation. Most retail investors often overestimate their judgment of China's stock market and make short-term investment blindly, tend to choose high-yield hot stocks based on their temporary prices, while the fluctuation as well as the risks are generally higher than the ordinary stocks. As a matter of fact, the short-term investment is more sensitive to stock price fluctuation in the trading session. The retail investors with speculative psychology mainly take profits through short-term investment and make it difficult to maintain the stability of stock prices. For instance, the critical panic of COVID-19 causes stock selling by short-term investors to increase so rapidly, and the conditions further deteriorate because of stock price keeping falling over the long term. At the same time, such fears are exacerbated by Sino-US trade friction and lead to the further decline in stock price, which strike the confidence of short-term retail investors as well. The continuous decline in China's stock prices caused by retail investors affects the long-term returns through the volatility spillovers of short-term investment, which is even unacceptable to the institutions preferring long-term investment.

Table 4 reports the negative volatility spillovers from the D5 decomposition scale to the D1 decomposition scale, and the robust t statistic of the coefficients φ_{21} demonstrates the significance at the 1% level. The long-term investment is verified to be the Granger causality of the short-term investment. Institutions preferring the long-term trading, therefore, are fundamental to maintaining the stability of stock prices in China's securities market and have a certain regulatory effect on the short-term volatility of stock prices [63]. Compared with the institutions of the ability to resist risks, retail investors generally tend to sell off stocks they held before when the stock price falls, for instance, during the period of Sino-US trade friction in 2018, leading to a further decline in stock prices. At this time, institutions with the characteristic of long-term investment preferences prepare to undertake the stocks transferred from retail investors and prevent the further decline in China's stock prices, which offsets the impact of falling prices through the volatility spillovers from the long-term investment to the short-term investment. However, when the prices of the stock market increase greatly under some certain circumstances, retail investors of short-term preference tend to snap up stocks especially cheap ones, making the situation of rapidly rising prices. Institutions are inclined to sell their shares to transmit the long-term volatility spillovers to the short-term returns concerned by retail investors and reduce the overheated rising in China's stock prices. It shows that China's institutional investors have played an important role to maintain the stability of China's stock market.

The estimation results of coefficient φ_{12} is higher than that of φ_{21}. It confirms the volatility spillovers from the short-term return to the long-term return are more significant, that is, the short-term investment has a rather high transmission effect on the long-term investment in terms of stock price. The volatility series of the long-term stock prices significantly depends on which of the short-term return. As a matter of fact, the volatility spillovers between the short-term investment of retail investors and the long-term investment of institutions are actually caused by the imbalance in market information access [9,64]. Institutions obtain public information like retail investors, while they also have access to some potential channels of inside information just open to organizations and hold absolute advantages in gathering information from all the sources. Hence, institutional investors of long-term investment are generally suitable for the value simulation and the empirical analysis of which has been conducted many times by plenty of literature, estimating the enterprise capitalization through the basic situations, such as the cash flow statement, balance sheet and income statement in the financial statements. With the limitation of access to financial information, retail investors of short-term investment tend to adopt the technology investment trading simply based on forecasts of stock prices. It indicates that the efficiency of information transmission in China's stock market is insufficient. According to the inside information, institutional investors adjust the investment before retail investors, leading to the volatility of stock prices. Merely taking the possible profits into account, the retail investors fond of speculation subsequently prefer to invest in stocks following the trend of institutional investment, and result in further fluctuation of stock prices which could spread to other financial markets through volatility spillovers. It is of vital importance for institutions to lead retail investors from the technology investment, which they are not good at, to the value simulation.

5 Conclusions

Since the securities markets are an essential part of the financial markets, volatility spillover effects between various investment preferences have a significant impact on the development of China's economy [30,65]. This paper investigates the volatility spillovers between retail investors and institutions in China's stock market for several reasons, and the question of which has become a matter of considerable concern. First, China's stock market has accumulated trillions of dollars from retail investors of short-term preference and institutions of long-term preference, and their investment strategies influence each other. Second, the roles of institutions and retail investors become more complex when the stock price fluctuates, bringing difficulties to portfolio and risk management [66,67]. Finally, the linkage between retail investors and institutions is gradually strengthened and thus likely to trigger a significant global financial crisis. Investors, risk managers, portfolio managers and derivative dealers should fully consider the impact of volatility spillovers to reduce potential risks.

We propose a new approach incorporating both DGC-t-MSV model and MODWT to analyze the daily returns of different wavelet scales from January 4, 2010, to March 2, 2020, in China's stock market. It analyzes the volatility spillovers between retail investors of short-term investment preference and institutions of long-term investment preference through DGC-t-MSV model. The results show significant bidirectional volatility spillovers between retail investors and institutions, and the short-term investment interacts with the long-term investment through the stock prices. The contribution to existent literature is among three dimensions as followed. First, to the best of my knowledge, it is the first paper to capture the multiscale features of volatility transmissions between short-term investment and long-term investment in the same market based on the wavelet multiresolution analysis. Second, it examines the direction and intensity of the volatility spillovers between retail investors and institutions through Granger causality. Finally, it is the first study to investigate the implications of institutional investors in promoting value simulation and maintaining stock price stability. It is of vital importance to consider the dynamic feature of volatility spillovers especially during a crisis period, and the results have a practical implication.

As far as the volatility spillovers are concerned, we found the response of long-term investment institutions to a shock on the volatility of short-term investment retail investors is negative and significant, and vice versa, indicating a financial crisis in China's stock market could stem from a volatility shock between different investment preference. It appears that the bidirectional volatility spillovers between these two investment preferences dominate a potential channel of financial crisis transmission. The results demonstrate that the magnitude of the short-term volatility caused by irrational trade of retail investors with speculative psychology is more significant than that of the long-term one, which introduces an additional source of disturbance to institutions. With the limitation of access to financial information, retail investors of short-term investment tend to adopt the technology investment trading simply based on forecasts of stock prices. Institutions of long-term investment, however, are fundamental to guide the simulation of business valuation and maintain the stability of stock prices in China's securities market. They need to pay more attention to the volatility spillovers from retail investors of short-term investment to long-term investment and be aware that the lagged shocks could have more important effects because of a high degree of persistence in volatility series of long-term volatility.

There are profound policy implications in our research which imply broader reforms than previous macroprudential policies, in order to prevent the potential systemic risks. It suggests when making stock market policies, the government sector should not omit the existence of volatility spillovers among different investment preferences in the same market and take measures to increase support for institutions preferring long-term investment. Specifically, the government could select and fund appropriate institutions with social responsibility whose main function is to maintain the stability of stock prices, indicating the gradual increase of the state's attention to the securities market. Institutions are of vital importance to lead retail investors to transform from the technology investment simply focusing on the fluctuations of stock prices to the value simulation estimating the enterprise capitalization through the basic situations such as the cash flow statement, balance sheet and income statement in the financial statements. In the plan outlined by NDRC (National Development and Reform Commission), the provision has already been established, including some measures that further develop the securities investment fund, expand the asset scale of institutions, and increase securities funds in commercial banks. Simultaneously, the implementation of Shanghai-Hong Kong Stock Connect program as well as Sci-Tech innovation board, and the cancellation of the QFII quota have relieved the situation of China's stock market in which the number of retail investors is more than institutions. In particular, there is evidence regarding the volatility spillovers between retail investors and institutions of different investment preferences that diversified funding is required to become more resilient to the fluctuation of China’s stock prices. Retail investors and institutions should pay more attention to value simulation in favour of effectively preventing the investment risks in China’s stock market and increase the adjusted performance of the hedged portfolio.

Acknowledgment:

The authors would like to extend their gratitude to the Ministry of Higher Education (MoHE) Malaysia (FRGS/1/2020/SS01/UKM/02/12/1) and Faculty of Economics and Management, University Kebangsaan Malaysia for providing the grant for this research project.

Conflict of interest

The authors declare that there is no conflict regarding the publication of this paper.

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