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Sector Volatility Spillover and Economic Policy Uncertainty: Evidence from China's Stock Market

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Abstract: Following generalized variance decomposition, we identify the transmission structure of financial shock among ten sectors in China. Then, we examine whether economic policy uncertainty (EPU) affects it through GARCH-MIDAS regression. We find that consumer discretionary, industrials, and materials sectors are systemically important industries during the sample period. Further research of dynamic analysis shows that each sector acts in a time-varying role in this structure. The results of the GARCH-MIDAS regression indicate that none of the selected EPU indexes has a significant long-term impact on the total volatility spillover of the inter-sector stock market in China. However, the EPUs do affect some sectors' spillover indexes in the long run, and they are significantly heterogeneous. This paper can provide regulatory suggestions for policymakers and reasonable asset allocation and risk avoidance methods for investors.

Keywords: financial risk; sector volatility spillover; dynamic structure; economic policy uncertainty; GARCH-MIDAS

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1. Introduction

Nowadays, financial risks have become much more complex and diversified with the development of the financial market, which leads to prevailing abnormal fluctuations and risk spillovers in the financial system and increases difficulties in financial risk management. The financial crisis, monetary and trade policies, sudden public health incidents, and the like can easily cause financial risks. They may further lead to anomalous rise and fall in the financial system and affect the spillover structure. These endogenous or exogenous shocks put forward high requirements for countries' financial risk management ability.

Correctly identifying the volatility spillover structure in the stock market is crucial to carry out financial risk management activities. Volatility spillovers exist widely among markets, industries, and individual stocks. Scholars have focused on it since the 1970s. They are unanimous in respect of the significant role that correlation structure within the financial system plays to understand and solve the crises [1]. It also has a guiding significance for establishing financial supervision, carrying out asset pricing and risk management activities, and preventing the outbreak of the financial crisis to discern the connectedness and spillover structure among financial institutions [2,3].

The natural upstream and downstream relationship in the supply chain and the asset allocation among investors in various sectors can lead to risk spillovers between industries. With the continuous development of computer and information technology, sectors are becoming increasingly interconnected. The rapid spread of information and capital flow in the stock market requires us to reliably discern inter-sector risk spillover structure. On the one hand, it is conducive to investors' understanding of the inter-sector information transmission process and risk contagion. So, they can effectively avoid some industry risks, choose more effective cross-sector portfolios and set up flexible hedging strategies. On the other hand, with a better grasp of the characteristics of inter-sector risk transmission, government regulators can accurately identify systemically important industries and industry correlation, in which way can they formulate more targeted industrial risk management measures and more feasible industrial development plans.

Countries have implemented different expansionary policies to cope with the changes caused by endogenous and exogenous factors, resulting in economic policy uncertainty (EPU), which can affect the financial system [4,5]. EPU refers to the uncertainty that government policymakers add to the market when fiscal, regulatory, or monetary policies are adopted. Such policy uncertainty can have various impacts on private sectors. It also harms the macroeconomy [6,7]. EPU can affect cash flow by changing stock risk premium. It also has a significant impact on asset pricing and stock returns [8–11]. Regional systemic risk in global stock markets can be affected by EPU [12]. Since the stock market can partly reflect the economic condition, policymakers can forecast the economy and lay down policies based on the stock market. From this perspective, it also seems to affect the EPU [13]. At present, the discussion between the stock market and EPU mainly focuses on three levels: the first one is to examine the risk premium effect of EPU on the stock market from the perspective of return rate. The second is to investigate the volatility spillover effect of EPU on the stock market. The third is to analyze the bidirectional spillover effect between the stock market and EPU indexes.

Traditional measurement methods require variables in one model to keep the same frequency, which is impossible for macroeconomic indicators such as EPU and stock market data. Macroeconomic indicators are mostly low-frequency data, mainly monthly and quarterly, while stock market data such as stock prices are high-frequency data, mostly daily or even intra-day. Therefore, when discussing the relationship between macroeconomic indicators and stock market fluctuations, we cannot directly use traditional methods. If we forcibly reduce the frequency of stock market data, we may lose plenty of high-frequency information. Moreover, we cannot explicitly depict the macroeconomic variables' influence on the stock market. If we convert low-frequency data to a higher one through interpolation, we will inevitably introduce noises to it. A mixed data sampling (Midas) model [14] was put forward to resolve the contradiction. This model allows us to use data with different frequencies in one equation. The GARCH model is introduced into the MIDAS framework to study the time-varying volatility of the market, thus forming the GARCH-MIDAS model [15,16]. This model decomposes the conditional variance into short-term and long-term factors, and the low-frequency indicators affect the conditional variance by changing the long-term variables.

Based on the existing literature, this paper investigates the inter-sector volatility spillover relationship in the Chinese stock market based on the spillover index method [17–19], and further studies the impact of different types of EPU on this relationship. The spillover index method is widely used in the research of different types of financial markets. Using this method to construct proxy variables to study the relations of inter-sector volatility spillover is natural. The reason for studying the influence of different types of EPU on the inter-sector volatility spillover relationship is that, first, the heterogeneity of the sector will cause the stock returns to show differences. Therefore, when there is an external shock, different industries will show different reactions. Second, due to the limited attention of investors, the impact of external shocks on the market may be asymmetrical and also lead to differences in performance between industries. Third, the existing literature has confirmed the impact of EPU on the stock market from the macro and micro levels, that is, the overall market or listed companies, but only a few researchers pay their attention from the meso level, that is, the sector level. The main contents are as follows. We first construct the inter-sector static volatility spillover structure of the Chinese stock market so that we can grasp the whole risk transmission relationship between sectors. Then, we build the inter-sector time-varying volatility spillover structure in the Chinese stock market to grasp the dynamic information of the time period. Finally, based on the above analysis, this paper uses the GARCH-MIDAS model to analyze the effects of EPU indices of different countries on the inter-sector spillover structure of the Chinese stock market. So that it can be clear whether the EPU indexes influence the risk transmission characteristics of various sectors of China's stock market, and whether they have heterogeneous effects on different sectors. The innovative contributions of this paper include: First, the research period covers the COVID-19, which is a sharp global shock. Countries generally adopted easing policies, so there was drastic adjustment in the financial markets. These exogenous shocks may affect the stock market spillover structure significantly. Incorporating this period into the discussion of the stock market spillover structure further enriches the existing literature on volatility spillover. Secondly, most of the existing studies use models to analyze the two-way spillover relationship between EPU and the stock market volatility, and regard EPU and stock market volatility as a whole for analysis. Due to the fact that volatility spillover between sectors can refer to risk transfer structure among sectors to some extent, describing the inter-sector volatility spillover structure of China's stock market first to analyze the characteristics of risk transmission of different sectors, and then taking EPU as an exogenous variable to consider its heterogeneous influence on the risk transmission effect of different sectors are of great significance. In addition, this paper comprehensively considers the impact of EPU indices of several countries and no longer focuses on global EPU or China's EPU only.

The rest of the paper is organized as follows: Section 2 reports a review of the relevant literature. Section 3 discusses the methodology for datasets and applications. Section 4 presents the main empirical results and analysis. The last part gives the conclusion of the study.

2. Literature Review

Plenty of discussions on the volatility spillover effect between stock markets have been carried out recently. Both theoretical and methodical aspects have been made. In theory, the effect is studied mainly from the perspective of 'tangible' connection and 'intangible' connection. 'Tangible' connection means that the volatility spillover is caused by economic and trade links, as well as the asset allocation of investors between markets. Related theories underlie the 'economic basis hypothesis' and 'capital flow hypothesis' [20–22]. 'Intangible' connections work through the psychological anticipation of investors. Because economic fundamentals cannot explain the catastrophe of 19 October 1987, and the subsequent tumble in the global stock market [23], scholars begin to use the herding effect, synergy and bounded rationality, and so on to explain the volatility spillover in the stock markets. They think as long as investors judge one market by the performance of another, the message will be transmitted, no matter whether the economic fundamentals change or not, which is known as the 'market contagion hypothesis'.

Research methods of volatility spillover are mainly divided into three categories. Firstly, Granger causality is used to analyze the dependence of the conditional first and second moment of the return distribution, which is used to characterize the spillover of the mean and fluctuation level of the return [24,25]. Secondly, VAR family models are adopted. Various proxies of volatility are created, such as the square of return rate [26]. Then the volatility spillover among different markets is investigated by constructing and analyzing the VAR model and its impulse response, and a set of volatility spillover index is constructed based on generalized variance decomposition of the VAR model or network topology, which can judge the direction of volatility spillover of various markets [17–19]. Monte Carlo analysis is used to estimate confidence intervals [27]. TVP-VAR, MS-VAR, and the like are widely used recently [28–30]. Thirdly, GARCH family models are adopted to explore the transmission of volatility among markets, sectors, and institutions [31–33]. Except for the original GARCH model, mostly adopted GARCH family models include AR-GARCH [34]; DCC-GARCH [35]; CCC-GARCH [36]; DCC-MVGARCH [37]; BEKK-GARCH [38], and so on.

As for the objects of study, scholars pay more attention to the volatility spillover between developed markets at the beginning [24,31,39–41]. Emerging markets begin to appear in this topic as they have boomed recently [37,42,43]. Later, the objects of study gradually become microcosmic. Scholars go deeper into different markets and even companies instead of countries or regions [44]. However, there are relatively few studies on the volatility spillover between industries within a country at the medium level generally. In the early days, there seemed to be disagreement about the importance of spillovers between industries. Some scholars believed that "the rise in the relative importance of industry factors seems to be only temporary, and the process of globalization has not yet led to significant and lasting changes in the correlation structure of international stocks" [45]. However, due to the more obvious time-varying characteristics of the correlation at the industry level, it is necessary to study the inter-sector spillovers even though the inter-sector correlation patterns of stocks in different countries vary. Sectoral diversification can be feasibly achieved. It appears to be much more important than country-specific combinations. Besides, due to the sectoral heterogeneity of contagion, some sectors can still provide channels to achieve international diversification benefits during a crisis, despite the widespread crisis at the market level [46]. Industry heterogeneity also appears in the different dynamic correlations between sectors and markets, and the distinct influencing factors [47]. Besides, many material markets are said to have significant spillover structures with various industries [48]. At present, the research on the spillover structure at the industry level has gone deep into the secondary sub-industries [49].

The influencing factors of volatility spillover is a much-talked-about topic now. The influence factors are mainly divided into two levels: micro part and macro part. In terms of microeconomic factors, many pieces of literature have confirmed that specific micro-financial factors, certain indicators of individual enterprises (Tobin-Q of financial institutions, the capital structure of financial institutions and the like), and tangible connections between individual enterprises (such as interbank lending, etc.) can lead to spillover effects in network structure and changes in credit risks [50–52]. From the perspective of macro factors, the influence on spillover effect is mainly from the perspective of economic base and market contagion, and instrumental variables, such as industrial added value and inflation rate, are selected as the indicators of macroeconomic characterization. Since traditional econometric models cannot deal with data of different frequencies at the same time, mixed-frequency models are mostly used to analyze the impact of macroeconomic indicators on volatility spillover [16,53,54]. Besides, many scholars focus on the relationship between quantitative easing monetary policy and spillover structure [41,54–56]. In particular, for the discussion of the relationship between EPU and spillover effect, the current literature mostly discusses the two-way volatility spillover relationship between the stock market and uncertainty through general equilibrium model, dynamic optimization, GARCH family model, or panel data. Few papers consider the influence of the EPU index on the time-varying volatility spillover structure that has been formed in the stock market.

In this paper, the generalized variance decomposition method [18] was used to study the inter-sector spillover effect of China's stock market, and the impact of EPU on the volatility spillover index is discussed. Compared with the existing studies, this paper has the following characteristics. First, the objects of study are more micro, and the perspective is no longer limited to the nation (region) but different industries in one country. Then, the influence of EPU on volatility spillover is analyzed so that we can make it clear how EPUs affect spillover structure.

Based on the daily stock index data of the SSE 180 Industry Index from 31 December 2013, till 29 January 2021, this paper conducts the following research: (1) The method of generalized variance decomposition is adopted to construct the full sample static volatility spillover structure of the Chinese stock market among industries. The research shows that in the whole sample period, different industries have various effects on risk transmission and absorption. Consumer discretionary, industrial, and materials sectors tend to spill over risk and are identified as systemically important sectors, which means that they have greater risk transmission capacity. Sector-specific policies need to consider the impact of these industries on other sectors and even on the overall national stock market. (2) The rolling window generalized VAR variance decomposition method is used to measure the time-varying character of inter-sector volatility spillover structure in the Chinese stock market. It is found that the systemically important industries in different periods can vary. With the guide of static analysis based only on the full sample, the policy-making process might ignore dynamic information, resulting in weak pertinence and low efficiency. However, in general, whether considering static spillover structure or dynamic structure, consumer discretionary, industrial, and materials industries all play a role in transferring risks to the outside to a greater extent. (3) GARCH-MIDAS method is used to study the influence of major EPU indices on the inter-sector spillover structure of the Chinese stock market. The results show that the EPU indices of selected countries have a long-term impact on the spillover structure of Chinese industries, and the sectors affected by the EPU indices of different countries differ, which means that there is significant heterogeneity among various EPU indices. This paper expands the study on inter-sector volatility spillover structure. Since the period studied includes COVID-19, it deepens the discussion on the inter-sector spillover structure of China's stock market in the context of global emergencies when countries generally adopt easing monetary policies. Secondly, this paper does not study the volatility spillover structure between the EPU index and the stock market. Instead, the mixed frequency model is used to explore the influence of the EPU indexes on the long-term volatility of the inter-sector spillover structure of the Chinese stock market, which means that the EPU indexes are regarded as exogenous explanatory variables in this paper. Thirdly, this paper comprehensively considers multiple EPU indexes' impact on the inter-sector volatility spillover structure.

3. Data and Methods

3.1. Data

Daily opening price, closing price, high price, and low price of the SSE 180 Industry Index compiled by SSE index Co. Ltd. is selected in this paper. These series are classified from the SSE 180 Index samples according to the industry classification standards of CSI, and then all the securities of each sub-industry are taken as the index samples of the corresponding industry index to form the SSE 180 industry index series to reflect the overall performance of securities in different industries. The SSE 180 sector index is the core of the SSE index series, complied based on the most representative 180 A-share samples (i.e., the blue-chip stocks in the Shanghai Stock Exchange), and regarded as the vane of the overall performance of the blue-chip stocks in the Shanghai Stock Exchange. The series has the following 10 indices: SSE 180 Energy Index (EI), SSE 180 Materials Index (MI), SSE 180 Industrials Index (II), SSE 180 Consumer Discretionary Index (CDI), SSE 180 Consumer Staples Index (CSI), SSE 180 Health Care Index (HCI), SSE 180 Financial Index (FI), SSE 180 Information Technology Index (ITI), SSE 180 Telecommunication Services Index (TSI), SSE 180 Utilities Index (UI). The Shanghai 180 sector index series is based at 1000 points on 31 December 2003. To maximize the sample space, the period is chosen to start from 31 December 2003, till 29 January 2021. The original data are collected from the WIND database.

The yield adopted in this paper is as follows:

$$r = \ln(C_t - C_{t-1}) \tag{1}$$

where r refers to the logarithmic return, while C_t and C_{t-1} is the closing price at time t and $t-1$, respectively.

Table 1 shows the yield of all industries in the whole sample interval. It can be seen that the yield of all sectors is similar, and the indexes of mean, maximum, and minimum have few differences. Among them, the average value of each industry is below 0.08%. The mean of EI and TSI is the smallest, respectively 0.004% and 0.009%, and CSI is the largest. The maximum yield of all industries is about 9%, and the minimum is about −10%. Considering the volatility of the industry return rate by standard deviation, ITI and TSI fluctuate violently, while UI is the steadiest. The statistical data of skewness and kurtosis show that the return series of ten industries all own the characteristics of left-skewness, sharp peak, and thick tail. The JB test further examines this judgment. The return series of the ten industry indexes do not follow the normal distribution. The results of the ADF unit root test show that the return series of each industry index is stable.

Table 1. Descriptive statistics of 10 sector indices' yield [1].

	Mean	Median	Max	Min	Std.Dev.	Skew	Kurt	JB	ADF
EI	0.004	0.007	9.35	−10.53	1.95	−0.22	6.47	2112.49 ***	−62.41 ***
MI	0.023	0.061	9.29	−10.51	2.01	−0.45	6.16	1869.83 ***	−60.94 ***
II	0.023	0.049	9.55	−9.89	1.84	−0.51	7.13	3134.66 ***	−60.90 ***
CDI	0.035	0.110	9.05	−10.40	1.96	−0.61	6.34	2181.06 ***	−61.75 ***
CSI	0.079	0.079	8.84	−10.34	1.8	−0.22	5.74	1328.88 ***	−46.64***
HCI	0.054	0.079	8.73	−10.53	1.98	−0.38	5.75	1405.09 ***	−47.57 ***
FI	0.041	−0.003	9.54	−10.04	1.89	−0.11	6.49	2119.16 ***	−64.33 ***
ITI	0.035	0.111	9.54	−10.63	2.39	−0.42	4.95	776.02 ***	−61.99 ***
TSI	0.009	−0.008	10.17	−10.59	2.23	−0.08	7.12	2935.11 ***	−48.00 ***
UI	0.013	0.019	8.33	−10.36	1.58	−0.4	7.96	4357.45 ***	−63.15 ***

[1] In this table, *** respectively indicates the null hypothesis is significantly rejected at the level of 1%.

3.2. Calculation of Stock Market Volatility of Various Industries

In this paper, the data used to estimate the inter-sector shock transmission structure is the daily stock volatility data of the CSI 180 industry index from 2004 to 2020. As the daily stock prices are easily available, and the change of industry stock prices (earnings) is forward-looking as they contain the expected information of the market, the stock prices of the industry are used. Referring to the research of Garman and Klass [57], this paper uses the daily maximum (H), daily minimum (L), daily opening price (O), and daily closing price (C) to calculate daily range volatility (RV) as follows:

$$RV_t = 0.511(H_t - L_t)^2 - 0.019[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)] - 0.383(C_t - O_t)^2 \tag{2}$$

where O_t, H_t, L_t and C_t represents the logarithm of the daily open, lowest, highest and closing price of each industry index respectively of time t.

Table 2 is the result of the descriptive statistical test and data structure feature test of volatility. The mean, median, maximum and minimum values of volatility in most industries all have the characteristics of aggregation. They are mainly concentrated around 0.020%, 0.010%, 0.750%, and 0.00035%. In these four groups of data, ITI and TSI are significantly different from others, which is shown as outlier data in the four-dimensional space. The mean and median of UI, and the minimum value of FI also show obvious outlier characteristics. In general, the volatility of UI is the smallest among the industry indexes, and the most volatile index is TSI. Obvious volatility can also be seen in II, CSI, FI, ITI, and other indexes. Skewness and kurtosis show that the volatility data of the ten industry indexes all have the characteristic of 'sharp peak and thick tail', and the JB test shows that none of the ten industry indexes' distribution follows the normal distribution. The results of the ADF unit root test indicate that the volatility series of the ten industry indexes are all stationary. The LM tests of the volatility of the ten industry indexes all support the ARCH effect of the correlation sequences.

3.3. Research Method

3.3.1. Subsubsection

This paper uses the network analysis method based on variance decomposition of GVAR [18] to identify the financial shock transmission network between different sectors in China. This network analysis is based on the variance decomposition of Generalized Vector Autoregression (GVAR) [18,19,58]. Compared with the network analysis method used in traditional social sciences, this method can identify the deeper level of association structure and can distinguish the node weight and direction of association structure at the same time [19].

Table 2. Descriptive statistics of 10 sector indices' volatility [2].

	Mean (%)	Median (%)	Max (%)	Min (%)	Std.Dev. (%)	Skew	Kurt	JB	ADF [3]	LM [4]
EI	0.021	0.011	0.755	0.00037	0.036	7.68	102.92	1,766,865 ***	−9.34 ***	527.01 ***
MI	0.022	0.011	0.654	0.00041	0.039	7.25	80.86	1,084,285 ***	−7.88 ***	1538.92 ***
II	0.018	0.008	0.739	0.00027	0.037	7.75	96.83	1,563,550 ***	−7.60 ***	701.91 ***
CDI	0.020	0.010	0.796	0.00036	0.037	8.11	106.61	1,901,290 ***	−8.09 ***	532.01 ***
CSI	0.019	0.011	0.524	0.00037	0.030	6.93	77.62	995,694.6 ***	−8.83 ***	1229.60 ***
HCI	0.022	0.012	0.676	0.00041	0.036	6.91	78.71	1,023,866 ***	−9.13 ***	859.97 ***
FI	0.020	0.010	0.683	0.00006	0.035	7.46	92.07	1,410,076 ***	−9.36 ***	744.04 ***
ITI	0.032	0.018	1.166	0.00053	0.052	8.45	129.43	2,812,614 ***	−7.07 ***	1703.87 ***
TSI	0.032	0.015	1.005	0.00002	0.058	5.96	55.71	504,896.9 ***	−8.21 ***	1436.09 ***
UI	0.015	0.007	0.706	0.00032	0.031	9.11	133.84	3,016,592 ***	−7.27 ***	207.53 ***

[2] In this table, *** respectively indicates the null hypothesis is significantly rejected at the level of 1%. [3] The lag order is automatically selected according to AIC and BIC information criteria. [4] In this paper, the 1–12 order lag results are all calculated, and all results are robust. In order to save space, only the 12-order lag results are shown here.

Firstly, the following VAR system with N variables are established:

$$X_t = \sum_{t=1}^{p} \Phi_i X_{t-1} + \alpha + \varepsilon_t \tag{3}$$

where, X_t is the volatility vector of the stock index of time t. α is the constant vector of the VAR system. $\varepsilon \sim (0, \Sigma)$ is the independent identically distributed random error term.

Because the VAR system needs to estimate too many coefficients and there are complex interaction effects among variables, it is difficult to directly explain the coefficients of the VAR system with N variables. Therefore, the moving average representation of these coefficient matrices (or their variant forms, such as impulse response equations or variance decomposition) is the key to the understanding the dynamic changes in the system. Its moving average process can be written as:

$$X_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{4}$$

where A_i is a $N \times N$ system matrix following the below iteration law:

$$A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p} \tag{5}$$

In which A_0 is a $N \times N$ unit matrix with $A_i = 0$ when $i < 0$.

In this paper, generalized vector autoregressive (GVAR) variance decomposition is used to calculate the H-step variance decomposition of X_i explained by X_j $(i \neq j)$. $\theta_{ij}^{g}(H)$, the H-step variance decomposition of GVAR is:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_j\right)} \tag{6}$$

where Σ is the variance-covariance matrix of ε. σ_{jj} is the estimation error term of the jth equation in the initially established VAR system. e_i is the selection vector whose ith factor is 1 and the rest is 0. In the generalized vector autoregressive variance decomposition, the sum of each row of the variance decomposition result is not necessarily equal to 1. Therefore, according to Diebold and Yilmaz [18,19], this paper divides the results of each row of GVAR variance decomposition by the normalization of the row:

$$\widetilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{7}$$

Then, according to Diebold and Yilmaz [19], the calculation formula of 'total connectedness' of all variables in the system is:

$$S^g(H) = \frac{\sum_{i,j=1;i\neq j}^{N} \widetilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}^{g}(H)} \times 100 \tag{8}$$

In this system, the calculation formula of the influence from other industries (market) to industry (market) i ("total influence from others to i", referred to as "FROM") is as follows:

$$S_{i\cdot}^{g}(H) = \frac{\sum_{j=1;i\neq j}^{N} \widetilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}^{g}(H)} \times 100 \tag{9}$$

Similarly, the total directional influence to others from i ("TO") is:

$$S_{\cdot i}^{g}(H) = \frac{\sum_{j=1;i\neq j}^{N} \widetilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ji}^{g}(H)} \times 100 \tag{10}$$

Thus, the net influence of industry (market) i on all other industries (market) ("net total influence of i", referred to as "NET") is:

$$S_{i}^{g}(H) = S_{\cdot i}^{g}(H) - S_{i\cdot}^{g}(H) \tag{11}$$

Finally, the net pairwise influences between any two industries i and industry j in the system are the differences between the influence of industry (market) i on industry (market) j and the influence of industry (market) j on industry (market) i:

$$S_{ij}^{g}(H) = \left(\frac{\widetilde{\theta}_{ji}^{g}(H)}{\sum_{i,\,k=1}^{N} \widetilde{\theta}_{ik}^{g}(H)} - \frac{\widetilde{\theta}_{ij}^{g}(H)}{\sum_{j,\,k=1}^{N} \widetilde{\theta}_{jk}^{g}(H)} \right) \times 100 \tag{12}$$

3.3.2. GARCH-MIDAS Model

To discuss the influence of the low-frequency EPU index on the inter-sector spillover structure of China's stock market, this paper adopts the GARCH-MIDAS model, which can make the conditional variance of the high-frequency data decompose into short-term and long-term components. The single-factor GARCH-MIDAS model is as follows:

$$s_{i,t} = \mu_t + \sqrt{\tau_t \times g_{i,t}}\varepsilon_{i,t} \tag{13}$$

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(r_{i-1,t}-\mu)^2}{\tau_t} + \beta g_{i-1,t} \tag{14}$$

$$\tau_t = m + \theta\sum_{k=1}^{K}\varphi_k(\omega_1,\omega_2)X_{t-k} \tag{15}$$

$$\varphi_k(\omega_1,\omega_2) = \frac{(k/K)^{\omega_1-1}(1-k/K)^{\omega_2-1}}{\sum_{j=1}^{K}(j/K)^{\omega_1-1}(1-j/K)^{\omega_2-1}} \tag{16}$$

Formula (13) is the mean value equation. $s_{i,t}$ represents the volatility spillover index of the stock market on the ith day of month t. μ_t is the conditional expectation of $s_{i,t}$. τ_t is the long-term low-frequency component of the conditional variance of $s_{i,t}$. $g_{i,t}$ is the short-term high-frequency component of the conditional variance of $s_{i,t}$. The conditional variance is the product of τ_t and $g_{i,t}$. $\varepsilon_{i,t}$ is a stochastic process subject to a conditional standard normal distribution, namely $\varepsilon_{i,t}|\Phi_{i-1,t} \sim N(0,1)$. $\Phi_{i-1,t}$ is the information set available on day $I-1$ in month t.

Formula (14) refers to a GARCH (1,1) process to measure short-term factor $g_{i,t}$. α and β are parameters that satisfy $\alpha + \beta < 1$, $\alpha > 0$ and $\beta \geq 0$.

Formula (15) is used to describe the long-term fluctuation process under the influence of low-frequency variable X_{t-k}. m is the constant term. X_t is the low-frequency explanatory variable. k is the number of lag periods. K is the maximum lag order of explanatory of variable X_t. According to the BIC information criterion, we choose $K = 12$ in this paper. θ represents the overall effect of all lagging explanatory variables on the long-term component. $\varphi_k(\omega_1, \omega_2)$ is a nonlinear weight polynomial function, and its value is the weight corresponding to the explanatory variable X_t which is in the lag period of k. ω_1 and ω_2 are parameters. In order to ensure that the weight of the lag variable is in the form of decay, that is, the closer it is to the current period, the greater the impact is on the current period. In general, let $\omega_1 = 1$, and the coefficient ω_2 determines the decay rate of the influence degree of low-frequency indexes on high-frequency data. Therefore, (16) can be simplified as:

$$\varphi_k(\omega_2) = \frac{(1 - k/K)^{\omega_2 - 1}}{\sum_{j=1}^{K}(1 - j/K)^{\omega_2 - 1}} \tag{17}$$

In this paper, the maximum likelihood function method is used to estimate the single-factor GARCH-MIDAS model. Formula (18) is the likelihood function, where T represents the total month and N is the number of days in each month.

$$LLF = -\frac{1}{2}\left[(2\pi)^{TN} + \sum_{t=1}^{T}\sum_{i=1}^{N} ln(\tau_t g_{i,t}) + \sum_{t=1}^{T}\sum_{i=1}^{N}\frac{(r_{i,t} - \mu)^2}{\tau_t g_{i,t}}\right] \tag{18}$$

This paper uses GARCH-MIDAS model to calculate the impact of EPU on inter-sector volatility spillover in China's stock market. The calculation process is as follows: firstly, the volatility spillover sequence of different industries is substituted into Equation (13) in the GARCH-MIDAS model, and the estimation of Equations (13) and (14) is carried out to obtain the parameters μ, α and β, which represent the short-term characteristics of the volatility spillover sequence. Then, an EPU index is further substituted into Model (15), and parameters of (15) and (16) are estimated to analyze the long-term impact of EPU on the volatility spillover sequence and the weight attenuation.

4. Empirical Results

4.1. Full Sample Financial Shock Transmission Structure

This section discusses the financial shock transmission structure in the system composed of 10 industries in the Chinese stock market from 2004 to 2020. According to Diebold and Yilmaz [19], institutions with high positive net volatility spillover impact (NET) in the financial shock transmission network and high impact (TO) on other institutions (departments) are defined as systemically important financial institutions (SIFIs). Specifically, the variables of the VAR model include ten industries in China, namely a total of 10 variables. According to the Akaike Information Criterion (AIC), the lag period of the VAR system was selected as 1. According to relevant literature [17,18], we use the 10-step (equivalent to two weeks) prediction of generalized vector autoregressive to calculate the structure of the full-sample financial shock transmission network [19]. The inter-sector financial shock transmission structure network in China is shown in Table 3. The index of FROM represents the sum of the shocks from all other industries within the sample interval. TO represents the impact of the industry on all other industries. NET is numerically equal to the difference between the TO and FROM indices and represents the net risk spillover effect a certain sector suffers. TS represents the total spillover index of the ten industries in the sample period.

Table 3. Full sample financial shock transmission structure (2004–2020).

	EI	MI	II	CDI	CSI	HCI	FI	ITI	TSI	UI	From
EI	21.12	11.30	10.70	10.62	8.03	7.21	11.23	4.29	6.75	8.76	78.88
MI	9.35	17.48	12.50	12.09	8.47	9.31	7.69	7.93	6.88	8.31	82.52
II	8.67	12.24	17.12	12.94	8.34	9.03	7.21	8.57	6.92	8.96	82.88
CDI	8.32	11.45	12.52	16.56	9.15	10.44	7.57	8.99	6.20	8.80	83.44
CSI	7.93	10.11	10.16	11.53	20.86	10.14	7.70	7.33	6.60	7.64	79.14
HCI	6.90	10.77	10.66	12.75	9.83	20.21	6.65	8.98	5.50	7.75	79.79
FI	12.06	9.98	9.55	10.37	8.37	7.46	22.68	3.67	7.51	8.35	77.32
ITI	4.88	10.90	12.02	13.03	8.44	10.67	3.89	24.02	5.68	6.46	75.98
TSI	8.18	10.08	10.36	9.59	8.11	6.97	8.48	6.06	25.62	6.53	74.38
UI	9.04	10.37	11.41	11.59	7.99	8.36	8.02	5.86	5.56	21.80	78.20
To	75.34	97.20	99.88	104.51	76.72	79.60	68.44	61.69	57.60	71.55	TS =
Net	−3.54	14.68	17.00	21.06	−2.42	−0.19	−8.88	−14.29	−16.78	−6.64	79.25

Through the static structure network, we can come to the following conclusions:

Firstly, the inter-sector spillover effect of China's stock market is very significant. Note the total spillover index in the lower right corner of Table 3. Commercial activities and lending relationships among financial institutions are the main determinants of the degree of correlation among financial institutions [2,59–62]. Both commercial activities and lending linkages will be further strengthened in deeply developed financial markets. Within the sample interval, China's total inter-sector spillover index is 79.25%, which means that more than four-fifths of the volatility prediction error variance within the sample period comes from inter-sector spillover. The inter-sector correlation of China's stock market is very close, and stock market risks are easy to spread across industries.

Secondly, in China's industrial system, each industry has strong connectivity with itself, which is higher than the average level of connectivity in the whole system. This can be observed through the fact that the diagonal elements representing the self-effect range from 16.56% to 25.62%, all above the mean of the pairwise spillover index. The volatility spillover of each industry index is greatly affected by the overall influence of other industries, which is more than 74%.

Thirdly, there is another interesting phenomenon: the three industries of CDI, II, and MI have been identified as systemically important industries in China due to their high TO and NET values in the financial shock transmission network. This means that within the sample interval, these three industries play the role of net exporters of risks in China, and the risk spillover intensity is greater than that of other industries. On the one hand, in the upstream of the industrial chain, II and MI are the basis of many industries; On the other hand, these two industries are more vulnerable to macroeconomic and policy changes. Consumption has always been an important factor driving China's economic growth, and CDI has increasingly become the vital element of domestic demand. In general, the systemically important domestic industries identified by the static financial shock transmission structure network are consistent with the current cognition of domestic economic development.

Fourthly, ITI, TSI, FI, UI, EI, CSI, and HCI are net recipients of risk. First of all, in 2008, the telecom industry was restructured. A tripartite situation of China Mobile, China Unicom, and China Telecom was formed. Restricted by China's policies, TSI is still in the era of the planned economy to some extent, and its business field is strictly limited, so the risk is difficult to pass on. The same is true for UI. Second, since the financial industry mainly includes state-owned banks, large joint-stock commercial banks, and big brokerages and insurance companies, FI has been under strict financial regulation. The real estate industry has also been paid special attention. As a result, FI has a relatively minor impact on other sectors, acting as a net recipient in the system.

Fifthly, the net spillovers of TSI to all other sectors are all negative, which further confirms the vulnerability of this sector in the aspect of absorbing risk shocks from other sectors. II's net spillover effect to CDI is negative but it's positive to the rest industries.

CDI's net spillover effect on TSI is negative and is also positive for other industries. These facts all confirm the systemically important industry status of II and CDI in China. It is worth noting that the largest spillover index, except for the self-spillover index, occurs in the CDI to II. As the upstream of CDI, II is greatly affected by the demand of the optional consumption, so the volatility spillover effect of CDI on II is significant.

4.2. Dynamic Financial Shock Transmission Structure

As the generalized variance decomposition model parameters will change over time, the whole sample static analysis could smooth out the information of fluctuation in the period studied, leading to the inaccurate judgment of spillover structure. The rolling window method can depict the volatility sequences much better, as it can better extract time-varying characteristics of the spillover behavior of different industries. The systematically important industries identified this way seem to be more accurate. Therefore, after discussing the full sample static volatility spillover structure network, we analyze the dynamic inter-sector volatility spillover structure of China during the sample period by setting up the rolling time window method in this part. To understand the dynamic time-varying transmission structure of financial shocks among Chinese industries as well as the roles played by different sectors in this transmission structure, we use a 120-day fixed rolling window to extract the dynamic changes of the financial shock transmission structure between industries following [17–19]. Table 4 shows the dynamic financial shock transmission structure network obtained after averaging all windows. The total spillover index changes a little, namely from 79.25% to 71.36%. The overall conclusion was consistent with the static state.

Table 4. Average of the rolling window financial shock transmission structure (2004–2020).

	EI	MI	II	CDI	CSI	HCI	FI	ITI	TSI	UI	From
EI	29.58	10.79	10.43	8.96	5.89	5.43	10.22	5.69	5.49	7.51	70.42
MI	9.28	25.05	12.36	10.11	6.85	7.27	8.15	7.42	5.89	7.62	74.95
II	8.03	11.14	21.59	11.75	7.27	8.03	8.67	8.60	6.01	8.90	78.41
CDI	7.26	9.59	12.30	23.00	8.33	8.87	8.18	9.39	5.36	7.72	77.00
CSI	6.05	8.20	9.49	10.43	31.65	9.36	6.69	6.80	4.86	6.45	68.35
HCI	5.28	8.32	10.14	10.89	9.17	30.17	6.27	8.88	4.46	6.43	69.83
FI	10.00	9.23	10.94	9.70	6.39	6.28	27.97	6.39	5.69	7.42	72.03
ITI	5.61	8.52	11.01	11.46	6.50	9.01	6.47	28.51	6.50	6.41	71.49
TSI	6.46	8.09	8.90	7.66	5.48	5.28	6.78	7.40	38.25	5.70	61.75
UI	7.59	8.82	11.46	9.61	6.28	6.62	7.72	6.41	4.92	30.59	69.41
To	65.57	82.70	97.03	90.55	62.15	66.16	69.16	66.98	49.18	64.16	TS =
Net	−4.85	7.75	18.62	13.56	−6.20	−3.67	−2.87	−4.51	−12.57	−5.25	71.36

Figure 1 shows the time-varying total spillover index. The sample interval can be divided into the following cycles according to this figure. The first cycle is from 2004 to the end of 2005 when the Federal Reserve raised interest rates for five consecutive times and international crude oil futures prices continued to rise, leading to a high level of total spillover effect and strong inter-sector connectivity. The second cycle is from early 2006 to early 2011. During this period, the total spillover level continues to remain high, mainly because of the US subprime mortgage crisis triggered by the global financial market turmoil in 2007, the first round of quantitative easing policy in the US, China's 4 trillion stimulus plan, and the influence of European sovereign debt crisis of 2010. Facing this, investors tended to change their allocation constantly, leading to the rapid risk transfer among sectors. From the beginning of 2011 to the middle of 2014, the Japanese earthquake, the deepening of the European debt crisis, and the 120-billion-Euro stimulus package all pushed China's inter-sector connectivity to a high level. It was not until the second half of 2013, when the world economy gradually stabilized, that the total inter-sector spillover level of China's stock market decreased. The fourth cycle is from the second half of 2014 to the middle of 2017. The historic surge and crash in the Chinese stock market during this period have led to a high level of interconnection between Chinese industries. With the end of the slump, China's stock market entered the correction period, and the total spillover level among sectors gradually decreased. With the drastic changes of the US trade policy towards China, China's stock market has entered the fifth cycle, that is, from the second half of 2017 to the second half of 2019. The inter-sector risk spillover effect remains relatively high. Since the end of 2019, the global economy has been hit hard by the COVID-19 epidemic, with risks rapidly spreading across industries, leading to increased connectivity between sectors.

Figure 1. Time-varying chart of total inter-sector spillover index of China's stock market (2004–2020).

Figure 2 depicts the impact of each industry on other industries (TO) and the impact of other industries (FROM). Figure 3 is the net impact (NET) in the transmission structure of financial shocks. From the dynamic perspective, first of all, the spillover effect between industries in China's stock market is very significant, with close inter-sector linkage and cross-industry risk propagation. Secondly, CDI, II, and MI are still playing the role of the net exporter of risks in most periods in China from a dynamic perspective. Moreover, the risk spillover intensity is greater than that of other industries, that is, they are still identified as systemically important industries. Finally, TSI, ITI, FI, UI, EI, CSI, and HCI remain net recipients of risk over most periods. The above conclusions are consistent with the results obtained under static conditions.

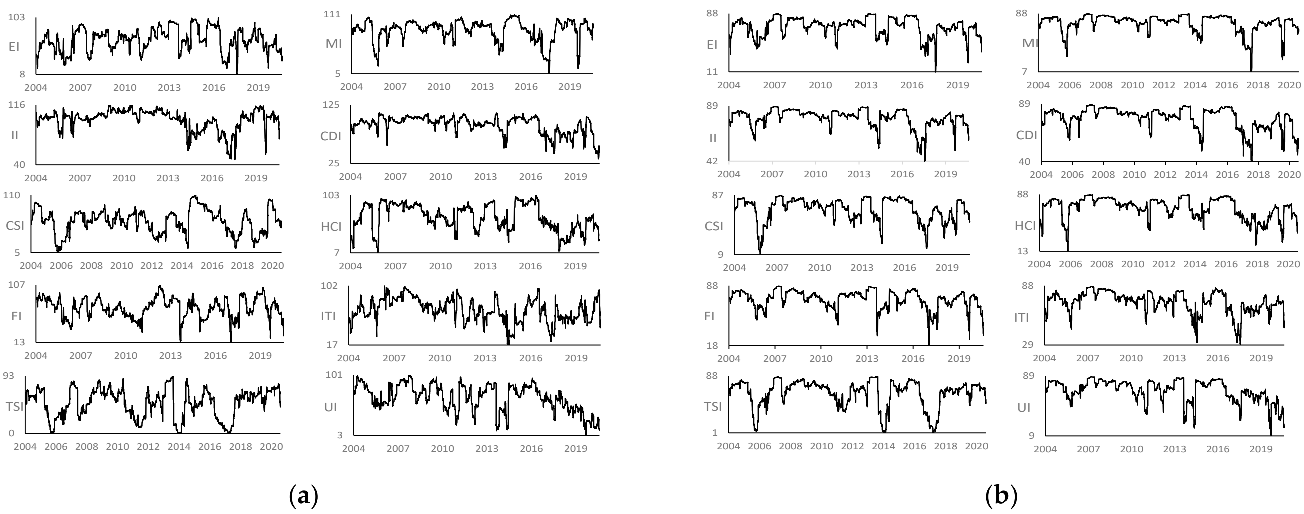

Figure 2. Directed volatility spillover index for 10 sectors in China's stock market (2004–2020). (**a**) shows the dynamic of "From" spillover index and (**b**) shows the dynamic of "To"spillover index.

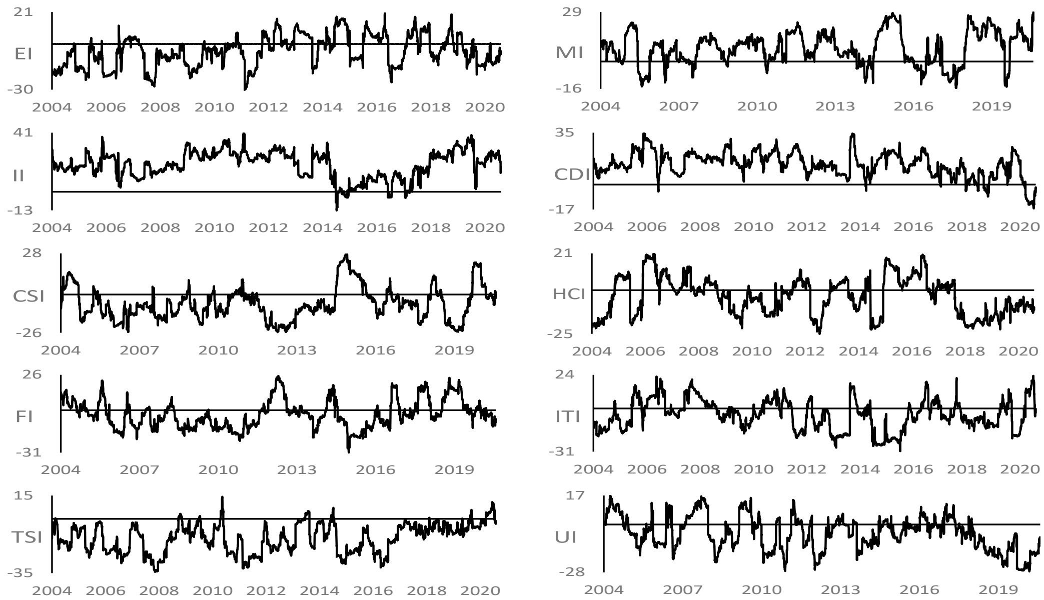

Figure 3. "Net" spillover index for 10 sectors in China's stock market (2004–2020).

According to Figures 2 and 3, the influence of each industry on and by other industries is constantly changing over time, and so is the net impact. In general, the trend of TO index and FROM index of all industries is similar, but the maximum value of three systemically important industries, namely MI, II, and CDI, is much higher than that of other sectors. The minimum value of the TO index of II is also much higher than others. The FROM indexes of II and CDI industries are significantly different from those of the other eight industries. The variation ranges of the two sectors' FROM indexes are relatively concentrated, which are almost half of that of other industries which range between 40–90%. This indicates that these two industries are always concentrated at a high level under the influence of other industries.

By contrast, NET indexes of different sectors appear to be very distinct. Table 5 reflects the change of the roles of the ten industries in the entire sample interval according to the NET indexes. When the Net index of this industry is greater than zero, it is considered to be a risk transmitter in the whole system. Otherwise, it is considered a risk absorber. As can be seen intuitively in Figure 3, the recognized net indexes of MI, II, and CDI industries in most cases are above the horizontal axis, and Table 5 provides a more direct proof. In particular, II and CDI are risk transmitters more than 94% of the time, while the TSI is a risk absorber with a ratio of 94.34%. It should be noted that HCI acts as risk transmitters nearly half of the time (41.04%). It does not seem very convincing to exclude sectors like HCI from systemically important industries simply because their proportions of risk transmitters do not reach half of the total sample time. It is worth noting that the HCI plays the role of risk transmitter from the end of 2005 to the second quarter of 2006, the FI's NET index remains to be positive from the end of 2011 to September 2012, and the NET index of CSI is also above zero from June 2014 to August 2015, as well as from September 2019 to March 2020. The net index of the CSI industry reaches 27.26% at its peak, accounting for more than 25% of the whole system. This may be related to China's policy of expanding domestic demand, especially in 2019. On the one hand, the trade war between China and the US has led to greater uncertainty in China's external environment, and on the other hand, the sudden outbreak of COVID-19 has put enormous downward pressure on the economy. In the meantime, the government has focused on stabilizing investment, stimulating consumption, and expanding domestic demand. Consumer goods belonging to CSI, such as automobiles, home appliances, and electronic products, are among the top priorities in policies to expand domestic demand. Therefore, the risk spillover level of the CSI industry to other industries remained positive during this period.

Table 5. Statistics on the proportion of roles undertaken by 10 sectors during the sample period.

Sector	EI	MI	II	CDI	CSI	HCI	FI	ITI	TSI	UI
Risk absorber	66.92%	21.07%	4.02%	5.11%	76.80%	58.96%	66.63%	65.61%	94.34%	69.45%
Risk carrier	33.08%	78.93%	95.98%	94.89%	23.20%	41.04%	33.37%	34.39%	5.66%	30.55%

4.3. The Impact of EPU on the Dynamic Financial Shock Transmission Structure

After obtaining the volatility spillover in China's stock market, this paper further investigates the effect of EPU on it. The formulation and adjustment of policies play a pivotal role in the fluctuation of asset prices. China's stock market is even called a "policy market" by many scholars. Literature shows that policies, especially discontinuous policies such as short-term policy events, are an important factor that causes the fluctuation of China's stock market prices [63–65]. Policy uncertainty caused by policy changes will also have an impact on China's stock market [13,43]. This influence is not only reflected in the whole Chinese stock market, but also directly reflected at the industry level. The change of policy will directly lead to the reallocation of asset portfolios among different industries, thus changing the original inter-sector volatility spillover structure. Although the US has been carrying out the policy of reshoring the manufacturing industry in recent years, the US, Japan, and other countries are closely watching the "de-Sinicization", and although the "anti-globalization" trend is becoming more and more obvious, the tide of globalization is still unstoppable. In this context, policies in other countries are bound to influence policymaking in China, leading to changes in the Chinese stock market. To sum up, this part considers the effects of five EPU indexes including the global EPU (GEPU), the United States' EPU (EPU_US), the United Kingdom's EPU (EPU_UK), China's EPU (EPU_CN), and Japan's EPU (EPU_JAP) on the inter-sector volatility spillover structure of the Chinese stock market. This paper adopts the index of policy uncertainty proposed by Baker et al. (2013). Each national EPU index reflects the relative frequency of own-country newspaper articles that contain a trio of terms about the economy (E), policy (P), and uncertainty (U). In other words, each monthly national EPU index value is proportional to the share of own-country newspaper articles discussed. The relative frequency of newspaper articles reflected by the EPU index for each country contains three aspects about the economy (E), policy (P), and uncertainty (U). In other words, each month the national EPU index value is proportional to the percentage of newspaper articles discussing economic policy uncertainty.

Table 6 shows the basic indicators of the selected EPU indexes. The five EPU indexes can be roughly divided into three categories: GEPU and EPU_UK belong to the first category, EPU_US and EPU_JAP belong to the second one, and EPU_CN belongs to the third. The mean values of GEPU and EPU_UK are both around 140, showing clustering characteristics. The mean and median levels of EPU_US and EPU_JAP are lower, especially the median of EPU_US, which is nearly 40 points smaller than that of GEPU. EPU_CN is an obvious outlier. It's mean and median are extremely high, which is caused by its linear rise from the end of 2018. This can also be seen from the maximum value of EPU_CN, which is 730 points higher than EPU_JAP, and about 400 points higher than other countries. As for the minimum value, EPU_US, EPU_UK, and EPU_CN are all between 24 and 37, while GEPU and EPU_JAP are relatively high. The standard deviation can also reflect that EPU_CN is an obvious outlier with an extremely violent fluctuation of 235.39, while other indexes mostly range from 62–83. EPU_JAP is the most stable one with a standard deviation that meets only 35.32.

Table 6. Descriptive statistics of EPU indexes in selected countries.

	Mean	Median	Max	Min	Std.Dev.
GEPU	137.78	122.61	429.43	48.82	68.83
EPU_US	101.24	84.20	503.01	37.27	62.17
EPU_UK	134.21	128.43	558.22	24.04	75.07
EPU_CN	243.71	151.31	970.83	26.14	235.39
EPU_JAP	107.75	105.41	240.23	48.37	35.32

4.3.1. The Impact of EPU on the Total Inter-Sector Spillover Structure in China

Firstly, the GARCH-MIDAS model is used to discuss the influence of EPU indices of different countries on the total volatility spillover level of China's stock market. The regression results are shown in Table 7. The parameters of GARCH, namely (μ, α, β) are statistically significant, which means that the total volatility spillover structure of the Chinese stock market shows a strong volatility aggregation effect. γ reflects the method used for regression of short-term components. When the parameter is significantly non-zero, asymmetric GJR-GARCH is used as the short component. If false, a simple GARCH (1,1) is employed. θ shows the long-term effect of EPU indexes on the total spillover. ω_2 is the optimal estimation coefficient of weight attenuation. The long-term impact of low-frequency indicators on the total volatility spillover can be calculated through θ and ω. It is worth noting that the corresponding θ of all the EPU indexes in Table 7 are not significant, which means that the selected EPU indexes do not show significant long-term influence on the total inter-sector volatility spillover structure in China's stock market. LLF is the maximum likelihood function value. BIC is the information criterion value.

Table 7. GARCH-MIDAS results of EPU index on total inter-sector spillover level in China [5].

	GEPU	EPU_US	EPU_UK	EPU_CN	EPU_JAP
μ	75.829 ***	75.748 ***	75.768 ***	75.765 ***	75.777 ***
	(0.775)	(0.226)	(0.635)	(0.393)	(0.187)
α	0.946 ***	0.686 ***	0.744 ***	0.776 ***	0.730 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β	0.000	0.304 ***	0.211 ***	0.146 ***	0.223 ***
	(0.001)	(0.000)	(0.000)	(0.011)	(0.001)
γ	0.084 *	0.001	0.069	0.129 ***	0.078 ***
	0.050	0.043	(0.076)	(0.042)	0.004
θ	−0.015	0.015	0.012	−0.005	0.028
	(0.019)	(0.038)	(0.027)	(0.012)	(0.040)
ω_2	1.000	1.002	14.952	1.000	2.535
	(2.822)	(11.067)	(46.651)	(5.146)	(2.227)
m	4.958	0.835	1.075	3.430 *	−0.551
	(1.659)	(3.915)	(2.202)	(2.008)	(5.069)
LLF	−11,894.72	−11,911.2	−11,831.94	−11,831.85	−11,895.93
BIC	23,847.16	23,880.11	23,721.55	23,721.37	23,849.58

[5] In this table, *** or * respectively indicates that the parameters are significant at the level of 1% or 10%.

4.3.2. Influence of EPU on the Volatility Spillover Level of Various Sectors in China's Stock Market

Further, the GARCH-MIDAS model is used to analyze whether the EPU indexes have an impact on the volatility spillover of each industry in China's stock market, that is, to discuss whether different EPU indexes have a long-term impact on the net index of each industry. The regression results are shown in Tables 8–12, which show obvious heterogeneity. The parameters of GARCH (μ, α, β) are used to describe the short-term characteristics of the volatility spillover indexes. The spillover indices are of strong fluctuation agglomeration effect if parameters μ, α and β are significant. The long-term effect of EPU on the volatility spillover indexes is reflected by θ. ω_2 is the optimal estimation coefficient of weight attenuation of the variable in the Beta function. According to θ and ω_2, the effect of low-frequency monthly index EPU on the long-term component of volatility spillover index can be estimated.

Table 8. GARCH-MIDAS regression results of GEPU index on volatility spillover levels of various industries in China [6].

	EI	MI	II	CDI	CSI	HCI	FI	ITI	TSI	UI
μ	−3.175 ***	10.710 ***	23.864 ***	12.911 ***	−9.223 ***	0.913 *	−3.605 ***	−3.213 ***	−7.300 ***	−1.952 ***
	(0.254)	(0.416)	(0.109)	(0.240)	(0.591)	(0.527)	(0.170)	(0.447)	(0.272)	(0.313)
α	0.836 ***	0.948 ***	0.869 ***	0.908 ***	0.982 ***	0.713 ***	0.866 ***	0.940 ***	0.938 ***	0.963 ***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
β	0.130 ***	0.018	0.099 ***	0.080 ***	0.000	0.283 ***	0.125 ***	0.039 ***	0.000	0.000
	(0.019)	(0.016)	(0.003)	(0.016)	(0.002)	(0.000)	(0.001)	(0.009)	(0.001)	(0.000)
γ	0.029	0.031	0.040 ***	−0.012	−0.027 ***	−0.012	0.125 ***	−0.010	0.056 ***	0.054 ***
	(0.028)	(0.036)	(0.013)	(0.043)	(0.004)	(0.008)	(0.001)	(0.027)	(0.005)	(0.011)
θ	−0.006	0.011 ***	0.007 **	0.008 **	−0.006	0.011 ***	−0.005	0.007 **	−0.005	−0.006
	(0.006)	(0.003)	(0.003)	(0.003)	(0.007)	(0.004)	(0.003)	(0.003)	(0.036)	(0.007)
ω_2	1.000	41.733 **	1.160	65.223 ***	1.000	1.375	10.972	15.332 *	1.000	1.000
	(1.729)	(20.440)	(0.835)	(7.536)	(2.100)	(0.963)	(10.400)	(8.172)	(49.204)	(1.078)
m	5.150 ***	2.394 ***	2.501 ***	2.734 ***	4.521 ***	1.960 ***	4.592 ***	3.260 ***	4.366	5.544 ***
	(1.197)	(0.589)	(0.502)	(0.686)	(0.850)	(0.657)	(0.697)	(0.692)	(4.337)	(1.088)
LLF	−12,631.07	−12,452.25	−11,823.48	−11,616.74	−12,236	−12,740.79	−12,198.99	−12,733.4	−12,403.13	−12,439.7
BIC	25,319.87	24,962.22	23,704.67	23,291.2	24,529.72	25,539.3	24,455.7	25,524.52	24,863.97	24,937.16

[6] In this table, ***, ** or * respectively indicates that the parameters are significant at the level of 1%, 5%, or 10%.

Table 9. GARCH-MIDAS regression results of EPU_US index on volatility spillover levels of various industries in China [7].

	EI	MI	II	CDI	CSI	HCI	FI	ITI	TSI	UI
μ	−3.442 ***	7.000 ***	23.837 ***	12.856 ***	−9.232 ***	0.991 ***	−3.576 ***	−3.297 **	−7.247 ***	−2.122 ***
	(0.210)	(0.447)	(0.118)	(0.285)	(0.888)	(0.513)	(0.157)	(0.537)	(0.223)	(0.291)
α	0.805 ***	0.955 ***	0.877 ***	0.913 ***	0.967 ***	0.720 ***	0.873 ***	0.940 ***	0.955 ***	0.933 ***
	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β	0.158 ***	0.027 **	0.095 ***	0.067 ***	0.003	0.277 ***	0.128 ***	0.025 *	0.000	0.032
	(0.008)	(0.013)	(0.006)	(0.016)	(0.023)	(0.000)	(0.006)	(0.013)	(0.001)	(0.024)
γ	0.018	−0.026	0.030	0.000	−0.008	−0.018 ***	−0.021	0.015	0.038 ***	0.030
	(0.034)	(0.028)	0.019	(0.045)	(0.039)	(0.007)	(0.021)	(0.030)	(0.001)	(0.052)
θ	−0.024 **	−0.008	0.001	0.005	−0.001	0.016 ***	−0.007	−0.007	−0.004	0.008 *
	(0.010)	(0.005)	(0.001)	(0.003)	(0.004)	(0.006)	(0.005)	(0.013)	(0.003)	(0.004)
ω_2	1.010	3.119 **	55.652 **	61.432 ***	45.513	1.000 ***	8.531	1.000	18.178 ***	22.090
	(0.767)	(1.231)	(21.649)	(12.899)	(88.701)	(0.33)	(5.465)	(7.370)	(6.663)	(22.232)
m	6.251 ***	4.777 ***	3.344 ***	3.322 ***	3.827 ***	1.828 ***	4.628 ***	4.887 ***	4.261 ***	3.375 ***
	(0.886)	(0.623)	(0.388)	(0.609)	(0.417)	(0.670)	(0.847)	(1.315)	(0.334)	(1.027)
LLF	−12,612.21	−12,546.74	−11,829.81	−11,629.97	−12,238.43	−12,742.54	−12,199.01	−12,743.43	−12,407.07	−12,437.35
BIC	25,282.13	25,151.2	23,717.34	23,317.65	24,534.59	25,542.79	24,455.74	25,544.58	24,871.86	24,932.41

[7] In this table, ***, ** or * respectively indicates that the parameters are significant at the level of 1%, 5%, or 10%.

Table 10. GARCH-MIDAS regression results of EPU_UK index on volatility spillover levels of various industries in China [8].

	EI	MI	II	CDI	CSI	HCI	FI	ITI	TSI	UI
μ	−3.234 ***	7.877 ***	23.831 ***	12.756 ***	−9.157 ***	1.027 ***	−3.638 ***	−3.256 ***	−7.290 ***	−2.005 ***
	(0.209)	(2.663)	(0.105)	(0.256)	(0.432)	(0.361)	(0.169)	(0.557)	(0.247)	(0.266)
α	0.900 ***	0.788 ***	0.880 ***	0.900 ***	0.979 ***	0.679 ***	0.862 ***	0.940 ***	0.860 ***	0.963 ***
	(0.000)	(0.001)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.021)	(0.000)
β	0.091 ***	0.182 ***	0.089 ***	0.088	0.001	0.326 ***	0.112 ***	0.035 ***	0.000	0.000
	(0.014)	(0.021)	(0.000)	(0.079)	(0.005)	(0.000)	(0.004)	(0.012)	(0.001)	(0.000)
γ	−0.003	−0.009	0.038 ***	−0.019	−0.021 ***	−032 ***	0.033 **	−0.007	0.140 ***	0.038 ***
	(0.022)	0.047	(0.009)	(0.073)	(0.008)	(0.008)	(0.015)	(0.029)	(0.030)	(0.004)
θ	−0.012	0.011	0.005 ***	0.005 *	−0.005 **	0.005 **	−0.003	0.004	−0.004	−0.005
	(0.007)	(0.090)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)
ω_2	1.000	1.000	77.711 ***	5.968	131.242 ***	1.000	1.000	2.505	1.000	1.005
	(1.220)	(19.255)	(7.948)	(11.428)	(9.030)	(1.096)	(1.814)	(5.098)	(2.221)	(0.951)
m	6.421 ***	2.102	2.956 ***	2.805	4.428 ***	2.450 ***	4.408 ***	3.575 ***	3.533 ***	4.888 ***
	(0.997)	(11.356)	(0.438)	(4.603)	(0.355)	(0.591)	(0.711)	(0.818)	(0.541)	(0.760)
LLF	−12,619.82	−12,555.81	−11,823.87	−11,621.96	−12,230.86	−12,743.71	−12,201.66	−12,741.75	−12,409.1	−12,436.06
BIC	25,297.36	25,169.34	23,705.47	23,301.63	24,519.43	25,545.13	24,461.03	25,541.21	24,875.92	24,929.83

[8] In this table, ***, ** or * respectively indicates that the parameters are significant at the level of 1%, 5%, or 10%.

Table 11. GARCH-MIDAS regression results of EPU_CN index on volatility spillover levels of various industries in China [9].

	EI	MI	II	CDI	CSI	HCI	FI	ITI	TSI	UI
μ	−3.134 *** (0.329)	10.636 *** (0.273)	23.876 *** (0.205)	12.873 *** (0.257)	−9.225 *** (0.667)	0.927* (0.487)	−3.616 *** (0.167)	−3.195 *** (0.444)	−7.282 *** (0.228)	−2.057 *** (0.280)
α	0.862 *** (0.000)	0.838 *** (0.000)	0.864 *** (0.000)	0.466 *** (0.000)	0.929 *** (0.001)	0.713 *** (0.000)	0.873 *** (0.000)	0.934 *** (0.000)	0.985 *** (0.000)	0.934 *** (0.001)
β	0.126 *** (0.000)	0.117 *** (0.015)	0.128 *** (0.002)	0.500 *** (0.000)	0.034 (0.026)	0.280 *** (0.000)	0.113 *** (0.003)	0.036 *** (0.001)	0.000 (0.000)	0.000 (0.001)
γ	0.022 (0.007)	0.051 ** (0.020)	0.057 (0.075)	0.008 (0.077)	−0.011 (0.035)	−0.007 (0.008)	0.008 (0.014)	0.007 (0.027)	0.181 (0.221)	0.082 *** (0.000)
θ	−0.000 (0.001)	0.004 *** (0.001)	0.002 (0.005)	0.004 ** (0.002)	−0.001 (0.003)	0.002 * (0.001)	−0.002 (0.001)	0.002 ** (0.001)	−0.001 (0.001)	−0.003 (0.002)
ω_2	1.000 (2.759)	65.724 ** (21.171)	1.000 (38.551)	1.000 (1.872)	1.052 (12.913)	2.224* (1.200)	10.788 (6.979)	6.872 *** (1.577)	1.000 (3.832)	8.258 * (4.543)
m	4.903 *** (0.398)	2.715 *** (0.811)	3.370 (2.410)	1.420 *** (0.446)	3.612 *** (0.495)	2.829 *** (0.558)	4.490 *** (0.677)	3.606 *** (0.484)	4.746 *** (0.436)	4.492 *** (0.587)
LLF	−12,637.13	−12,449.14	−11,823.5	−11,669.62	−12,238.13	−12,744.59	−12,197.44	−12,733.35	−12,412.08	−12,437.36
BIC	25,323.74	24,955.99	23,696.46	23,388.72	24,533.98	25,546.9	24,452.6	25,524.42	24,881.87	24,932.44

[9] In this table, ***, ** or * respectively indicates that the parameters are significant at the level of 1%, 5%, or 10%.

Table 12. GARCH-MIDAS regression results of EPU_JAP index on volatility spillover levels of various industries in China [10].

	EI	MI	II	CDI	CSI	HCI	FI	ITI	TSI	UI
μ	−3.408 *** (0.226)	6.494 *** (0.465)	23.817 *** (0.110)	12.802 *** (0.303)	−9.213 *** (1.864)	1.127 *** (0.248)	−3.616 *** (0.159)	−3.455 *** (0.709)	−7.363 *** (0.223)	−2.000 *** (0.331)
α	0.788 *** (0.000)	0.940 *** (0.000)	0.900 *** (0.000)	0.892 *** (0.000)	0.959 *** (0.001)	0.697 *** (0.000)	0.849 *** (0.000)	0.945 *** (0.000)	0.909 *** (0.001)	0.944 *** (0.000)
β	0.157 *** (0.019)	0.041 *** (0.012)	0.071 (0.004)	0.090 *** (0.014)	0.000 (0.011)	0.305 *** (0.000)	0.137 *** (0.011)	0.032** (0.012)	0.000 (0.001)	0.000 (0.001)
γ	0.029 *** (0.003)	−0.021 (0.027)	0.032 * (0.017)	−0.003 (0.043)	−0.012 (0.029)	−0.022 *** (0.000)	0.010 (0.030)	−0.010 (0.028)	0.091 *** (0.013)	0.063 *** (0.001)
θ	−0.025 ** (0.010)	0.005 (0.005)	0.003 (0.005)	0.004 (0.004)	−0.011 (0.029)	0.028 ** (0.012)	0.001 (0.009)	0.007 ** (0.003)	0.009 * (0.005)	−0.003 (0.010)
ω_2	1.000 (2.471)	1.000 (2.465)	101.218 ** (50.277)	91.337 (134.850)	1.000 (15.460)	1.894 *** (0.493)	4.828 (3.724)	65.800 *** (12.116)	33.758 ** (13.988)	2.984 (1.876)
m	6.236 *** (0.984)	3.260 ** (0.879)	3.209 ** (0.659)	3.198 *** (0.927)	4.634 (3.026)	0.215 (1.703)	3.829 *** (1.191)	3.438 *** (0.450)	2.313 *** (0.602)	4.298 *** (1.208)
LLF	−12,607.82	−12,550.13	−11,829.17	−11,630.82	−12,233.3	−12,735.88	−12,203.58	−12,740.47	−12,403.04	−12,442.99
BIC	25,273.35	25,157.98	23,716.06	23,319.36	24,524.31	25,529.48	24,464.87	25,538.66	24,863.79	24,943.69

[10] In this table, ***, ** or * respectively indicates that the parameters are significant at the level of 1%, 5%, or 10%.

From Table 8, GEPU has a significant long-term influence on the volatility spillover of MI, II, CDI, HCI, and ITI. All of the θs are positive, indicating that when GEPU increases in a month, the long-term component of the volatility spillover in the next month will also increase. The θs of GEPU on MI and HCI are particularly significant and relatively large than others. This might because China's materials industry, especially steel, high performance carbon fiber, polyimide and so on, is heavily dependent on imports. The international environment and economic policy changes in other countries undoubtedly increase the internal risks of China's raw material industry. Since MI plays a fundamental role in China's industrial system and plays the role of risk transmitter in 78.93% of the selected period, the increase of its internal risks can also lead to more risks spilling into the entire Chinese stock market. It is a similar story in HCI. From the perspective of impact duration, the long-term effects of GEPU on MI, CDI, and ITI attenuate faster, while those on II and HCI are slowly.

Table 9 depicts that EPU_US has a significant long-term impact on EI, HCI, and UI, with a negative influence on EI and positive ones on others. At present, the United States has gradually become a major supplier of gasoline, and emerging economies led by China have become the main growth drivers in the energy market. The global energy supply and demand pattern has undergone profound changes. However, at the same time, the United States has withdrawn from the Paris Agreement and the global energy governance landscape is also changing. Therefore, the world's major countries and regions have adjusted their medium- and long-term energy development strategies in recent years in this context. The Chinese government has made great efforts to develop strategic energy policy to stabilize the domestic energy industry, reducing the impact of the uncertainty of EPU_US. For HCI, in September 2018, the United States launched a trade war against China. The Trump administration announced a 10% tariff on 200 billion Chinese products, including 22 kinds of medical devices, aiming to suppress the upgrading of China's medical device industry. With the change of EPU_US, the risks and spillover effects of China's HCI also show the same trend of it.

As can be seen from Tables 10–12, the long-term influence of EPU_UK on II, CDI and HCI is positive, while it on CSI is negative. EPU_CN has a significant long-term positive effect in MI, CDI, HCI, and ITI. EPU_JAP has a negative effect on the long-term composition of EI and a positive effect on HCI, ITI and TSI. For sectors where θ is not significant, the impact of the EPU indexes may be absorbed within a month and thus may affect the sectors' spillover level in the short term, but will not have a long-term impact on the future risk spillover. It can be seen that most of the EPU sequences have a long-term positive impact on sector volatility spillover, that is, the spillover effect of sector volatility will increase with the increase of EPU. In a word, the increase of EPU will lead to the enhanced risk spillover effect of some industries to the entire Chinese stock market system.

4.4. Robustness Test

To avoid the influence of different rolling window settings on results, Figure 4 shows the total spillover index obtained by setting different rolling windows (*rw*) and decomposition periods (*h*). The middle subgraph is the total volatility spillover index selected in the text for analysis. As shown in the figure, an increase in window length causes the total spillover to be smoothed out and some information to be lost. However, in general, the window setting and decomposition period have little influence on the total spillover index, because its trends under different conditions are the same.

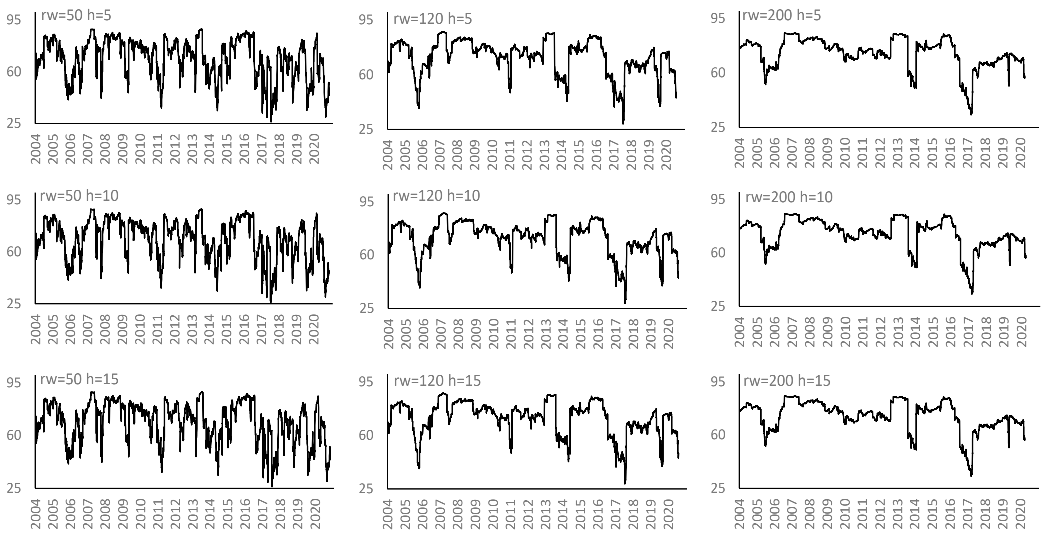

Figure 4. Robustness test of the inter-sector spillover index of China's stock market.

5. Conclusions

This paper studies the volatility spillover structure of China's inter-sector stock indexes from 2004 to 2020, and discusses the impact of major countries' EPU indexes on it, and draws the following four conclusions:

Firstly, no matter from the whole static sample or the rolling window, the volatility spillover effect of China's inter-sector stock index is particularly significant, which means that the inter-sector correlation of China's stock market is extremely strong. The stock market risks are easy to be transmitted among industries.

Secondly, CDI, II, and MI are identified as systemically important industries because they play the role of net volatility spillovers in the whole system. Among them, II and MI, as the basis of other industries, have relatively strong fluctuation spillover to other industries. CDI, as the downstream sector of many industries, has an impact on them from the demand end, thus producing similar effects as II and MI. The rest are net recipients of risk, especially TSI. At present, there is little literature on the inter-sector volatility structure of China's stock market, and the conclusion is consistent with that of this paper. They all believe that the evolution process of inter-sector spillover effect corresponds to specific events in political and financial markets, and the CDI and II play leading roles in China's stock market [44,66].

Thirdly, during the sample period, GEPU, EPU_US, EPU_UK, EPU_CN, and EPU_JAP have no significant long-term influence on the total inter-sector volatility spillover level of China's stock market. However, the above EPU indexes have a heterogeneous influence on the volatility spillover of each certain industry in China. GEPU has a positive long-term influence on the spillover fluctuation structure of MI, II, CDI, HCI, and II, which is the same for EPU_US to HCI and UI, EPU_UK to II, CDI and HCI, EPU_CN to MI, CDI, HCI, and ITI, as well as EPU_JAP to HCI, ITI, and TSI. EPU_US has a negative long-term influence on the spillover fluctuation structure of CSI, so as for EPU_UK and EPU_JAP to EI. As for the influence of EPU indexes on the stock markets' volatility spillover structure, existing literature mainly discusses their two-way volatility spillover relationship. It is concluded that policy uncertainty is highly connected with China's industrial stock market, and there is a two-way spillover relationship between them, mainly in the medium and long term [67–69]. However, this paper takes EPU indexes as exogenous variables and considers their influence on the inter-sector volatility spillover structure of China's stock market. This paper analyzes the heterogeneity of the impact of different countries' EPU indexes on the risk transmission characteristics of various sectors in China's stock market. Even in the relationship with long-term effect, various EPU indexes have different impact intensity and duration on volatility spillover of China's sectors.

Based on the above conclusions, this paper puts forward the following three suggestions: Firstly, when the government carries out risk management policies, only taking a certain sector into account is far from enough. They should also place a high value on the other industries that have obvious spillover relationship with the target sector, especially for the three systemically important industries, namely CDI, II, and MI, as their fluctuations can be quickly transmitted to other industries. Besides, when a major crisis comes up, these three sectors should be stabilized first to avoid the second expansion of the crisis due to their rapid risk transmission ability. What's more, the role of each industry changes over different periods. Therefore, in a given economic environment, policymakers should also consider whether a particular industry is a risk carrier in the whole system, rather than just considering the three most basic systemically important industries mentioned above. Secondly, although the EPU indexes seem to have no significant long-term impact on the total volatility spillover structure of China's industries, the EPU indexes of different countries have an impact on the entire Chinese stock market by affecting various sectors' volatility spillover level. Policymakers can make a certain judgment on the risk transmission structure in different sectors by observing the change of EPU indexes in different countries, to promote the effectiveness of policy implementation. Thirdly, investors should pay full attention to the inter-sector risk spillover effect, the relationship between upstream and downstream industries, and the long-term impact of different EPU indexes on the inter-sector volatility spillover structure in China to control risks from an overall perspective when conducting asset allocation through investment portfolios.

This paper comprehensively analyzes the inter-sector volatility spillover structure of China's stock market, and discusses the influence of the world's major EPU indexes on the inter-sector volatility spillover structure of China's stock market. With the increasing abundance of literature on EPU, different types of uncertainty indexes have been proposed, such as monetary policy uncertainty and trade policy uncertainty. These indexes lay a foundation for further research on the influence of different types of uncertainty indexes on the inter-sector volatility spillover structure of China's stock market. At the same time, although we have discussed the impact of different EPU indexes on the inter-sector volatility spillover structure of China's stock market, further research is needed on the transmission path of this impact, so as to better cope with the impact of uncertainty and achieve proper management of financial risks. In addition, in the future analysis of the influencing factors of inter-sector volatility spillover structure, except for the heterogeneity among industries, the possible upstream and downstream supply chain relations of different industries can also be further considered, so as to measure the influence of different macro variables more accurately.

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