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Market Risk of Lithium Industry Chain—Evidence from Listed Companies

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Abstract: Lithium, a crucial raw material for new energy vehicles, is experiencing significant market price fluctuations due to escalating geopolitical conflicts, periodic mismatches in supply and demand, and increased attention to lithium resources from countries around the world. These factors may adversely affect the development of the new energy vehicle industry. This paper adopts the TVP-VAR-DY model, which measures dynamic spillover effects by allowing for variance changes through the estimation of a stochastic Kalman filter, thereby measuring risk spillover among upstream and downstream firms in the lithium industry chain. We selected 16 listed companies and six regional financial markets as the research sample, with the sample period from 4 July 2018, to 30 June 2023. The main conclusions are as follows: Between 2018 and 2020, the overall risk spillover in the lithium industry chain demonstrated a declining trend, though it experienced a sudden surge in 2020 as a result of the COVID-19 pandemic. This increase was followed by a gradual decline as the global economy improved and market stability was restored, leading to a reduction in risk aversion. Regarding the reception of risk spillovers, upstream firms exhibited a generally consistent level of directional risk spillovers, whereas downstream firms experienced more significant fluctuations. Chinese firms exhibited a higher level of received risk spillovers compared to their international counterparts, with less variation in these spillovers. From the perspective of risk spillover effects, significant variations were observed between firms in both the upstream and downstream markets. Chinese firms exhibited a higher level of risk inflow than international firms, with more pronounced changes in risk spillovers. Upstream enterprises should enhance their market competitiveness to mitigate the adverse effects of economic uncertainty. Downstream enterprises can alleviate the rise in raw material costs resulting from market price fluctuations through strategic cooperation. Additionally, the government should increase the market supply of resources, which will contribute to the establishment of a more robust lithium industry chain system.

Keywords: lithium; industry chain; risk spillover; market risk

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1. Introduction

The non-renewable nature of fossil energy means that its excessive exploitation and utilization will eventually lead to its depletion. Additionally, issues such as climate warming caused by carbon dioxide emissions during the use of fossil energy have drawn worldwide attention. Countries around the world are initiating energy transitions, promoting the application of clean energy technologies, reducing carbon dependence in industries, and driving the transformation of energy systems from carbon-intensive fossil energy systems to environmentally friendly clean energy systems. The clean energy system demands a greater amount of key mineral resources. For example, the metal usage in electric vehicles is six times that of conventional fuel vehicles, and the metal demand for onshore wind power plants is ten times that of natural gas power plants [1]. The global energy transition has led to a surge in demand for these critical minerals, significantly increasing the proportion of renewable energy in the total new power capacity [2]. The geographical distribution of key minerals is uneven, with countries like Congo possessing 70% of the world's cobalt resources, South Africa holding 71% of the world's platinum resources, China having 90% of the world's rare earth resources, and the Lithium Triangle in South America accounting for 76% of global lithium reserves. The mineral resource policies of these major exporting countries will have a significant impact on the global energy transition [3].

Lithium, a critical raw material for power batteries [4], plays a significant role in clean energy technologies [5]. The rapid development of the new energy vehicle market has led to a dramatic surge in the demand for power batteries [6]. Consequently, countries worldwide are increasing their capital investments to establish a lithium industry chain [7,8]. However, sharp fluctuations in lithium market prices pose challenges to the production and operational activities of both upstream producers and downstream consumers, adversely affecting the development of the lithium industry chain. The increase in upstream production, as a metal mineral resource, necessitates exploration, development, mining, and smelting, all of which require substantial fixed capital investment and result in longer production cycles. Additionally, rapid changes in market demand from downstream industries create periodic mismatches between supply and demand for lithium resources, triggering severe price volatility in the lithium market. The market risks arising from these economic cycle changes may spill over along the lithium industry chain. Risk spillover refers to the phenomenon whereby risks from a specific market, asset, or economy are transmitted to other markets, assets, or economies, thereby impacting them. This phenomenon is prevalent and serves as an important manifestation of the interconnectedness of global markets. In the risk transmission process, upstream producers and downstream consumers occupy different roles, including risk acceptors, risk transmitters, and risk intermediaries. Each role adopts various market strategies to manage market risks; risk transmitters attempt to shift their risks to other market participants, while risk acceptors strive to minimize the impact of market price fluctuations on production costs, thereby reducing their influence on business operations. Therefore, this paper examines the process and direction of market risk transmission within the lithium industry chain, using the new energy vehicle industry as a case study, and analyzes the role positioning of enterprises within the chain. Furthermore, overheated investments may intensify market competition in lithium-related industries, and regional financial markets will also be included in the study of risk transmission within the lithium industry.

2. Literature Review

The study of risk transmission mechanisms is of great significance for understanding market dynamics and formulating risk management strategies. In recent years, many scholars have conducted extensive research on market risk spillover, including different dimensions of risk spillover, transmission mechanisms, scale, and its impact on interconnected financial systems [9–14]. Market risk spillovers often have dynamic characteristics. Engle (2002) introduced the concept of dynamic conditional correlation to model the time-varying dependencies between asset returns, capturing the evolving nature of risk spillover over time [15]. Diebold and Yilmaz (2012) proposed using connectivity indicators to quantify the degree of risk transmission between financial markets, measuring the interconnectedness of the global financial system [16]. Baruník and Křehlík (2018) conducted an analysis from a frequency domain perspective, studying how the Diebold and Yilmaz model can extend the measurement of the strength and direction of risk spillover effects [17]. Ferrer et al. (2018) focused on clean energy companies in the United States, using the Baruník and Křehlík method to analyze whether there is a time–frequency variation problem between energy fuel stock prices, energy fuel prices, and financially related dynamic variables, finding significant fluctuations in the short term but not in the long term [18]. Zhang et al. (2020) analyzed the tail risk connectivity of China's stock market sectors based on conditional value at risk (CoVaR) and single-index model (SIM) quantile regression, finding that during market crashes, the stock market faces more systemic risk and increased connectivity [19]. Geng et al. (2021) took an international perspective to analyze the revenue and volatility networks of global new energy companies, examining their dynamic characteristics [20].

Market risk spillover may exhibit asymmetry. Reboredo et al. (2016), using the foreign exchange and stock markets of emerging economies as research samples, found asymmetries in both upward and downward risk spillovers and in the scale of risk spillover between the stock and foreign exchange markets [21]. Li et al. (2020) studied the risk spillover between financial technology companies and traditional financial institutions during a period of rapid technological advancement, discovering that the risk spillover from financial technology institutions to financial institutions is positively correlated with an increase in systemic risk among financial institutions [22]. Du and He (2015) utilized daily data from the S&P 500 index and West Texas Intermediate mid-grade crude oil futures returns to examine the spillover effects of extreme risks between the crude oil and stock markets. They found that before the financial crisis, there was a positive risk spillover from the stock market to the crude oil market and a negative risk spillover from the crude oil market to the stock market; after the financial crisis, bidirectional positive risk spillover significantly increased [23]. Restrepo et al. (2023) studied the risk spillover of key raw materials such as copper, lithium, nickel, and cobalt, finding that companies with greater risks are not necessarily larger companies but those with less diversified production investment portfolios [24]. Corbet (2020), to deeply analyze the interconnections between various submarkets faced by resource reserves in the energy market across the entire industry chain, applied the spillover index method of Diebold and Yilmaz (2014) with an effective integration of DCC-FIGARCH, examining the spillover effect between oil prices and energy company stock prices, which showed a significant negative correlation [25]. Konstantinos et al. (2024) studied the volatility spillover effects between ten major commodities and the stock market. The research study found that the relationships among hard commodities were stronger as they served not only as raw materials but also as investment products, whereas the relationships among agricultural products were relatively weaker [26]. Therefore, the impact of regional financial markets on the lithium industry chain is worthy of attention.

Scholars have studied the extent and roles different market entities play in the process of risk transmission. Zhu and Luo (2023) utilized industry data from the Chinese stock market to investigate the degree of risk spillover across different industries in China and analyzed the risk roles of different sectors [27]. Wu (2019) examined the risk spillover among various segments of the Chinese stock market, finding that the industrial sector plays a pivotal role in the Chinese stock market [28]. Bruyckere et al. (2013) investigated the contagion between European banks and sovereign debt default risk during 2007–2012, discovering that banks with weaker capital buffers, more fragile financing structures, and less engagement in traditional banking activities are particularly vulnerable to risk spillover [29].

The existing literature mainly focuses on the risk impact of individual market entities on the overall financial system, while research on the direction of risk transmission and spillover effects among different entities within the same market is relatively scarce. Moreover, the market risks arising from the periodic mismatch between supply and demand sides in the lithium industry chain cannot be ignored. Due to the differences in information transmission channels between various markets, the directions of risk spillover vary across markets and exhibit dynamic and time-varying characteristics. Furthermore, lithium, as a commodity, possesses both commodity and investment attributes, making the volatility spillover from the stock market a significant factor influencing the lithium industry chain.

This paper employs the TVP-VAR connectivity method to analyze the risk spillover between the upstream and downstream markets of the lithium industry chain, as well as the risk spillover between the lithium industry chain and regional financial markets, distinguishing between Chinese and international companies within the lithium ore industry chain. The possible marginal contribution of this paper is that it measures the degree and direction of risk spillover between upstream and downstream markets of the lithium industry chain and regional financial markets, and analyzes the heterogeneity of risk spillover between Chinese and international companies. The TVP-VAR-DY method is used to analyze the overall and directional transmission of risk spillover between industries, and based on the degree of risk spillover, companies are classified as risk exporters, risk acceptors, and risk intermediaries.

3. Materials and Methods

In the research field of risk spillover effects, various methods are employed based on considerations of correlation, systemic risk, and risk spillover, including Granger causality tests, VAR (vector autoregressive) models, GARCH (generalized autoregressive conditional heteroskedasticity) family models, copula functions, and the DY spillover index model proposed by Diebold and Yilmaz (2014). Cointegration tests and Granger causality tests are limited to describing low-dimensional structures, which complicates the explanation of the intricate risk spillover network structures. Furthermore, multivariate GARCH models have their own limitations: among the commonly used multivariate GARCH family models, the GARCH-BEKK model can only identify the direction of risk spillover, while the DCC-GARCH model, although capable of capturing time-varying characteristics, cannot specify the direction of risk spillover. The DY spillover index can measure the degree and direction of risk spillover among multiple market participants; therefore, this paper adopts the DY index method for the research.

Diebold and Yilmaz (2014) proposed the DY index method, which estimates the forecast error variance decomposition of the VAR model [30]. The DY method can measure the interconnectedness between system variables, thus finding wide application in the measurement of risk spillover effects. Antonakakis et al. (2020) proposed the TVP-VAR method, which extends the Diebold and Yilmaz method for measuring dynamic spillover effects by allowing for variance changes through the estimation of a stochastic Kalman filter with a forgetting factor [31]. The TVP-VAR(p) model can be written as follows:

$$\mathrm{y_t} = \upbeta_\mathrm{t}\mathrm{z_{t-1}} + \upvarepsilon_\mathrm{t} \tag{1}$$

$$\mathrm{vec}(\upbeta_\mathrm{t}) = \mathrm{vec}(\upbeta_\mathrm{t-1}) + \mathrm{v_t} \tag{2}$$

where $\mathrm{y_t}$ and $\mathrm{z_{t-1}} = \left[\mathrm{y_t}, \cdots, \mathrm{y_{t-p}}\right]'$ represents the $\mathrm{n} \times 1$ vector and $\mathrm{np} \times 1$ vector. $\upbeta_\mathrm{t}$ is an $\mathrm{n} \times \mathrm{np}$ time-varying coefficient matrix. $\upvarepsilon_\mathrm{t}$ represents error vector. Then, we transform the TVP-VAR into a TVP-VMA model:

$$\mathrm{y_t} = \sum_{j=0}^{\infty} \mathrm{B_{jt}}\upvarepsilon_{\mathrm{t}-j} \tag{3}$$

where $\mathrm{B_{jt}} = \mathrm{J'M_t^{\mathit{j}}J}$ is an $\mathrm{n} \times \mathrm{n}$ matrix, and J and $\mathrm{M_t}$ represent the $\mathrm{np} \times \mathrm{n}$ matrix and $\mathrm{np} \times \mathrm{np}$ matrix:

$$\mathrm{J} = [I, 0, \cdots, 0]', \mathrm{M_t} = \begin{bmatrix} \upbeta_\mathrm{t} & 0 \\ I_{n\mathrm{p}-1} & 0 \end{bmatrix} \tag{4}$$

The H-step-ahead generalized forecast error variance decomposition (GFEVD) and scaled GFEVD can be defined as follows:

$$\Phi_{ijt}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H}\left(e'_i B_{ht} P_t e_j\right)^2}{\sum_{h=0}^{H}\left(e'_i B_h \prod_t B'_h e_j\right)} \tag{5}$$

$\prod_t$ represents the covariance matrix of the error vector $\upvarepsilon_\mathrm{t}$. P_t is a lower triangular matrix. σ_{jj} represents the jth diagonal element of the matrix $\prod_t$. e_j is an $\mathrm{m} \times 1$ selection vector with unity in the jth position and is zero otherwise. This article constructs a series of network overflow indicators based on the principle of total overflow index proposed by Diebold and Yilmaz (2012, 2014) and the generalized variance decomposition matrix as follows:

(1) Total spillovers

We can define the total volatility spillover index:

$$total = \frac{100 \times \sum_{i,j=1,i \neq j}^{N} \Phi_{ijt}(H)}{\sum_{i,j=1}^{N} \Phi_{ijt}(H)} \tag{6}$$

(2) Directional spillovers

We can define the directional connectedness from others ($from_{j \to i,t}$) and to others ($to_{i \to j,t}$).

$$from_{j \to i,t}(H) = \frac{100 \times \sum_{j=1,i \neq j}^{N} \Phi_{jit}(H)}{\sum_{i,j=1}^{N} \Phi_{jit}(H)} \tag{7}$$

$$to_{i \to j,t}(H) = \frac{100 \times \sum_{j=1,i \neq j}^{N} \Phi_{ijt}(H)}{\sum_{i,j=1}^{N} \Phi_{ijt}(H)} \tag{8}$$

(3) Net spillovers

The net volatility spillover is simply the difference between the gross volatility shocks transmitted to and those received from all other markets.

$$net_{i,t}(H) = from_{j \to i,t}(H) - to_{i \to j,t}(H) \tag{9}$$

4. Data

The research sample of this paper consists of the stock returns of sixteen listed companies that have a significant impact on the lithium industry chain, including eight upstream companies and eight downstream companies. International companies primarily engaged in lithium resource development, such as Albermarle Corporation (Charlotte, NC, USA), Sociedad Quimica y Minera (Santiago, Chile), Pilbara Minerals Limited (West Perth, Australia), and Mineral Resources Ltd. (Vincent, Australia), represent the upstream sector of the international lithium industry chain. Chinese companies primarily engaged in lithium resource development, such as Sinomine Resource Group Co., Ltd. (Hong Kong, China), Ganfeng Lithium Group Co., Ltd. (Xinyu, China), Tianqi Lithium Corporation (Chengdu, China), and Sichuan Yahua Industrial Group Co., Ltd. (Chengdu, China), represent the upstream sector of the Chinese lithium industry chain. International lithium battery manufacturers such as Enersys (USA), Panasonic (Japan), LG Chem (South Korea), and Samsung SDI (South Korea) represent the downstream sector of the international lithium industry chain. Chinese companies, such as Contemporary Amperex Technology Co., Ltd. (Ningde, China), Byd Company Limited (Shenzhen, China), Sunwoda Electronic Co., Ltd. (Shenzhen, China), and Eve Energy Co., Ltd. (Huizhou, China), represent the downstream sector of the Chinese lithium industry chain.

The financial market's cross-market risk spillover to the lithium industry chain is also worth attention. Therefore, this paper selects six regional markets with abundant global mineral resources and relatively high levels of financial marketization as research subjects: China, Australia, the United Kingdom, the United States, Canada, and Russia. The FTSE China A600 Industrial Metals and Mining Index represents the Chinese market, the ASX 300 Metals & Mining Index represents the Australian market, the FTSE Metals & Mining Index represents the UK market, the S&P Metals & Mining Select Industry Index represents the US market, the TSX Metals & Mining Index represents the Canadian market, and the MOEX Metals and Mining Index represents the Russian market.

Due to the different impacts of public holidays on stock markets in different countries and the different opening and closing times, there is a non-complete correspondence between the time series data and dates, with some missing data. Therefore, to obtain a complete time series corresponding to the dates, non-public trading day data are excluded. The sample period for all data is from 4 July 2018, to 30 June 2023. The forward-adjusted prices of each listed company are selected as the basis for calculating returns to avoid the influence of outliers in closing prices caused by individual company factors. All data are sourced from the WIND database and Investing.com. The research sample is shown in Table 1.

Table 1. Research samples.

Name	Code	Country	Position
Albermarle Corporation	ALB	America	Upstream
Sociedad Quimica y Minera	SQM	America	Upstream
Pilbara Minerals Limited	PLS	Australia	Upstream
Mineral Resources Ltd.	MIN	Australia	Upstream
Sinomine Resource Group Co., Ltd.	ZK	China	Upstream
Ganfeng Lithium Group Co., Ltd.	GF	China	Upstream
Tianqi Lithium Corporation	TQ	China	Upstream
Sichuan Yahua Industrial Group Co., Ltd.	YH	China	Upstream
Enersys	ENS	America	Downstream
LG Chem Ltd.	LG	Korea	Downstream
Panasonic	PC	Japan	Downstream
Samsung SDI	SDI	Korea	Downstream
Contemporary Amperex Technology Co., Ltd.	ND	China	Downstream
Byd Company Limited	BYD	China	Downstream
Sunwoda Electronic Co., Ltd.	XWD	China	Downstream
Eve Energy Co., Ltd.	YW	China	Downstream
FTSE A600 Industrial Metals and Mining	A600	China	China Market
ASX 300 Metals & Mining	ASX	Australia	Australia Market
FTSE Metals & Mining	FTSE	England	England Market
S&P Metals & Mining Select Industry	SP	America	America Market
TSX Metals & Mining	TSX	Canada	Canada Market
MOEX Metals and Mining	MOEX	Russia	Russia Market
China Securities New Energy	CNNE	China	China New Energy Industry

From Figures 1–3, it can be observed that stock price trends of upstream enterprises in the international lithium industry chain are basically consistent with those of domestic lithium mining upstream enterprises. From 2018 to 2020, due to the increase in production of major global lithium resource projects, lithium prices entered a long-term downward channel. The mining cost of lithium does not change with the market price of lithium, resulting in a continuous compression of enterprise profit margins and a decline in stock prices. The COVID-19 outbreak at the end of 2019 led to labor shortages overseas, with many major lithium mining areas experiencing production cuts and shutdowns and many planned capacity expansions being delayed. Supply has tightened and is difficult to recover in the short term. On the demand side, countries around the world have set targets for vehicle electrification, and major car manufacturers have begun to invest heavily in the development of new electric and hybrid vehicle models. The industry has entered a virtuous cycle of growth, with demand rapidly increasing. The strong demand and limited supply have led to soaring lithium prices and an increase in the stock prices of upstream enterprises. After 2023, the global supply of lithium resources gradually increased, lithium production capacity continued to be released, and lithium demand fell short of expectations, leading to a downward trend in lithium prices and a decline in the stock prices of upstream enterprises. For downstream consumer enterprises in the lithium industry chain, the demand for lithium batteries has surged as the technology of new energy vehicles has gradually matured. However, with the strong rise in the prices of upstream lithium raw materials, the profit margins of downstream lithium battery manufacturing enterprises have been compressed, leading to a decline in the stock prices of downstream enterprises.

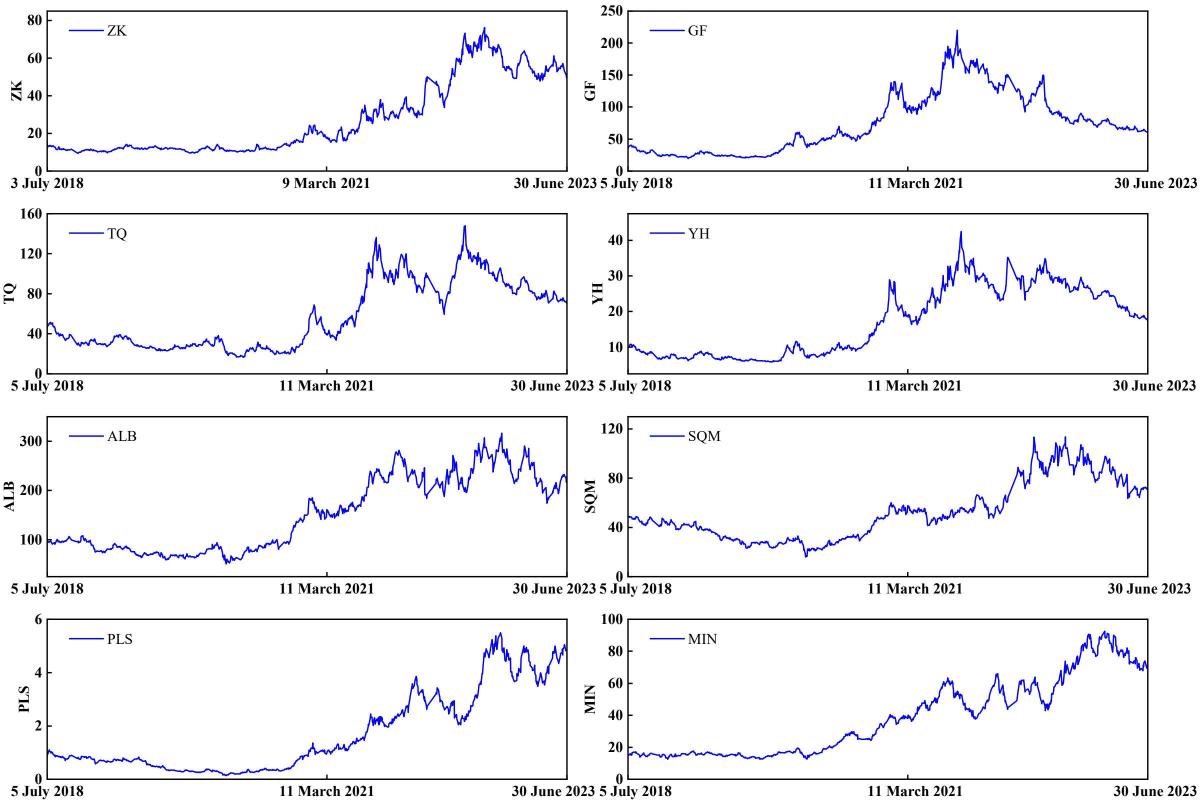

Figure 1. Upstream companies' price time series.

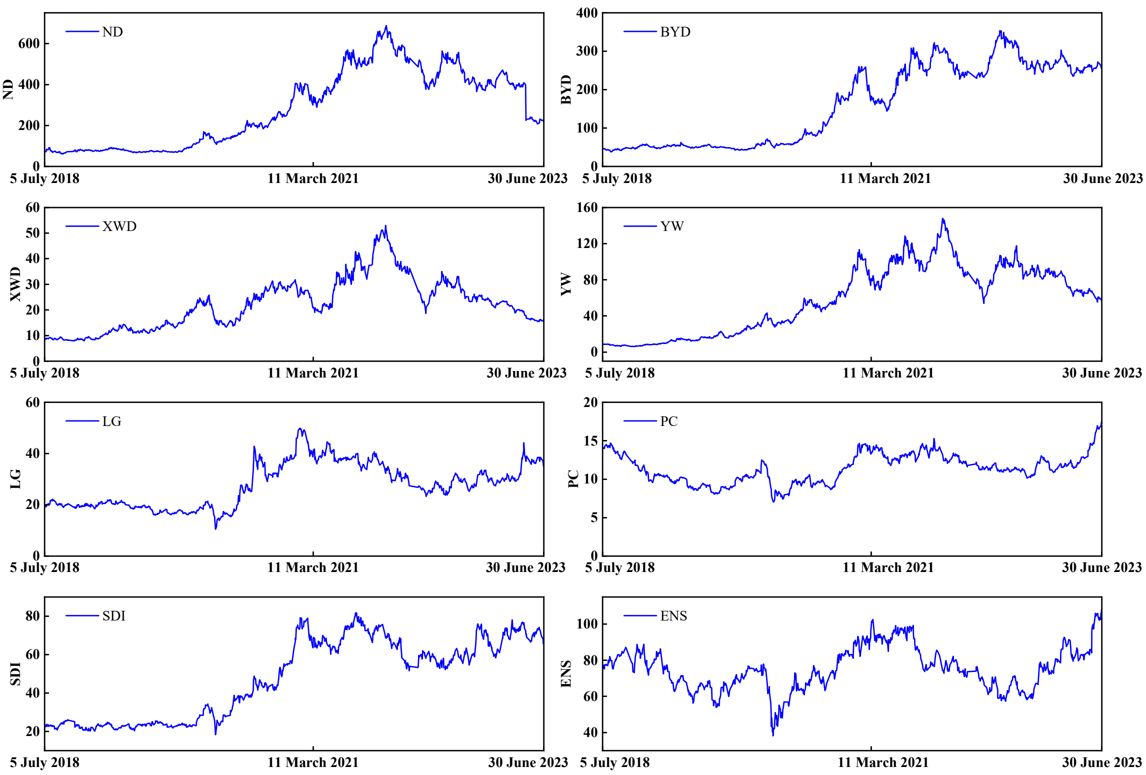

Figure 2. Downstream companies' price time series.

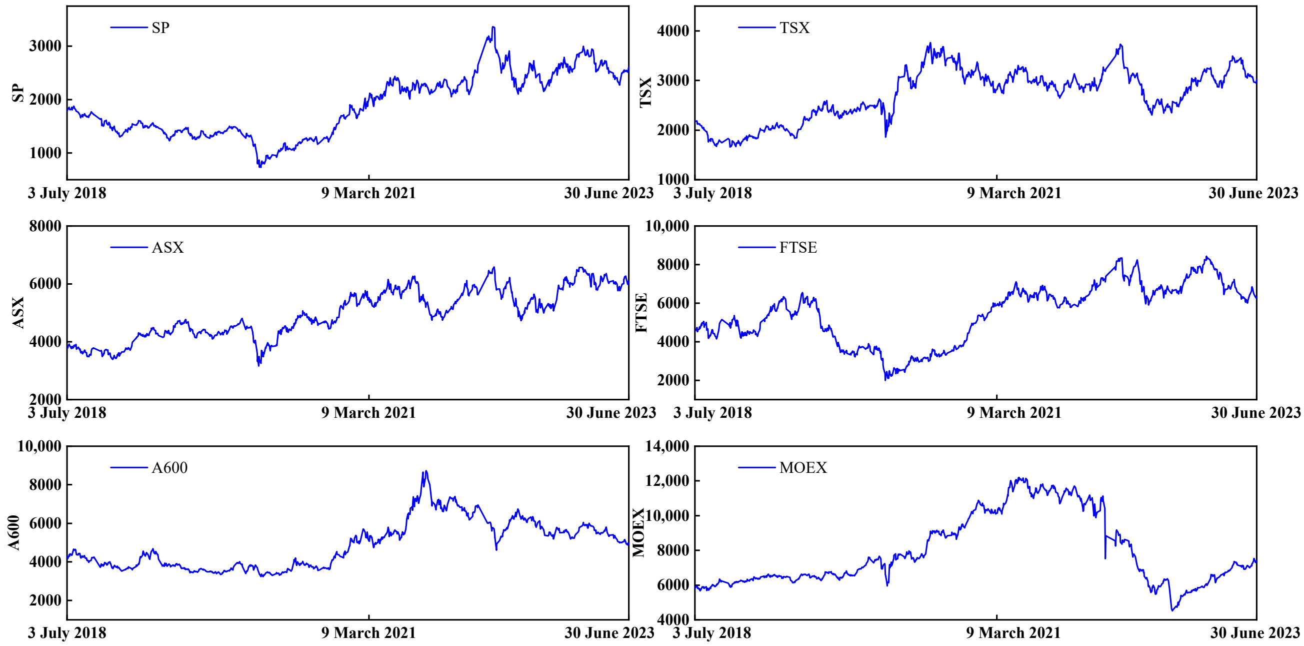

Figure 3. Stock price time series.

Descriptive statistical analysis was conducted on the volatility series of all indicators to analyze the basic statistical distribution of the return series. The daily return equation is as follows:

$$R_t = \ln \frac{P_t}{P_{t-1}} = \ln P_t - \ln P_{t-1} \tag{10}$$

The statistical results of each return rate are shown in Table 2:

Table 2. Summary statistics.

	ZK	GF	TQ	YH	ALB	SQM	PLS	MIN
Nobs	898	898	898	898	898	898	898	898
Minimum	−0.337	−0.319	−0.277	−0.233	−0.222	−0.269	−0.249	−0.123
Maximum	0.172	0.155	0.191	0.191	0.232	0.247	0.202	0.215
Mean	0.001	0.001	0.000	0.001	0.001	0.000	0.002	0.002
Median	0.000	0.000	−0.002	0.000	0.002	0.002	0.000	0.003
Stdev	0.040	0.041	0.044	0.038	0.037	0.037	0.050	0.032
Skewness	−0.549	−0.900	0.024	−0.074	−0.538	−0.410	−0.171	0.257
Kurtosis	7.185	8.100	3.150	5.005	5.953	7.659	3.134	3.174
	ND	BYD	XWD	YW	LG	PC	SDI	ENS
Nobs	898	898	898	898	898	898	898	898
Minimum	−0.570	−0.208	−0.273	−0.197	−0.195	−0.138	−0.191	−0.174
Maximum	0.173	0.181	0.182	0.177	0.282	0.113	0.177	0.154
Mean	0.001	0.002	0.001	0.002	0.001	0.000	0.001	0.000
Median	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.001
Stdev	0.039	0.033	0.040	0.042	0.033	0.022	0.030	0.029
Skewness	−3.332	0.129	−0.119	0.008	0.821	−0.043	0.245	−0.542
Kurtosis	50.895	3.775	4.296	2.406	10.429	4.804	5.008	6.069
	SP	TSX	ASX	FTSE	A600	MOEX		
Nobs	898	898	898	898	898	898		
Minimum	−0.164	−0.104	−0.077	−0.184	−0.143	−0.324		
Maximum	0.178	0.119	0.108	0.161	0.125	0.161		
Mean	0.000	0.000	0.001	0.000	0.000	0.000		
Median	0.001	0.000	0.001	0.002	0.000	0.001		
Stdev	0.027	0.023	0.019	0.029	0.022	0.021		
Skewness	−0.141	−0.069	0.143	−0.486	−0.492	−4.919		
Kurtosis	5.314	2.963	4.094	4.312	6.286	80.722		

It can be seen from Table 2 that the average return rate of lithium industry chain enterprises is positive and close to zero. In terms of standard deviation, the standard deviation of the return rate of upstream enterprises in the lithium industry chain is generally greater than that of downstream enterprises, indicating greater volatility in return rates. As for skewness, the skewness levels are close to zero, indicating no significant deviation. In terms of kurtosis, the kurtosis levels of all industries are much greater than 3, indicating a pronounced peak. Figure 4 shows the time series plot of the return rates of various enterprises during the sample period.

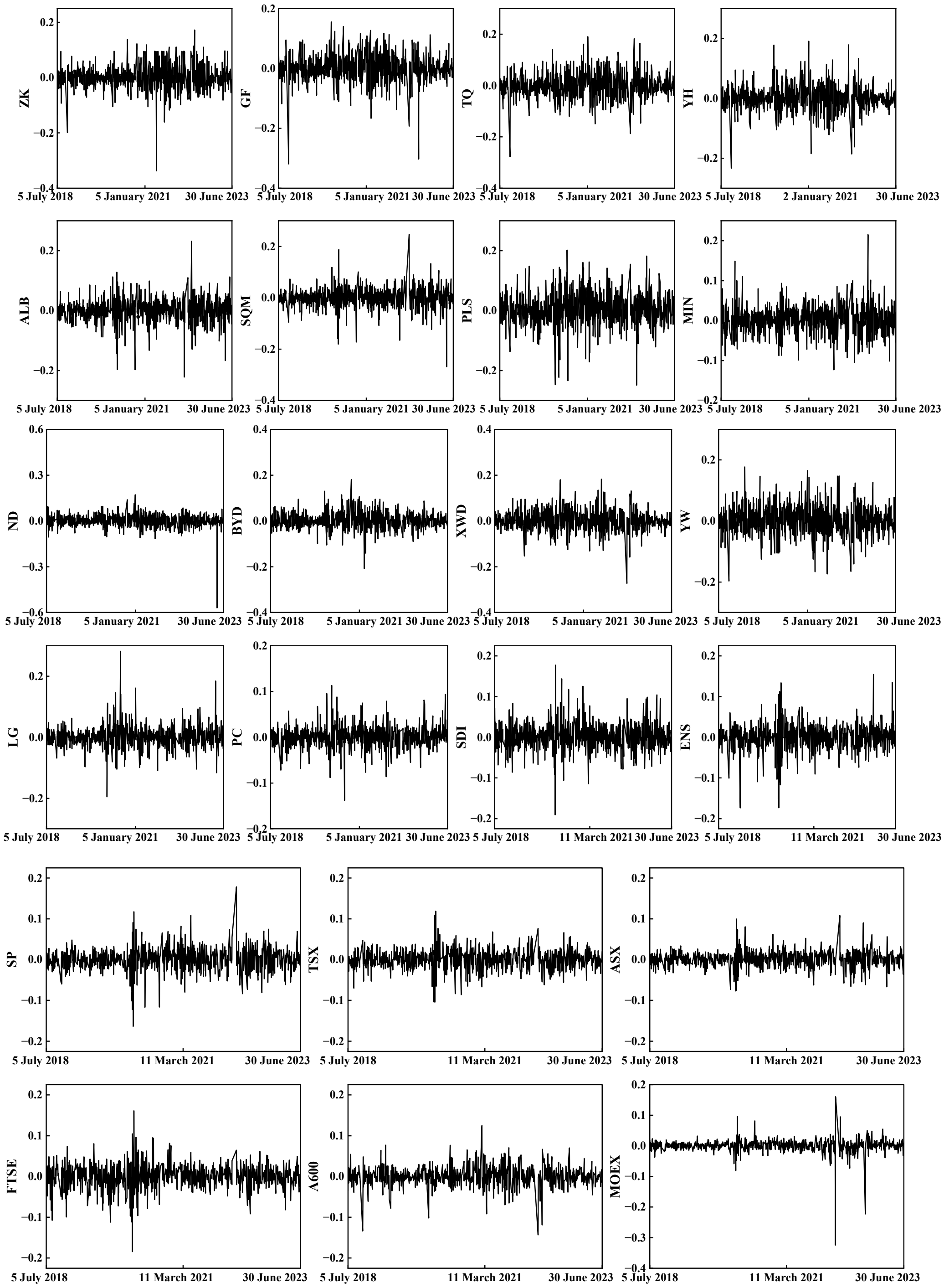

Figure 4. Stock returns.

Before measuring the spillover effects, it is necessary to first ensure that the time series is stationary to avoid spurious regression problems. The unit root test results for each financial series are shown in Table 3. As can be seen from Table 3, the ADF test, KPSS test, and PP test all indicate that the time series are stationary. Specifically, the ADF test shows that all return rate series are stationary at the 1% confidence level, the KPSS test indicates that most return rate series are stationary at the 10% confidence level, and the PP test shows that most return rate series are stationary at the 1% confidence level, meeting the requirements of the VAR model.

Table 3. Unit root test.

Variable	ADF	P	KPSS	P	PP	P
ZK	−10.88	0.01	0.16	0.10	−866.43	0.01
GF	−8.31	0.01	0.26	0.10	−923.28	0.01
TQ	−8.70	0.01	0.16	0.10	−811.17	0.01
YH	−9.40	0.01	0.17	0.10	−829.99	0.01
ALB	−9.25	0.01	0.13	0.10	−811.43	0.01
SQM	−10.61	0.01	0.16	0.10	−825.07	0.01
PLS	−9.10	0.01	0.44	0.06	−939.75	0.01
MIN	−9.81	0.01	0.09	0.10	−961.84	0.01
ND	−8.47	0.01	0.39	0.08	−857.32	0.01
BYD	−8.10	0.01	0.14	0.10	−850.87	0.01
XWD	−8.69	0.01	0.28	0.10	−865.00	0.01
YW	−9.34	0.01	0.3	0.09	−833.35	0.01
LG	−10.08	0.01	0.05	0.10	−853.10	0.01
PC	−8.94	0.01	0.29	0.10	−865.60	0.01
SDI	−9.53	0.01	0.09	0.10	−826.88	0.01
ENS	−9.86	0.01	0.09	0.10	−913.37	0.01
SP	−8.75	0.01	0.16	0.10	−908.21	0.01
TSX	−8.97	0.01	0.05	0.10	−805.35	0.01
ASX	−9.26	0.01	0.02	0.10	−916.97	0.01
FTSE	−9.15	0.01	0.11	0.10	−916.85	0.01
A600	−9.06	0.01	0.11	0.10	−872.73	0.01
MOEX	−10.58	0.01	0.21	0.10	−890.59	0.01

For the VAR model, it is necessary to determine the lag order of the variables. If the lag order chosen is too large, it will result in too few degrees of freedom, affecting the overall fit of the model. Conversely, if the lag order chosen is too small, there will be omitted variable information that falls into the disturbance term, causing autocorrelation issues in the disturbance term. As shown in Table 4, the optimal lag order under the AIC criterion, HQ criterion, SC criterion, and FPE criterion is all 1. Therefore, this paper chooses a lag order of 1 for the model.

Table 4. Lag order selection.

Lag	AIC	HQ	SC	FPE
1	−161.5751	−160.5320	−158.8462	−161.5751
2	−161.4171	−159.3762	−156.0781	−161.4171
3	−161.0658	−158.0271	−153.1165	−161.0658
4	−160.7515	−156.7151	−150.1920	−160.7515
5	−160.3553	−155.3212	−147.1857	−160.3553
6	−159.8574	−153.8255	−144.0775	−159.8574
7	−159.4568	−152.4271	−141.0667	−159.4568
8	−159.0729	−151.0455	−138.0726	−159.0729
9	−158.6371	−149.6119	−135.0266	−158.6371
10	−158.2299	−148.2069	−132.0092	−158.2299

AIC stands for Akaike Information Criterion, SC stands for Schwarz Information Criterion, HQ stands for Hannan–Quinn Information Criterion, FPE stands for Final Prediction Error Criterion.

5. Empirical Analysis

5.1. Static Risk Spillover Analysis

In this paper, the forecast period is set to 10 periods, and the risk spillover index matrix of return rates within the sample period is shown in Figure 3. The first row in the figure represents the sources of risk spillover, indicating the directional risk spillover effects that market entities receive from other market entities. The first column represents the targets of risk spillover, indicating the directional risk spillover effects that market entities exert on other market entities. The diagonal data show the contribution of market shocks to the forecast error variance of the elements themselves, reflecting the proportion of each market affected by its own risk spillover.

The systemic risk spillover index is 64.97, which means that 64.97% of the fluctuations within the system's variables are caused by the fluctuations of other variables, indicating a significant spillover relationship among the variables. From the absolute values on the diagonal, it can be discerned that the average value for the upstream market of the lithium industry chain is 31.09%, while the downstream market's average value is 37.58%. This indicates that the flow of market information in the upstream market is relatively robust, and changes in the external economic environment exert a greater impact on upstream enterprises. The average value for Chinese companies in the upstream industry chain is 26.25%, while the average value for international companies is 35.93%. For the downstream industry chain, the average value for Chinese companies is 32.44%, while the average value for international companies is 42.72%. This shows that in the lithium industry chain, market risk for Chinese enterprises primarily originates from other enterprises within the chain, with market price fluctuations having a greater impact on them. In the lithium stock market, the risk spillover from the Canadian and Russian stock markets exceeds 50%, suggesting that these markets are less affected by spillovers from other variables within the system. A possible explanation is that Canada possesses abundant lithium ore resources, rendering it less susceptible to shocks from external markets, whereas the Russian market experiences poor financial liquidity with other markets, resulting in a diminished influence from other market participants.

Correspondingly, based on Figure 5, the risk spillover degree of each company to the upstream, downstream and financial markets of the lithium industry chain can be calculated. "To_top" is the sum of the non-diagonal elements in the column for the upstream of the lithium industry chain, representing the total directional risk spillover from each company to other companies in the upstream of the lithium industry chain. "To_Down" is the sum of the non-diagonal elements in the column for the downstream of the lithium industry chain, representing the total directional risk spillover from each company to other companies in the downstream of the lithium industry chain. "To_Stock" is the sum of the non-diagonal elements in the column for the financial market, representing the total directional risk spillover from each company to the financial market. "From_Top" is the sum of the non-diagonal elements in the row for the upstream of the lithium industry chain, representing the total directional risk spillover received by each company from other companies in the upstream market. "From_Down" is the sum of the non-diagonal elements in the row for the downstream of the lithium industry chain, representing the total directional risk spillover received by each company from other companies in the downstream of the lithium industry chain. "From_Stock" is the sum of the non-diagonal elements in the row for the financial market, representing the total directional risk spillover received by each company from the financial market. "From" is the sum of the non-diagonal elements in the row, indicating the total risk spillover received by a company from other companies; the "To" row can be viewed as the spillover output index, indicating the total risk spillover a company exerts on other companies; and the "Net" row indicates the net risk spillover of a company, calculated by subtracting the "From" value from the corresponding "To" value.

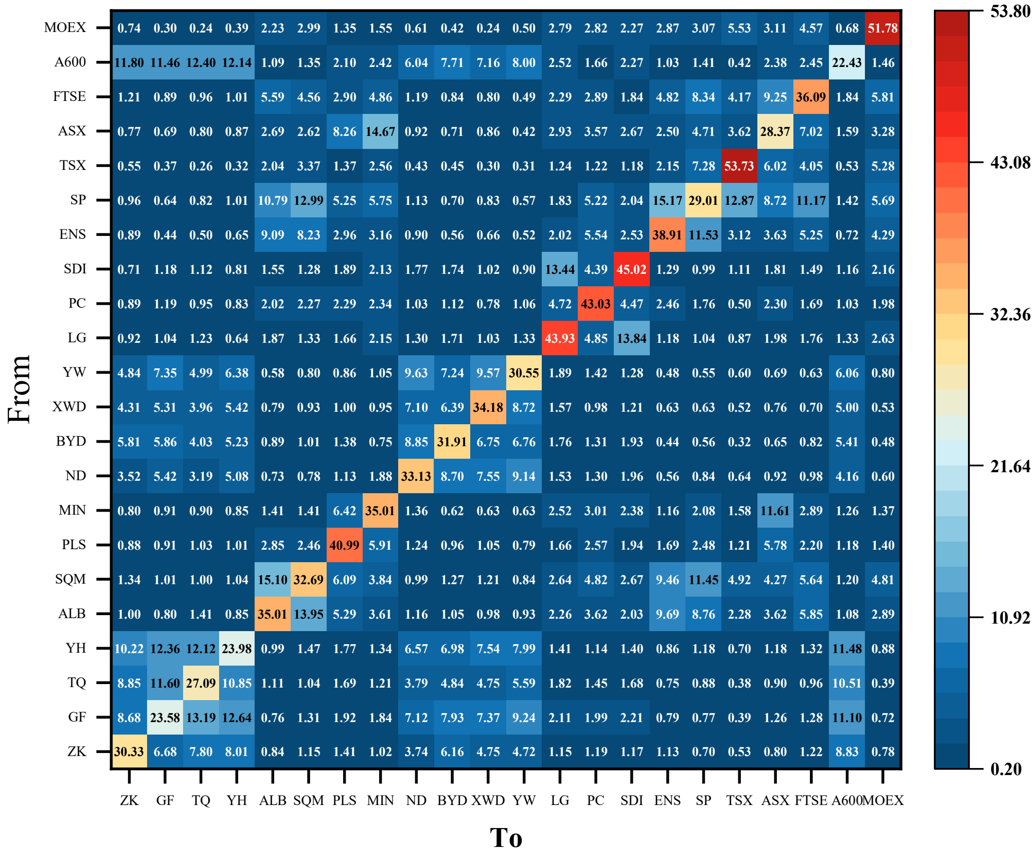

Figure 5. Heatmap of static risk spillover index.

Table 5 presents the risk spillover effects in the upstream market of the lithium industry chain. From Table 5, it can be observed that for Chinese companies in the upstream segment of the lithium industry chain, "To_Top" is greater than "To_Down" and "To_Stock", indicating that the primary risk spillover target for Chinese companies is the upstream market, followed by the downstream market. Some risks are transmitted downstream along the industry chain, and competition among Chinese companies is relatively intense. For international companies, "To_Stock" is greater than "To_Top" and "To_Down", suggesting that the primary risk spillover target for international companies is the stock market, followed by the upstream market. Market competition among international companies is relatively low, and risks are mainly transferred through the capital market. For Chinese companies, "From_Top" is greater than "From_Down" and "From_Stock", indicating that the primary source of risk spillover for Chinese companies is the upstream market, followed by the stock market. For international companies, "From_Stock" is greater than "From_Top" and "From_Down", with the primary source of risk spillover being the stock market, followed by the upstream market. Price fluctuations in upstream raw materials have a greater impact on Chinese companies, while capital investment has a greater impact on international companies. The average level of risk spillover accepted by Chinese companies is higher than that accepted by international companies, indicating that compared to the international lithium industry chain, the upstream segment of the Chinese lithium industry chain is subject to greater external shocks and higher risk levels. From the net risk spillover, it can be seen that the main risk exporter in the upstream market is Ganfeng Lithium Group Co., Ltd. (GLG), with a net risk output index of 15.32%. GLG has the largest lithium reserves in the China, and changes in its production can significantly impact the entire market. The main risk receiver is Mineral Resources Limited (MRL), with a net risk input index of 19.72%. This may be because the lithium business is just one of many businesses of MRL, and its overall impact on the market is relatively small.

Table 5. Upstream market risk spillover effect.

	ZK	GF	TQ	YH	ALB	SQM	PLS	MIN
To_Top	26.91	40.34	36.35	40.27	26.91	29.42	15.05	12.70
To_Down	24.01	38.76	24.67	33.89	21.72	23.90	11.90	12.31
To_Stock	12.86	15.52	14.02	16.74	24.48	32.29	14.25	20.79
From_Top	34.63	36.72	39.66	37.78	23.5	23.29	25.26	19.30
From_Down	21.89	27.79	19.97	25.04	17.52	16.63	13.17	14.41
From_Stock	16.03	14.79	15.48	16.39	24.43	36.11	21.23	31.81
To	63.78	94.62	75.04	90.90	73.11	85.61	41.20	45.80
From	72.55	79.3	75.11	79.21	65.45	76.03	59.66	65.52
Net	−8.77	15.32	−0.07	11.69	7.66	9.58	−18.46	−19.72

Table 6 presents the risk spillover effects in the downstream market of the lithium industry chain. From Table 6, it can be observed that for the downstream segment of the lithium industry chain, the average level of "To_Top" for both Chinese and international companies is greater than "To_Down" and "To_Stock". This indicates that the primary risk spillover targets for both Chinese and international companies are the upstream market, followed by the downstream market. The risk spillover in the downstream segment of the lithium industry chain is mainly transmitted to the upstream market through changes in market supply and demand relationships. The average levels of "From_Top" and "From_Down" for both Chinese and international companies are similar and greater than "From_Stock", indicating that the primary sources of risk spillover for downstream companies are other companies in the upstream and downstream segments of the industry chain, while the stock market has a relatively smaller impact on the risk spillover in the downstream segment of the lithium industry chain. The average level of risk spillover accepted by Chinese companies is higher than that accepted by international companies, indicating that compared to the international lithium industry chain, the downstream segment of the Chinese lithium industry chain is subject to greater external shocks and higher risk levels. From the net risk spillover, it can be observed that most companies in the downstream market are risk receivers. Among them, the net risk value for Chinese companies ranges from −1.76% to −8.42%, while for international companies, it ranges from 6.08% to −19.28%. This indicates that the downstream segment of the Chinese industry chain has greater resilience, possibly due to China's emphasis on the development of the new energy industry, leading to a more well-developed downstream market in the lithium industry chain.

Table 6. Downstream market risk spillover effect.

	ND	BYD	XWD	YW	LG	PC	SDI	ENS
To_Top	21.73	24.96	22.67	26.85	10.84	12.78	10.67	25.92
To_Down	30.74	27.8	26.6	31.51	25.24	15.64	24.55	12.73
To_Stock	8.14	8.24	8.14	9.33	9.61	9.26	8.72	28.54
From_Top	25.97	29.81	28.28	30.73	15.57	19.79	15.48	25.53
From_Down	30.58	27.46	27.36	28.43	26.93	19.79	27.22	7.04
From_Stock	10.32	10.83	10.19	10.29	13.6	17.38	12.27	28.54
To	60.61	61.00	57.41	67.69	45.69	37.68	43.94	67.19
From	66.87	68.10	65.83	69.45	56.10	56.96	54.97	61.11
Net	−6.26	−7.10	−8.42	−1.76	−10.41	−19.28	−11.03	6.08

Table 7 presents the risk spillover effects in the downstream market of the lithium industry chain. From Table 7, it can be observed that the primary spillover targets of the Chinese stock market are the upstream and downstream markets, with the mining index having a greater impact on the upstream market and the new energy index having a greater impact on the downstream market. Apart from the Chinese stock market, the United States has a net risk spillover of 34.56%, making it a risk exporter, while the United Kingdom has a net risk spillover of 2.61%, acting as a risk intermediary. The net risk spillover indices of other stock markets are all less than 0, indicating that they are risk receivers.

Table 7. Stock market risk spillover effect.

	SP	TSX	ASX	FTSE	A600	MOEX
To_Top	38.21	10.84	31.37	21.98	54.76	9.79
To_Down	27.49	7.28	14.58	15.16	36.39	12.52
To_Stock	39.87	23.16	20.22	29.41	8.12	16.96
From_Top	28.3	11.99	29.42	21.36	46.64	13.24
From_Down	17.9	7.68	12.74	13.32	24.87	13.47
From_Stock	24.81	26.61	29.48	29.26	6.06	21.52
To	105.57	41.28	66.17	66.55	99.27	39.27
From	71.01	46.28	71.64	63.94	77.57	48.23
Net	34.56	−5.00	−5.47	2.61	21.70	−8.96

5.2. Dynamic Spillover Analysis

5.2.1. Total Risk Spillover Index

Since the static risk spillover index can only represent the average level of each variable over the entire sample period and cannot reflect the time-varying characteristics of interactions between markets, market fluctuations may experience significant changes under the influence of special events. Therefore, this paper will further analyze the dynamic spillover index between markets, as shown in Figure 6. From Figure 6, it can be seen that the total market risk spillover level exhibits obvious time-varying characteristics, fluctuating significantly between 40% and 66% and being sensitive to extreme events. From 2018 to 2020, the overall spillover level showed a downward trend. In 2020, due to the impact of the COVID-19 pandemic, factors such as labor shortages and logistics disruptions caused the overall risk spillover level to rise sharply. With the effective control of the pandemic and the global economic recovery, the overall risk spillover level gradually declined. It can be observed that under the impact of extreme sudden events, the risk spillover index of the entire sample rises significantly. When the global economy is performing well and the market tends to stabilize, investors' risk aversion decreases, and the total systemic risk spillover index decreases.

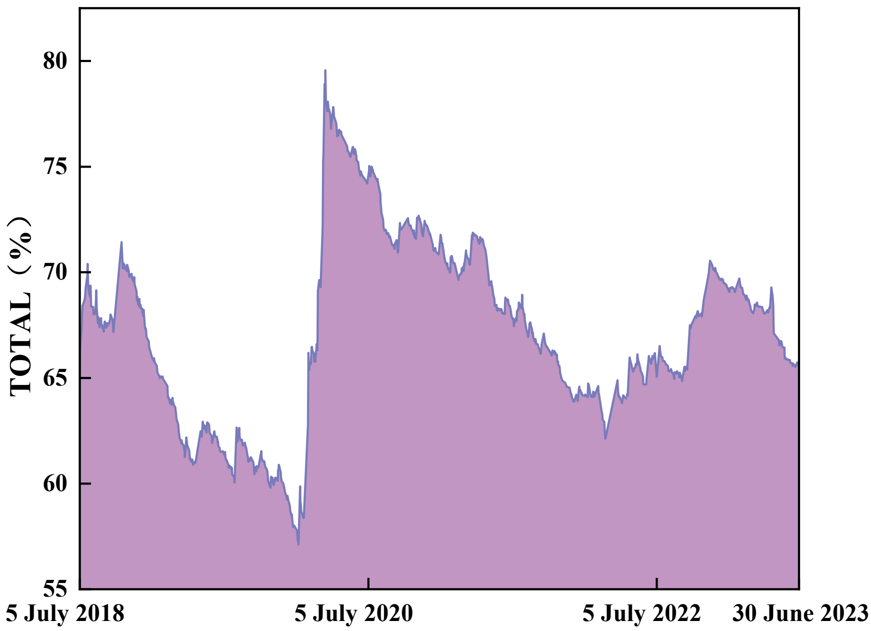

Figure 6. Total risk spillover.

5.2.2. Directional Risk Spillover

Further, the time-varying characteristics of the risk spillover index for each company are analyzed using the dynamic directional risk index. "TO" indicates the dynamic risk spillover from the price fluctuations of a particular company (market) to other markets, while "FROM" indicates the dynamic risk spillover received by a particular company from other companies (markets).

Figure 7 shows the risk inflow and risk spillover of various companies in the upstream market of the lithium industry chain over time. From the perspective of risk inflow, the directional risk inflow of companies in the upstream market remains relatively stable overall and is positively correlated with the overall system's risk spillover changes. The risk inflow level of Chinese companies fluctuates less, mainly concentrated in the range of 3.0–3.5. Chinese companies are more affected by external risk shocks, while the risk inflow level of international companies fluctuates more, and the time-varying characteristics of risk spillovers are more apparent. International companies are less affected by external risk shocks. From the perspective of risk spillover, the risk spillover level of Chinese companies is higher than that of international companies, with relatively smaller changes in risk spillover. Overall, the upstream segment of the Chinese lithium industry chain is more susceptible to external shocks, and the resilience of the upstream industry chain needs to be strengthened.

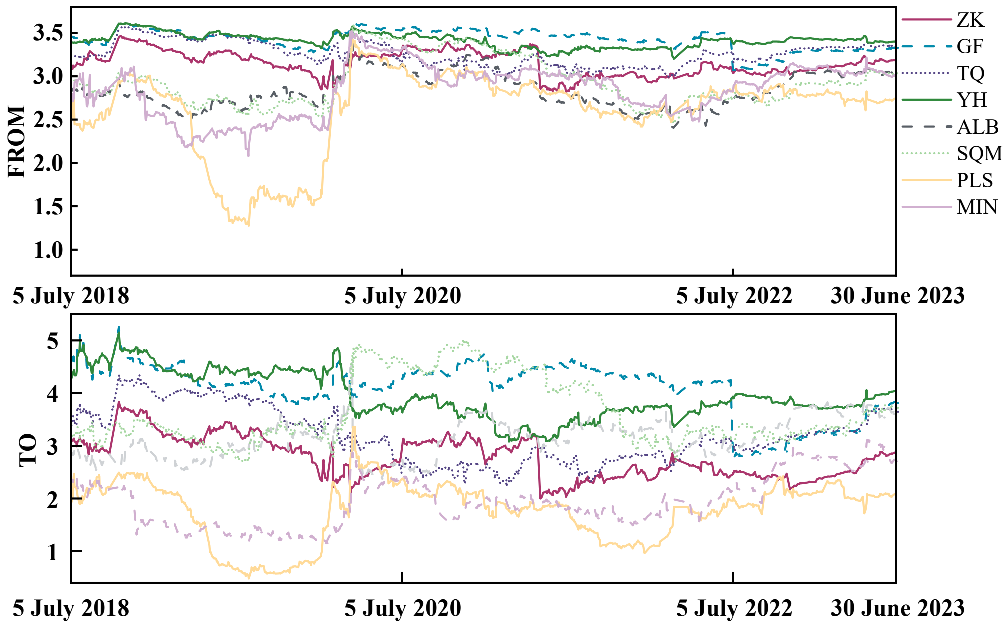

Figure 7. Risk spillover in the upstream market.

Table 8 shows the risk inflow of various companies in the upstream supply market of the lithium industry chain. The mean and median risk inflow of Chinese companies are higher than those of international companies, while the standard deviation is lower, and the absolute value of kurtosis is lower. This is because the international companies selected in the sample, such as Albemarle in the United States and SQM (Sociedad Química y Minera de Chile), have lower lithium mining costs. Therefore, compared to Chinese companies, international companies have lower risk inflow levels and are less affected by external risk shocks. The time-varying characteristics of risk spillovers are more apparent, and the risk inflow of Chinese companies fluctuates less.

Table 8. Descriptive statistics of risk inflow in the upstream market.

Variable	ZK	GF	TQ	YH	ALB	SQM	PLS	MIN
Nobs	898	898	898	898	898	898	898	898
Minimum	2.8187	3.0512	2.9836	3.1994	2.4064	2.4540	1.2758	2.0771
Maximum	3.4641	3.6213	3.5780	3.6122	3.5296	3.6088	3.4271	3.5193
Mean	3.1535	3.4290	3.2661	3.4154	2.8448	2.9484	2.5949	2.8487
Median	3.1630	3.4561	3.2502	3.4232	2.7876	2.9148	2.7714	2.9338
Stdev	0.1449	0.1187	0.1401	0.0821	0.1993	0.2716	0.4940	0.3035
Skewness	−0.1650	−0.9704	0.1754	−0.0065	0.3238	0.55050	−1.2700	−0.3640
Kurtosis	−0.6816	0.6914	−0.8719	−0.1609	−0.7461	−0.7452	0.6131	−0.6776

Table 9 shows the risk spillover of various companies in the upstream supply market of the lithium industry chain. The risk mean values of international companies such as Albemarle in the United States, SQM (Sociedad Química y Minera de Chile), and Chinese companies such as Ganfeng Lithium and Sichuan Yahua Industrial Group are relatively high, indicating that these companies have a relatively large impact on other markets. The risk spillover level of Chinese companies is higher than that of international companies, and the standard deviation of Chinese companies is lower, indicating smaller variations in risk spillover. Considering both risk inflow and risk spillover overall, the upstream segment of the Chinese lithium industry chain is more susceptible to external shocks, and the resilience of the upstream industry chain needs to be strengthened.

Table 9. Descriptive statistics of risk outflow in the upstream market.

Variable	ZK	GF	TQ	YH	ALB	SQM	PLS	MIN
Nobs	898	898	898	898	898	898	898	898
Minimum	1.9984	2.7334	2.2471	3.0798	2.3922	2.7349	0.4814	1.1453
Maximum	3.8407	5.2548	4.3691	5.1508	4.5785	5.0043	3.3602	3.1088
Mean	2.7843	4.1191	3.2251	3.9660	3.1373	3.6726	1.7644	1.9452
Median	2.8130	4.2531	3.1460	3.8458	3.1318	3.3860	1.8971	1.9042
Stdev	0.4034	0.4988	0.5344	0.4583	0.3819	0.6237	0.5789	0.4863
Skewness	0.2483	−1.2080	0.2770	0.2027	0.1973	0.6797	−0.6223	0.3663
Kurtosis	−0.7934	0.6923	−1.0490	−0.8338	−0.5174	−0.9405	−0.4129	−0.7602

Figure 8 shows the risk inflow and risk spillover of various companies in the downstream consumer market over time. From the perspective of risk inflow, the directional risk inflow in the downstream market follows a similar trend to the directional risk spillover in the upstream market. Notably, the risk inflow for international companies shows a significant downward trend after March 2020, while the risk inflow for Chinese companies remains high with less fluctuation, mainly concentrated in the range of 2.7–3.5. From the perspective of risk spillover, the risk spillover level in the downstream market varies greatly, with Chinese companies having a higher risk spillover level than international companies.

Table 10 shows the risk inflow in the downstream consumer market of the lithium industry chain. The mean and median values for Chinese companies are higher than those for international companies. Overall, the risk inflow level for Chinese companies is higher than that for international companies, indicating that the Chinese market is more susceptible to shocks from other markets and has weaker risk resistance in the downstream consumer market of the lithium industry chain. The standard deviation for Chinese companies is lower than that for international companies, indicating that the risk inflow in the Chinese market has less variation, while the time-varying characteristics of risk inflow in the international market are more pronounced.

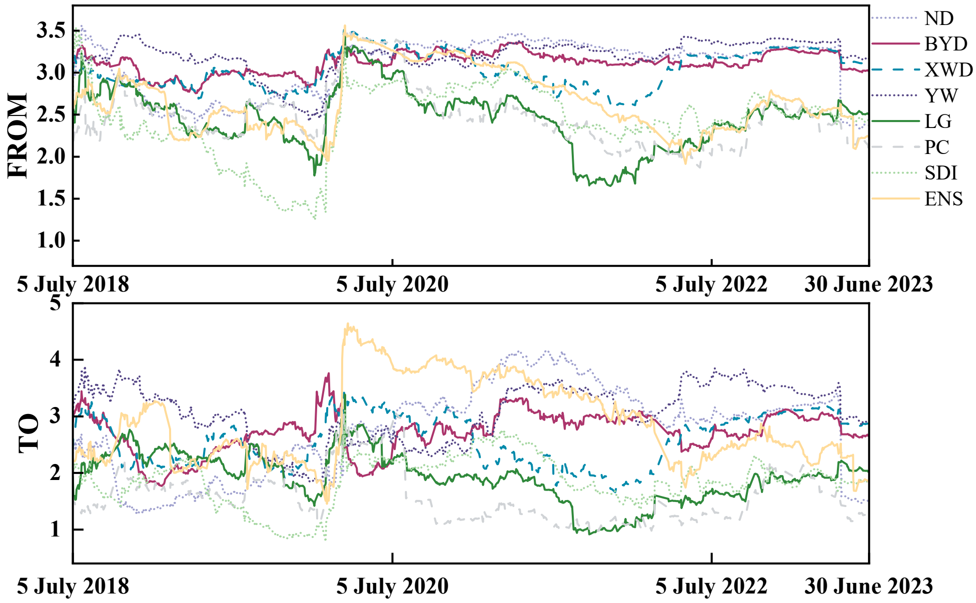

Figure 8. Risk spillover in the downstream market.

Table 10. Descriptive statistics of risk inflow in the downstream market.

Variable	ND	BYD	XWD	YW	LG	PC	SDI	ENS
Nobs	898	898	898	898	898	898	898	898
Minimum	2.3345	2.7553	2.5659	2.4243	1.6495	1.8708	1.2552	1.9122
Maximum	3.5631	3.3614	3.5300	3.4582	3.4304	3.5371	3.5405	3.5624
Mean	3.0770	3.1188	3.0410	3.1966	2.4793	2.4955	2.4264	2.6786
Median	3.2348	3.1304	3.0317	3.2256	2.5061	2.4540	2.4365	2.6195
Stdev	0.3365	0.1335	0.2219	0.2019	0.3525	0.3606	0.4386	0.3710
Skewness	−0.7880	−0.5290	0.0462	−1.8262	−0.0951	1.1167	−0.6790	0.3289
Kurtosis	−0.9299	−0.2650	−1.0713	3.4794	0.1321	1.0289	0.2877	−0.9080

Table 11 shows the risk spillover in the downstream consumer market of the lithium industry chain. The mean and median values for Chinese companies are higher than those for international companies. Overall, the risk spillover level of Chinese companies is higher than that of international companies. The rapid development of China's new energy industry and the surging demand for lithium-ion batteries have led to Chinese companies having a greater influence in the downstream market compared to the international market.

Table 11. Descriptive statistics of risk outflow in the downstream market.

Variable	ND	BYD	XWD	YW	LG	PC	SDI	ENS
Nobs	898	898	898	898	898	898	898	898
Minimum	1.2833	1.7694	1.6578	1.8344	0.9135	0.9644	0.7847	1.4534
Maximum	4.1588	3.7626	3.4185	3.8905	3.3850	3.1618	3.1034	4.6422
Mean	2.7450	2.7190	2.5825	3.0656	1.9455	1.5947	1.8631	2.8903
Median	2.9300	2.7546	2.6693	3.1175	1.9501	1.4521	1.8635	2.5773
Stdev	0.8225	0.3728	0.4527	0.5050	0.4307	0.4861	0.4385	0.7438
Skewness	−0.1836	−0.5388	−0.1082	−0.5625	−0.2637	1.1305	−0.4193	0.4351
Kurtosis	−1.0329	−0.0495	−1.4172	−0.7362	0.0330	0.6843	−0.0993	−1.0375

5.2.3. Net Directional Spillover Index

To further analyze whether each company in the lithium industry chain is a risk receiver, risk exporter, or risk intermediary, Figure 9 depicts the time-varying characteristics of the net directional spillover, which is the fluctuation after offsetting the spillover effect and inflow effect of each company (market). If the net spillover index of a market entity is positive, it indicates that the company is a net exporter of risk spillover; if it is negative, the company is a net receiver of risk spillover. If the net spillover index is close to 0, indicating that the risk spillover level and risk inflow level are similar, the company acts as a risk intermediary, amplifying the effect of information spillover in the system. Prior to the COVID-19 pandemic, the risk net spillover indices of upstream enterprises, downstream enterprises, and the stock market exhibited a downward trend. Following the onset of the pandemic, these indices experienced significant fluctuations: the risk net spillover indices of upstream enterprises and the stock market declined, whereas the index for downstream enterprises increased. The production disruptions caused by the pandemic led to a rapid decline in global demand for lithium resources, resulting in a sustained decrease in lithium market prices. This situation hindered upstream enterprises' ability to mitigate market risks through the prices of mineral products. Over time, as the global economy began to recover and demand for lithium resources increased, the risk net spillover index for upstream enterprises rose, while that for downstream enterprises fell, enabling upstream enterprises to transfer their market risks via commodity trade. As global capital increasingly focused on the lithium industry chain, the risk net spillover index for the stock market displayed an upward trend.

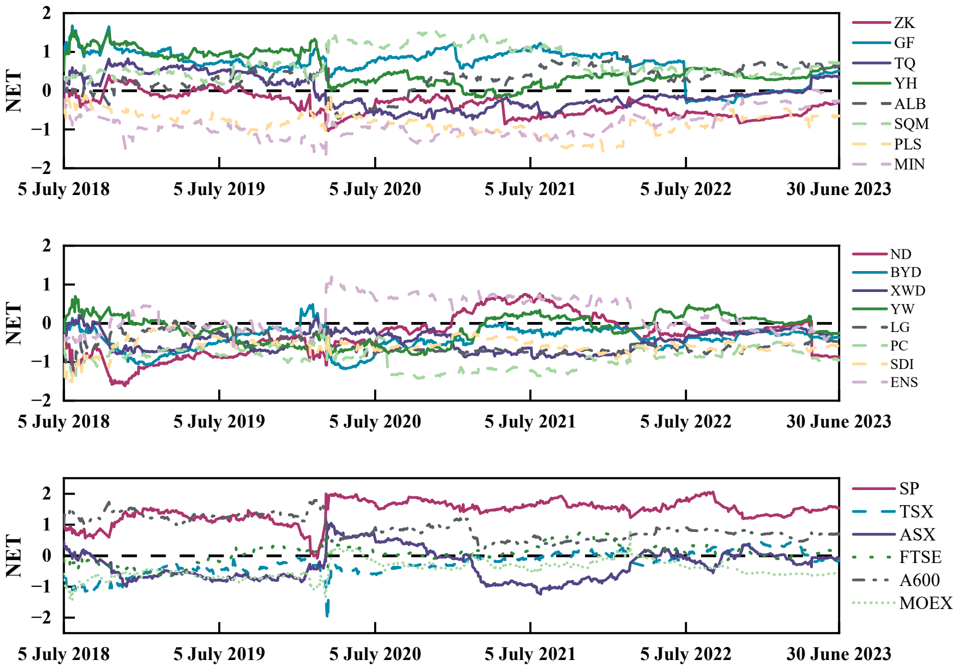

Figure 9. Net risk spillover.

Table 12 shows the roles of market entities in the risk spillover within the lithium industry chain. In the upstream supply market, companies that dominate the market, such as Albemarle Corporation, Sociedad Quimica y Minera, Sinomine Resource Group Co., Ltd., and Sichuan Yahua Industrial Group Co., Ltd., have net directional spillover indices greater than 0 and relatively large values, making them the main exporters of risk spillover. Tianqi Lithium Corporation's net risk spillover index is close to 0, making it a risk intermediary. In the downstream consumer market, except for Enersys, companies have net risk spillover indices less than 0, playing the role of risk receivers in the lithium industry chain, and other consumers are risk receivers. In the financial stock market, excluding China, the United States is the main exporter of risk, while Canada, Russia, and Australia are risk receivers. The United Kingdom's net risk spillover index is close to 0, making it a risk intermediary.

Table 12. Roles of market entities.

Code	Market Entity	Role
ALB	Albermarle Corporation	Risk Exporter
SQM	Sociedad Quimica y Minera	Risk Exporter
PLS	Pilbara Minerals Limited	Risk Taker
MIN	Mineral Resources Ltd.	Risk Taker
ZK	Sinomine Resource Group Co., Ltd.	Risk Exporter
GF	Ganfeng Lithium Group Co., Ltd.	Risk Taker
TQ	Tianqi Lithium Corporation	Risk intermediary
YH	Sichuan Yahua Industrial Group Co., Ltd.	Risk Exporter
ENS	Enersys	Risk Exporter
LG	LG Chem Ltd.	Risk Taker
PC	Panasonic	Risk Taker
SDI	Samsung SDI	Risk Taker
ND	Contemporary Amperex Technology Co., Ltd.	Risk Taker
BYD	Byd Company Limited	Risk Taker
XWD	Sunwoda Electronic Co., Ltd.	Risk Taker
YW	Eve Energy Co., Ltd.	Risk Taker
A600	FTSE A600 Industrial Metals and Mining	Risk Exporter
ASX	ASX 300 Metals & Mining	Risk Taker
FTSE	FTSE Metals & Mining	Risk intermediary
SP	S&P Metals & Mining Select Industry	Risk Exporter
TSX	TSX Metals & Mining	Risk Taker
MOEX	MOEX Metals and Mining	Risk Taker
CNNE	China Securities New Energy	Risk Exporter

6. Robust Test

Since there is a certain degree of subjectivity in selecting the lag order and the forecast error variance decomposition period during the research process, a robustness check is conducted to verify whether the results depend on the choice of model parameters. The lag order is adjusted to 2 and 3, respectively, and the overall risk spillover effect is re-estimated. The results are shown in Figure 10. The time-varying trend of the overall risk spillover effect is basically the same under different lag orders, indicating that the empirical results have a certain degree of robustness.

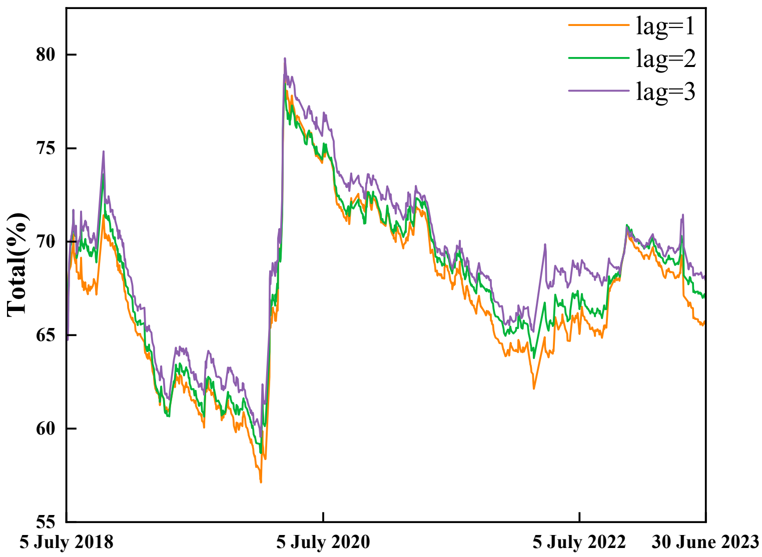

Figure 10. Robustness test: changing the lag order.

Regarding the forecast error variance decomposition periods, the forecast periods were changed to 5 and 10 periods, respectively. As shown in Figure 11, the overall risk spillover effects calculated under different forecast error variance decomposition periods basically overlap, indicating that the impact of changing the forecast error variance decomposition periods on the empirical results can be almost ignored.

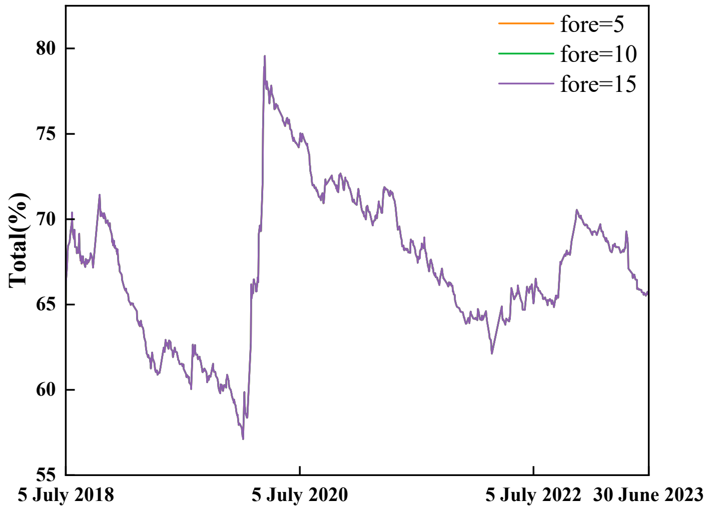

Figure 11. Robustness test: forecast error variance decomposition periods.

7. Conclusions

This paper uses the DY spillover index to measure the static risk spillover effects between the upstream and downstream of the lithium industry chain and employs the TVP-VAR-DY model to measure the dynamic risk spillover effects between the upstream and downstream of the lithium industry chain. This study finds that the upstream market is more affected by its own market risk spillover, while the downstream consumer market is more affected by risk spillover from other markets. For the lithium industry chain, more attention needs to be paid to the upstream supply market, especially the operating conditions of key enterprises that dominate the market, to prevent external shocks from impacting China's lithium mining industry. The downstream of China's lithium industry chain has strong resilience and can withstand a certain degree of external risk shocks. The empirical results are outlined below.

From 2018 to 2020, the overall risk spillover level showed a downward trend. In 2020, due to the impact of the COVID-19 pandemic, factors such as labor shortages and logistics disruptions led to a sharp increase in the overall risk spillover level. With the effective control of the pandemic and the global economic recovery, the overall risk spillover level gradually decreased. It can be observed that under the impact of extreme events, the risk spillover index of the lithium market rises significantly, while when the global economy is operating well and the market is stable, the risk aversion sentiment decreases and the risk spillover index gradually falls. In the lithium industry chain, most of the downstream market risks are internal risks, influenced by their own price fluctuations, whereas the upstream market enterprises' risks are more from external risks. The risk sources for Chinese enterprises are mainly external risks, while international enterprises' risks are more internal. In the lithium stock market, the stock markets of Canada and Russia account for more than 50%, indicating that compared to other countries, their risks are more influenced by their own price fluctuations and less by the risk spillovers from other variables within the system. The price impacts from risk fluctuations in the lithium industry chain or other regional markets are relatively small.

For the upstream supply market, the main risk spillover targets for Chinese enterprises are the upstream market, followed by the downstream market, with some risks transmitted downstream through the industry chain, indicating intense competition among

Chinese enterprises. For international enterprises, the main risk spillover targets are the stock market, followed by the upstream market, with relatively lower market competition among international enterprises and risks primarily transferred through the capital market. From the perspective of risk spillover, the directional risk spillover of upstream market enterprises is generally stable. Chinese enterprises are more affected by external risk shocks, while the risk spillover of international enterprises fluctuates significantly, showing more pronounced time-varying characteristics. From the perspective of risk spillover, the risk spillover level of Chinese enterprises is higher than that of international enterprises, with relatively smaller changes in risk spillover. Overall, China's upstream supply market is more susceptible to external shocks, and the resilience of the upstream industry chain needs to be strengthened.

For the downstream consumer market, the main sources of risk spillover for Chinese enterprises are the upstream market, followed by the stock market, while for international enterprises, the main sources of risk spillover are the stock market, followed by the upstream market. The price fluctuations of upstream raw materials have a greater impact on Chinese enterprises, while capital investment has a greater impact on international enterprises. From the perspective of risk spillover, the risk spillover fluctuations of Chinese enterprises are relatively small, with a greater impact from external risk shocks, while the risk spillover fluctuations of international enterprises are more significant, showing more pronounced time-varying characteristics. International enterprises are less affected by external risk shocks, and as the global economy recovers, the risk spillover level decreases significantly, while the risk spillover of Chinese enterprises remains high. From the perspective of risk spillover, the risk spillover level of the downstream market fluctuates greatly, with Chinese enterprises having a higher risk spillover level than international enterprises. Due to the rapid development of China's new energy industry and the surging demand for lithium power batteries, Chinese enterprises have a greater influence in the downstream market than international markets.

From the perspective of net risk spillover, for the upstream supply market, market-dominant enterprises such as Albermarle Corporation, Sociedad Quimica y Minera, Ganfeng Lithium Group Co., Ltd., and Sichuan Yahua Industrial Group Co., Ltd., have a net directional spillover index greater than 0, with relatively large values, acting as major risk spillover sources, while other suppliers are risk recipients. For the downstream consumer market, except for Enersys, enterprises have a net risk spillover index less than 0, playing the role of risk recipients in the lithium industry chain, while Enersys has a net risk spillover index close to 0, acting as a risk intermediary. For the financial stock market, except for China, the United States is the main risk spillover source, while the markets of Canada, Russia, and Australia are risk recipients, with the UK market having a net risk spillover index close to 0, acting as a risk intermediary. Therefore, enterprises need to pay more attention to the development of leading enterprises in the industry and closely monitor the trends of the US stock market, which can represent the global economic trend to a certain extent. As a capital-intensive industry, the lithium mining industry needs to closely monitor capital movements to prevent financial market risks from impacting the lithium industry chain.

For upstream enterprises in the lithium industry chain, it is recommended that they enhance their focus on the stock capital market to mitigate the adverse effects of economic uncertainty on their operational activities. Additionally, increasing investment in lithium mining projects and improving the market competitiveness of these enterprises is advised. For downstream enterprises in the lithium industry chain, strengthening the management of raw material inventories, seeking strategic cooperation with upstream producers whenever possible, and effectively utilizing financial instruments to lock in raw material procurement costs are suggested to reduce the impact of market risk spillover. For the government, increasing capital investment in lithium resource exploration and development projects, maintaining trade partnerships with major resource-exporting countries, and enhancing the market supply of lithium resources are recommended, as these actions will contribute to the establishment of a more robust lithium industry chain system.

This paper investigates market risk spillover within the lithium industry chain; however, it acknowledges certain limitations and shortcomings. Given China's notable achievements in the new energy sector, the proportion of Chinese enterprises in the selected research sample is disproportionately high, which may introduce subjective bias. The uncertainty surrounding global economic policies can significantly affect market risk spillover, potentially transmitting through the stock market to both upstream and downstream enterprises in the lithium industry chain. Due to limitations in the sample data period and the model, it is not feasible to examine the influence of economic uncertainty on risk spillover. This study measures the degree of risk spillover through stock volatility, categorizing the price fluctuations of listed companies into increases and decreases. Further research and discussions are needed to determine whether these fluctuations have heterogeneous effects on market risk spillover within the lithium industry chain.

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