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Tail Dependency and Risk Spillover between Oil Market and Chinese Sectoral Stock Markets—An Assessment of the 2013 Refined Oil Pricing Reform

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Abstract: The Chinese refined oil pricing reform in 2013 has brought its refined oil price to be more aligned with the international oil price, helping to mitigate prior distorted pricing mechanisms. Its impact on the correlation, tail risks, and spillover effects between the international crude oil market and Chinese sectoral stock markets warrants empirical assessments. Time-varying copula models and conditional VaR (CoVaR) are employed to examine the correlation between the international oil market and Chinese sectoral stock indexes before and after the 2013 pricing reform, as well as the tail risk and spillover effects of the extreme and moderate oil markets. The results show that: (1) the correlation between the oil market and all 11 Chinese stock sectors is positive both before and after the reform, but the correlation is weaker after the reform than before; (2) The downside tail risk of the extreme and moderate oil markets to most Chinese stock market sectors, and the upside tail risk of the moderate oil market to most stock sectors are lower after the reform; (3) Tail risk spillover effects of extreme oil market on all sectors exist before and after the reform; (4) The upside tail risk spillover effects of moderate oil market exist in most sectors before the reform, but they almost all disappear after the reform. The downside risk spillover effects of the moderate oil market do not exist before or after the reform. The findings provide valuable references for portfolio management and future policy update.

Keywords: Chinese refined oil pricing reform; crude oil market; tail risk spillover effect; time-varying copula model

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1. Introduction

The crude oil market plays a vital role in the global economy and financial markets [1–3]. Extreme oil market fluctuations may render tail risk spillover effects to stock markets [4–6]. For example, between 22 September and 24 October 2008, the crude oil futures prices fell from \$120.92 to \$64.15 per barrel, a drop of 46.95%, while the Shanghai Composite Index fell from 2877.73 to 2172.87, a hefty decline of 24.49%. China is the world's largest oil importer and the second largest oil consumer [6–9]. Since 1998, China has undergone four major refined oil pricing reforms, progressively shifting from complete planning to a market-oriented approach. The last reform that took effect on 27 March 2013 is considered a milestone in the history of the Chinese refined oil pricing reform [10]. Investigating the impact and efficacy of the 2013 reform, by comparing the correlation, tail risk, and risk spillover between the international oil market and Chinese stock markets before and after the reform, can not only help investors to optimize their portfolios, but also helps regulators to further adjust policies to alleviate risk contagion between the markets.

The relationship between the oil market and Chinese stock market has evolved with the Chinese refined oil pricing mechanisms [11,12]. As China became a net oil importer in 1993, the entirely government controlled refined oil pricing mechanism was dated and inconsonant with the fast-growing market economy [6]. Effective 3 June 1998, the Crude Oil and Refined Oil Price Reform Program stipulated that the Chinese refined oil prices would be determined in accordance with the average price of the previous month in the Singapore oil market, marking the beginning of the alignment of its domestic refined oil price with the international market. In November 2001, the pricing mechanism extended its reference to the Singapore, Rotterdam, and New York oil markets. In response to price fluctuation and market speculation, the refined oil pricing mechanism was revised in 2009, stipulating that when the average price of crude oil in the international market changes by more than 4% over 22 consecutive working days, the refined oil price shall be adjusted accordingly. Although this round of reform strengthened refined oil marketization and further impelled convergence with the international market, its implementation revealed problems such as a lack of production motivation by domestic refined oil enterprises and the hoarding of oil products by speculators due to the long adjustment cycle. In order to further improve the pricing mechanism, the National Development and Reform Commission rolled out another round of reform on 27 March 2013, which is considered a giant step towards complete market-based pricing [10]. Specifically, the new mechanism shortens the price adjustment cycle from 22 working days to 10 working days, and removes the threshold of the 4% cumulative price change in international oil markets [2,10,12]. It also adjusts the types of reference oil in the international market according to the composition of imported crude oil to China. Moreover, it improves the pricing control regime by allowing necessary intervention—including suspending, delaying, or lessening price adjustment—when the international oil market experiences short-term extreme turbulence. Overall, this reform significantly loosens the control over Chinese refined oil prices—they can more sensitively reflect changes in international oil prices, which makes it more conducive for companies to use foreign resources to protect domestic market supply.

This study investigates the impact of this latest round of reform on the correlation, tail risk, and spillover effect between the international oil market and different sectors in the Chinese stock market. In the empirical analysis, we use the daily data of the West Texas Intermediate (WTI) crude oil futures price and 11 Chinese Wind primary sector indexes from January 2009 to August 2021. The WTI crude oil futures contract is selected to represent the international oil price because of its higher trading volume than the other popular international benchmark, Brent Crude, and its insensitivity to speculative bubbles [13–15], despite its extremely rare glitch (such as the negative price on 20 April 2020) and disconnection from the global market [16]. The Wind sector stock indexes draw on the authoritative Global Industries Classification Standard, with minor adjustments to fit the Chinese markets [17]. Its 11 primary sector indexes cover all the A shares listed in the Shanghai and Shenzhen Stock Exchanges.

The 2013 reform makes China's domestic refine oil market—and stock market, by extension—more exposed to the global oil market, but does it increase or reduce risk? Intuitively, it may have magnified the risk due to the increased exposure. After all, the previous pricing mechanisms, particularly the 22 + 4% mechanism between 2009 and 2013, are supposed to have shielded the domestic markets from fluctuations in the global market.

On the other hand, it may have reduced the risk compared to the previous 22 + 4% regime. Consider two scenarios. In the first one, the international oil price jumps by 4% early in the adjustment window. Does it necessarily mean that domestic prices will increase at the end of the window before the 2013 reform? No one can be certain what will happen in the remaining days of the adjustment window. As this issue will not be resolved right away, the uncertainty lingers during the remainder of the window. The old regime thus may have created additional risk. In the second one, the international oil price increases (or decreases) slowly but steadily during the window. If this trend persists, by the end of the 22-day window, the cumulative change will quite likely exceed the 4% threshold, resulting in a domestic price change. In this case, a gradual move in the global oil market would cause an abrupt domestic price change. So, the 22 + 4% mechanism before 2013 may have elevated the risk by not allowing a timely response in the domestic market. These two examples show that the 2013 reform, by enabling a timelier adjustment without the 4%

threshold constraint, may have mitigated the uncertainty created by the old mechanism and thus reduced the tail risk and spillover effect from the international oil market to China's refined oil market and stock market. Therefore, the impact of the 2013 pricing reform warrants a thorough empirical investigation.

This study sheds new light on several intriguing questions. The results show that: (1) the correlation between the oil market and 11 Chinese stock sectors is always positive, but it is weaker after the 2013 reform than before; (2) The downside tail risk of the extreme and moderate oil markets to most Chinese stock market sectors and the upside tail risk of moderate oil market to most stock market sectors are lower after the reform; (3) Tail risk spillover effects of the extreme oil market on all sectors exist before and after the reform; (4) The upside tail risk spillover effects of the moderate oil market exist on most sectors before the reform, but they largely disappear after the reform. Downside tail risk spillover effects of moderate oil market do not exist either before or after the reform.

This study serves dual objectives. It assesses the impact of the 2013 pricing reform. The findings help market participants and regulators to better understand the risk contagion between the two markets, and provide empirical reference for future pricing reform. Meanwhile, this investigation helps stock market investors to construct portfolios based on sector asset allocation by incorporating the correlation and tail risk spillover effects of the oil market [18]. As shocks in the oil market often pose considerable risk to stock markets, in-depth knowledge on the association between oil market and different sectors of the stock markets is advantageous for portfolio risk management.

This paper contributes to the literature in three aspects. Prior studies on the subject usually use the Shanghai Composite Index (SHCI) as the proxy for Chinese stock market [19–22]. However, as a composite index, SHCI cannot capture the idiosyncratic characteristics of individual sectors [18]. As the pricing reform in 2013 has made China's refined oil prices more closely connected to the international oil price, investigations at the sector level can provide deeper insight regarding the effect of the international crude oil market on the Chinese stock market.

From the methodological perspective, three complementary risk measures are employed to delineate the dependence of oil price movements and stock returns. These measures are sequentially built on each other, with each one providing additional information. First, the copula model captures the nonlinear and time-varying linkage and risk contagion between the two markets [23,24]. The nonparametric Kendall correlation coefficient indicates the degree to which returns in two markets move in the same direction. The Kendall correlation is superior to the popular Pearson correlation coefficient, which measures only linear associations and is unreliable for extremal dependence in tails. Second, conditional value-at-risk (CoVaR), proposed by Adrian and Brunnermeier [25], is used to characterize tail dependency or the comovement of the international oil market and Chinese sectoral stock markets. Assigned as the measure of tail risk, CoVaR characterizes the magnitude of extreme risk arising from the two markets beyond association and direction. Third, we quantify the spillover effect with the difference between conditional stock return risk (measured using CoVaR) and its unconditional risk (measured using VaR). The spillover effect depicts the change in sectoral stock index tail risk caused by the oil price movement, and thus the risk "spilling over" from it. The Kolmogorov–Smirnov (KS) bootstrapping test is conducted to test for the significance of the spillover effect.

While many studies focus on extreme risk dependence [5,11], this study examines the effects of both extreme and moderate price movements in the oil market on Chinese sectoral stock markets. Modest changes in the international crude oil market may still yield shocks to refined oil prices in China, due to its unique pricing mechanisms. As discussed above, the pricing reform in 2013 may engender unexpected consequences due to the increased exposure. Additionally, we examine the effects of both upward and downward fluctuations, and so the findings are helpful for stock market investors taking long or short positions.

The balance of the paper is structured as follows. Section 2 presents the related literature. Section 3 presents models and risk measurements, and Section 4 describes the data. Section 5 reports and discusses the empirical results. Section 6 concludes.

2. Literature Review

Oil, as a vital bulk commodity, may affect the stock market via multiple avenues. Many reason that higher oil prices lead to higher production costs for firms and affect their investment and financing behaviors, which in turn will be reflected in stock markets [5]. Jones and Kaul [4] and Peng et al. [6], among many others, argue that since a stock price reflects the present value of expected future cash flows, volatility in oil markets indirectly affects stock returns by altering expected future cash flows and/or expected returns. It is attested that oil market shocks impact on oil importers and exporters differently [26–29].

Contrasting findings exist regarding the relationship between the crude oil and stock markets. One group of literature reveals a negative relation between the two markets. For example, Reboredo [30] reports a significantly negative impact of higher oil prices on stock prices based on a Markov regime switching model. Raza et al. [31] made a similar finding via a nonlinear ARDL approach. It is argued that oil price hikes reduce the current or expected profit by increasing the cost of the firm, which leads to declining stock prices [11].

Another group of literature finds a positive correlation between the oil and stock markets. By decomposing the volatility of the oil market into expected volatility, unexpected volatility, and negative unexpected volatility, Zhang and Chen [32] find a small positive impact of oil market shocks on Chinese stock markets. Chen and Lv [11] examined the progressive correlation between the crude oil market and the Chinese stock market based on the Extreme Value Theory, and found that the positive extreme correlation tends to increase sharply during crises. In a nonlinear autoregressive distributed lag model, Alamgir and Bin Amin [33] report a positive correlation between the oil and stock markets, with significant asymmetry in the effect of positive and negative shocks from the oil market to the stock market. The positive comovement between the two markets exist in many markets around the globe, and has significantly strengthened after the 2008 financial crisis [5,24]. An influential explanation of the positive correlation is the "business cycle theory," which argues that the oil market acts as a macroeconomic indicator of early economic expansion [34]. Positive innovations in the global economic cycle will stimulate both the oil market and the stock market, creating a positive correlation between the two.

Researchers have interpreted the conflicting findings from different perspectives. Ramos and Veiga [35] argue that the oil market can negatively affect oil importing countries and positively affect oil exporting countries. Chen and Lv [11] assert that the Chinese refined oil pricing mechanism distorts the correlation between the oil market and the Chinese stock market. Jiang et al. [21] argue that the relationship is contingent on credit conditions—the oil price negatively affects stock returns when the US economy is under normal credit conditions, while the relation reverses under tight credit conditions. Arampatzidis et al. [36] contend that the impact of the oil market on the US stock market depends on the type and timing of the shock.

Another body of research examines tail risk spillover caused by the correlation between oil and stock markets. Xu et al. [37] found an asymmetric tail risk spillover effect between the two markets, with bad volatility spillovers dominating good volatility spillovers. Wen et al. [38] found that the tail risk spillover effect to the Chinese stock market was stronger after the financial crisis in 2008 than before. Peng et al. [6] examined the tail risk spillover effect of the oil market on Chinese sectoral stock market using quantile Granger causality tests, and showed that the risk contagion of oil price shocks on corporate revenue depends on sector characteristics. Kirkulak-Uludag and Safarzadeh [39] report a significant volatility spillover effect of the oil market on the Chinese sectoral stock market in a VAR-GARCH model.

The Chinese refined oil pricing reform in 2013 has enhanced the exposure of its domestic market to the international crude oil market, but few studies have been conducted on its exact impact. The reform thus may have altered the relationship between the oil market and the Chinese stock market. By applying a cross-correlation function (CCF) approach, Bouri et al. [12] found the causality-in-mean between the two markets is strengthened after the reform, whereas the causality-in-variance almost disappears. Xiao et al. [10] showed that the 2013 reform has mitigated the impact of the Oil Volatility Index (OVX) on the Chinese stock market. This study aims to extend this strand of literature by providing new evidence on the impact of the 2013 reform.

Peng et al. [6] used VaR to measure the tail risk of the oil and Chinese stock markets, and examined their causal relationship using quantile Granger causality tests. They found that the oil market after the reform has stronger downside tail risk spillover effects on Chinese stock markets, but weaker upside tail risk spillover effects, than before the reform. Due to the lack of subadditivity of VaR [40–42], alternative tail risk measures have been proposed, such as CoVaR and marginal expected shortfall (MES) [43]. As a systemic risk measure, CoVaR has been widely adopted for studying risk in connection, rather than in isolation [43–45]. Given our interest in risk correlation and risk spillover, CoVaR is a natural fit, as it captures the tail-dependence between the crude oil and stock markets. As oil price typically fluctuates within a moderate range, Reboredo and Ugolini [46] proposed to explore the risk spillover of the moderate oil market on stock markets as well. They found no evidence of risk spillover by the moderate oil market to stock markets in three developed economies (US, UK, and European Monetary Union) and the five BRICS countries.

3. Methodology

The CoVaR proposed by Adrian and Brunnermeier [25] is adopted to measure the tail risk of the oil market to Chinese sectoral stock markets. CoVaR is defined as the tail risk value of an asset or portfolio conditional on another asset or portfolio being at its tail risk at the confidence level $1 - p$. CoVaR can be differentiated between the downside conditional value-at-risk $CoVaR_{p,q,t}^{down}$ and the upside conditional value-at-risk $CoVaR_{p,q,t}^{up}$, depending on the long or short investment position:

$$P\left(r_{1,t} \leq CoVaR_{p,q,t}^{down} \middle| r_{2,t} \leq VaR_{q,t}^{down}\right) = p \tag{1}$$

$$P\left(r_{1,t} \geq CoVaR_{p,q,t}^{up} \middle| r_{2,t} \geq VaR_{q,t}^{up}\right) = p \tag{2}$$

where $r_{1,t}$ denotes a Chinese sectoral stock market return, and $r_{2,t}$ denotes the oil market return. Both p and q are tail probabilities, which take the value of 0.05 in this paper.

Next, the copula function is applied to associate the marginal distribution of the oil market and the marginal distribution of the Chinese sector stock market into a joint probability distribution:

$$C\left[F_{r_{1,t}}(CoVaR_{p,q,t}^{down}), F_{r_{2,t}}(VaR_{q,t}^{down}); \theta\right] = F_{r_{1,t},r_{2,t}}(CoVaR_{p,q,t}^{down}, VaR_{q,t}^{down}) \tag{3}$$

where C is the copula function, $F_{r_{1,t}}$ and $F_{r_{2,t}}$ are the distribution functions of $r_{1,t}$ and $r_{2,t}$, respectively, and θ is the parameter vector of the copula function.

The Kendall correlation coefficient τ, defined in the following form, is used to examine the correlation between the oil market and the Chinese sector stock market:

$$\tau(r_{1,t}, r_{2,t}) = 4\int_0^1 \int_0^1 C(u_1, u_2) dC(u_1, u_2) - 1 \tag{4}$$

Based on the definitions of $CoVaR_{p,q,t}^{down}$ and $CoVaR_{p,q,t}^{up}$, we can transform the conditional distribution into the ratio of the joint distribution to the marginal distribution, and then use the copula function to obtain the joint probability distribution of the oil and stock markets. Thus, Equations (1) and (2) can be transformed into Equations (5) and (6), respectively:

$$CoVaR_{p,q,t}^{down} = \mu_{1,t} + F_{z_{1,t}}^{-1}(q_1)\sigma_{1,t} \tag{5}$$

$$CoVaR^{up}_{p,q,t} = \mu_{1,t} + F^{-1}_{z_{1,t}}(q_2)\sigma_{1,t} \tag{6}$$

where the conditional mean $\mu_{i,t}$ and the conditional standard deviation $\sigma_{i,t}$ can be estimated from the ARMA-TGARCH model. $F^{-1}_{z_{1,t}}(q_1)$ denotes the q_1 quantile of the standard residual $z_{1,t}$; q_1 and q_2 are the solutions to $C(F_{r_{1,t}}(CoVaR^{down}_{p,q,t}), q) = pq$ and $q + C(F_{r_{1,t}}(CoVaR^{up}_{p,q,t}), 1-q) - F_{r_{1,t}}(CoVaR^{up}_{p,q,t}) = pq$, respectively.

Conventional CoVaR measures only the tail risk of the extreme oil market to the stock market. However, the oil price fluctuates within a moderate range most of the time. To measure tail risk posed by the moderate oil market to the stock market, Reboredo and Ugolini [46] proposed revised measures of CoVaR. Specifically, $CoVaR^{down}_{p,(\theta,q),t}$ denotes the downside tail risk of moderate oil price fluctuation within $\left[VaR^{down}_{\theta,t}, VaR^{down}_{q,t}\right]$ to the stock market:

$$P(VaR^{down}_{\theta,t} \leq r_{2,t} \leq VaR^{down}_{q,t}) = q - \theta \tag{7}$$

where, following Reboredo and Ugolini [46], θ and q take the values of 0.2 and 0.4, respectively. $(\theta, q) = (0.2,\ 0.4)$ corresponds to moderate negative (between quantiles 0.2 and 0.4) daily oil price fluctuations. For our sample, the range is between −1.59% and −0.33%. Similarly, $CoVaR^{up}_{p,(\theta,q),t}$ denotes the upside tail risk of moderate oil price fluctuation within $\left[VaR^{up}_{\theta,t}, VaR^{up}_{q,t}\right]$ to stock markets:

$$P(VaR^{up}_{\theta,t} \leq r_{2,t} \leq VaR^{up}_{q,t}) = \theta - q \tag{8}$$

where θ and q take the values of 0.4 and 0.2, respectively. $(q, \theta) = (0.2,\ 0.4)$ corresponds to moderate positive (between quantiles 0.6 and 0.8) daily oil price fluctuations, which is between 0.52% and 1.60% in our sample.

Thus, $CoVaR^{down}_{p,(\theta,q),t}$ and $CoVaR^{up}_{p,(\theta,q),t}$ can be defined as:

$$P\left(r_{1,t} \leq CoVaR^{down}_{p,(\theta,q),t} \middle| VaR^{down}_{\theta,t} \leq r_{2,t} \leq VaR^{down}_{q,t}\right) = p \tag{9}$$

$$P\left(r_{1,t} \geq CoVaR^{up}_{p,(\theta,q),t} \middle| VaR^{up}_{\theta,t} \leq r_{2,t} \leq VaR^{up}_{q,t}\right) = p \tag{10}$$

Following Reboredo and Ugolini [46], Equations (9) and (10) can be transformed to Equations (11) and (12) using the copula function:

$$CoVaR^{down}_{p,(\theta,q),t} = \mu_{1,t} + F^{-1}_{z_{1,t}}(q_3)\sigma_{1,t} \tag{11}$$

$$CoVaR^{up}_{p,(\theta,q),t} = \mu_{1,t} + F^{-1}_{z_{1,t}}(q_4)\sigma_{1,t} \tag{12}$$

where q_3 is the solution to $C(F_{r_{1,t}}(CoVaR^{down}_{p,(\theta,q),t}), q) - C(F_{r_{1,t}}(CoVaR^{down}_{p,(\theta,q),t}), \theta) = p(q-\theta)$ and q_4 to $\frac{\theta - q - \left[C(F_{r_{1,t}}(CoVaR^{up}_{p,(\theta,q),t}), 1-q) - C(F_{r_{1,t}}(CoVaR^{up}_{p,(\theta,q),t}), 1-\theta)\right]}{\theta - q} = p$.

4. Variables and Data

The daily data of West Texas Intermediate (WTI) crude oil futures prices and the closing prices of 11 Chinese primary sector indices from 5 January 2009 to 30 August 2021 are retrieved from the Wind financial database. Prices of the main (dominant) WTI futures contract—the one most actively traded—are adopted. The main contract is usually a contract with near-term maturity in the WTI futures market. The highly active trading ensures that its return best reflects the WTI market movement. Included in the 11 primary sector indexes are Energy Index (EI), Real Estate Index (REI), Material Index (MI), Public Utility Index (PUI), Telecom Service Index (TSI), Financial Index (FI), Health Care Index (HCI), Industrial Index (II), Optional Consumption Index (OCI), Daily Consumption Index (DCI), and Information Technology Index (ITI). In order to compare the results before and after the reform of the refined oil product pricing, the sample is divided into two phases: the pre-reform period from 5 January 2009 to 26 March 2013, and the post-reform period from 27 March 2013 to 30 August 2021.

The descriptive statistics for the daily return of the WTI crude oil market and the 11 Chinese sectoral stock indexes are reported in Table 1.

Table 1. Descriptive statistics of log-return series.

Market	Period	Obs.	Mean	Std. Dev.	Skewness	Kurtosis	JB	LB	ARCH	ADF
EI	Before	993	0.000	0.018	−0.037	3.536	510.681 ***	8.19	126.501 ***	−30.905 ***
	After	2011	0.000	0.017	−0.777	5.696	2904.796 ***	32.291 **	432.030 ***	−18.555 ***
REI	Before	993	0.000	0.021	−0.456	2.048	205.109 ***	19.22	81.908 ***	−31.845 ***
	After	2011	0.000	0.019	−0.566	4.938	2137.727 ***	40.814 ***	473.840 ***	−30.364 ***
MI	Before	993	0.000	0.019	−0.492	1.533	135.488 ***	11.011	115.453 ***	−21.271 ***
	After	2011	0.001	0.019	−1.023	6.265	3619.811 ***	48.937 ***	672.590 ***	−29.859 ***
PUI	Before	993	0.000	0.015	−0.513	1.665	156.151 ***	10.518	130.179 ***	−31.407 ***
	After	2011	0.000	0.016	−1.080	10.867	10,230.833 ***	91.277 ***	807.710 ***	−13.985 ***
TSI	Before	993	0.000	0.018	0.016	1.856	140.183 ***	21.938	58.544 ***	−31.789 ***
	After	2011	0.000	0.022	−0.336	4.170	1485.193 ***	24.051	388.910 ***	−31.570 ***
FI	Before	993	0.000	0.016	−0.063	2.500	255.375 ***	14.12	94.684 ***	−32.74 ***
	After	2011	0.000	0.016	−0.256	6.434	3469.889 ***	57.047 ***	243.090 ***	−14.023 ***
HCI	Before	993	0.001	0.017	−0.363	0.951	58.245 ***	48.801 ***	58.826 ***	−9.431 ***
	After	2011	0.001	0.018	−0.690	4.839	2109.166 ***	47.770 ***	604.060 ***	−31.216 ***
II	Before	993	0.000	0.017	−0.581	1.688	171.469 ***	17.329	84.826 ***	−30.727 ***
	After	2011	0.000	0.019	−0.989	7.176	4616.669 ***	58.615 ***	664.900 ***	−30.207 ***
OCI	Before	993	0.001	0.017	−0.491	1.479	128.593 ***	19.919	91.157 ***	−30.489 ***
	After	2011	0.000	0.018	−1.011	6.733	4118.301 ***	57.132 ***	639.680 ***	−30.610 ***
DCI	Before	993	0.001	0.016	−0.388	1.209	84.104 ***	18.122	90.293 ***	−30.102 ***
	After	2011	0.001	0.017	−0.758	4.736	2059.394 ***	52.982 ***	542.450 ***	−31.312 ***
ITI	Before	993	0.001	0.019	−0.560	0.855	81.188 ***	24.235	79.727 ***	−11.094 ***
	After	2011	0.001	0.023	−0.711	3.869	1415.352 ***	46.187 ***	595.310 ***	−30.331 ***
Oil	Before	993	0.001	0.024	−0.085	5.359	1174.783 ***	32.18 **	294.004 ***	−23.522 ***
	After	2011	0.000	0.033	−2.900	75.828	482,180.45 ***	124.100 ***	412.110 ***	−12.076 ***

Note: ***, ** indicate significance at 1% and 5% respectively. JB, LB, ARCH, and ADF are the Jarque–Bera test, Ljung–Box test, ARCH-LM test, and unit root test for the returns, respectively.

The mean daily returns of the Chinese sectoral stock markets and the oil market are very small, as expected. After the reform, the volatility of 9 out of the 11 sectoral indexes is higher than or equal to the volatility before the reform. Meanwhile, the volatility of the oil market is higher after the reform. Almost all series demonstrate greater negative skewness and much greater kurtosis after the refined oil pricing reform in 2013. The normal distribution is rejected for each return series by the Jarque–Bera normality test. According to LB statistics, the return of most sectoral indexes exhibits significant autocorrelation after the reform, but none before. The ARCH statistics indicate the presence of heteroskedasticity in Chinese sectoral stock markets and the international crude oil market. The ADF tests show that each return is a smooth series.

5. Empirical Results

5.1. The Return Characteristics

5.1.1. The Volatility Clustering Effect and Leverage Effect

The ARMA(m,n)-TGARCH(h,k) model is applied onto the sectoral stock indexes and the oil market price before and after the reform, with residual distribution assumed to follow a Gaussian distribution, *t* distribution, or skewed-*t* distribution. As per the principle of maximum likelihood estimation, it is found that the ARMA(1,1)-TGARCH(1,1)-*t* model or the ARMA(1,1)-TGARCH(1,1)-skewed-*t* model can best describe the return characteristics. The estimation results of the marginal distribution before and after reform are shown in Table 2 and Table 3 respectively.

Table 2. Estimates of marginal distribution models (before the reform).

Market	Residual	ϕ_0	ϕ_1	φ_1	ω	α	β	λ	η	ν
EI	Skewed-t	0.000	0.090 ***	−0.131 ***	0.000	0.047 ***	0.960 ***	−0.281 *	0.989 ***	4.946 ***
		(0.001)	(0.017)	(0.022)	(0.000)	(0.005)	(0.003)	(0.162)	(0.049)	(0.577)
REI	Skewed-t	0.000	−0.545 ***	0.511 ***	0.001 **	0.049 **	0.938 ***	0.066	0.937 ***	5.817 ***
		(0.001)	(0.018)	(0.012)	(0.000)	(0.015)	(0.020)	(0.238)	(0.039)	(0.925)
MI	Skewed-t	0.000	−0.763 ***	0.794 ***	0.001 **	0.079 ***	0.893 ***	0.082	0.84 ***	8.620 ***
		(0.001)	(0.024)	(0.018)	(0.000)	(0.017)	(0.030)	(0.196)	(0.033)	(2.211)
PUI	Skewed-t	0.000	−0.986 ***	0.996 ***	0.000 **	0.063 ***	0.926 ***	0.044	0.878 ***	7.456 ***
		(0.000)	(0.003)	(0.000)	(0.000)	(0.018)	(0.020)	(0.201)	(0.036)	(1.474)
TSI	Skewed-t	−0.001	0.871 ***	−0.905 ***	0.000 **	0.052 ***	0.934 ***	−0.126	0.949 ***	6.081 ***
		(0.000)	(0.018)	(0.019)	(0.000)	(0.014)	(0.019)	(0.184)	(0.039)	(1.138)
FI	Skewed-t	0.000	−0.144 ***	0.095 ***	0.000 **	0.049 ***	0.957 ***	−0.054	1.029 ***	4.89 ***
		(0.000)	(0.024)	(0.028)	(0.000)	(0.008)	(0.003)	(0.174)	(0.039)	(0.602)
HCI	Skewed-t	0.001	−0.246	0.361 *	0.001	0.089 ***	0.847 ***	0.166	0.873 ***	10.444 ***
		(0.001)	(0.195)	(0.188)	(0.001)	(0.025)	(0.070)	(0.230)	(0.038)	(3.220)
II	Skewed-t	0.000	−0.909 ***	0.928 ***	0.001 *	0.075 ***	0.898 ***	0.249	0.821 ***	7.25 ***
		(0.001)	(0.017)	(0.018)	(0.000)	(0.015)	(0.030)	(0.207)	(0.036)	(1.374)
OCI	Skewed-t	0.000	−0.941 ***	0.954 ***	0.001	0.086 ***	0.895 ***	0.182	0.822 ***	8.605 ***
		(0.001)	(0.012)	(0.005)	(0.000)	(0.020)	(0.035)	(0.170)	(0.032)	(2.120)
DCI	Skewed-t	0.000	−0.012	0.064	0.001 **	0.105 ***	0.863 ***	0.130	0.860 ***	14.600 **
		(0.001)	(0.062)	(0.063)	(0.000)	(0.025)	(0.039)	(0.147)	(0.033)	(5.860)
ITI	Skewed-t	0.000	−0.430 ***	0.482 ***	0.001 **	0.093 ***	0.877 ***	0.068	0.751 ***	15.698 **
		(0.001)	(0.015)	(0.014)	(0.000)	(0.017)	(0.028)	(0.127)	(0.033)	(6.418)
Oil	Skewed-t	0.000	0.980 ***	−0.978 ***	0.000	0.067 ***	0.945 ***	0.821 ***	0.868 ***	6.751 ***
		(0.001)	(0.005)	(0.000)	(0.000)	(0.011)	(0.009)	(0.054)	(0.038)	(1.471)

Notes: Reported are parameter estimates, with corresponding p value in parentheses underneath. ***, **, * indicate significance at 1%, 5%, and 10%, respectively. η and ν are the skewness and the degree of freedom of the residual distribution, respectively.

Table 3. Estimates of marginal distribution models (after the reform).

Market	Residual	ϕ_0	ϕ_1	φ_1	ω	α	β	λ	η	ν
EI	Skewed-t	0.000	−0.245 ***	0.252 ***	0.000 **	0.072 ***	0.935 ***	−0.160	0.946 ***	4.633 ***
		(0.000)	(0.011)	(0.011)	(0.000)	(0.018)	(0.018)	(0.136)	(0.028)	(0.496)
REI	t	0.000	0.895 ***	−0.904 ***	0.000 ***	0.104 ***	0.906 ***	−0.033	−−	4.673 ***
		(0.000)	(0.007)	(0.006)	(0.000)	(0.017)	(0.015)	(0.092)	−−	(0.417)
MI	Skewed-t	0.000	−0.123 ***	0.148 ***	0.000 ***	0.098 ***	0.907 ***	0.105	0.831 ***	5.402 ***
		(0.000)	(0.010)	(0.014)	(0.000)	(0.018)	(0.017)	(0.113)	(0.028)	(0.658)
PUI	Skewed-t	0.000	0.828 ***	−0.844 ***	0.000 **	0.102 ***	0.916 ***	−0.087	0.870 ***	4.895 ***
		(0.000)	(0.019)	(0.022)	(0.000)	(0.018)	(0.014)	(0.094)	(0.027)	(0.572)
TSI	Skewed-t	0.000	−0.782 ***	0.785 ***	0.000 **	0.119 ***	0.903 ***	−0.108	0.987 ***	4.295 ***
		(0.000)	(0.008)	(0.008)	(0.000)	(0.023)	(0.018)	(0.108)	(0.032)	(0.434)
FI	Skewed-t	0.001 **	−0.267 ***	0.230 ***	0.000 **	0.080 ***	0.937 ***	−0.144	0.996 ***	3.514 ***
		(0.000)	(0.009)	(0.009)	(0.000)	−0.015	(0.011)	(0.121)	(0.030)	(0.28)
HCI	Skewed-t	0.000	0.721 ***	−0.742 ***	0.000 *	0.078 ***	0.936 ***	−0.014	0.832 ***	8.039 ***
		(0.000)	(0.064)	(0.061)	(0.000)	(0.015)	(0.012)	(0.098)	(0.027)	(1.397)
II	Skewed-t	0.000	−0.578 ***	0.603 ***	0.000 **	0.100 ***	0.911 ***	0.131	0.857 ***	4.882 ***
		(0.000)	(0.009)	(0.008)	(0.000)	(0.020)	(0.019)	(0.121)	(0.027)	(0.523)
OCI	Skewed-t	0.000	−0.821 ***	0.843 ***	0.000 **	0.087 ***	0.925 ***	0.143	0.845 ***	5.418 ***
		(0.000)	(0.056)	(0.056)	(0.000)	(0.018)	(0.016)	(0.113)	(0.025)	(0.657)
DCI	Skewed-t	0.001 ***	−0.781 ***	0.794 ***	0.000 **	0.089 ***	0.919 ***	0.023	0.910 ***	6.613 ***
		(0.000)	(0.030)	(0.027)	(0.000)	(0.017)	(0.016)	(0.116)	(0.031)	(0.96)
ITI	Skewed-t	0.000	−0.805 ***	0.820 ***	0.000 *	0.073 ***	0.939 ***	0.050	0.873 ***	7.296 ***
		(0.000)	(0.011)	(0.013)	(0.000)	(0.013)	(0.011)	(0.106)	(0.029)	(1.177)
Oil	Skewed-t	0.000	0.170 ***	−0.196 ***	0.000 ***	0.081 ***	0.923 ***	0.623 ***	0.853 ***	5.598 ***
		(0.000)	(0.010)	(0.010)	(0.000)	(0.014)	(0.013)	(0.149)	(0.026)	(0.695)

Notes: Reported are parameter estimates, with corresponding p value in parentheses underneath. ***, **, * indicate significance at 1%, 5%, and 10%, respectively. η and ν are the skewness and the degree of freedom of the residual distribution, respectively.

The mean equation shows that the AR coefficient ϕ_1 and MA coefficient φ_1 of nine sectoral stock indexes, with the exception of health care and daily consumption, are significant, both before and after the reform. The GARCH coefficient β in the variance equation shows the presence of the volatility clustering effect in all series. The asymmetric effect coefficient λ shows that the oil market has a highly significant leverage effect, both before and after the reform. Among the sectoral indexes, only the energy index (EI) shows a significant leverage effect before the reform, but it disappears afterwards.

The goodness-of-fit test statistics (untabulated) indicate that the standard residuals from the ARMA-TGARCH models are largely free from autocorrelation and heteroskedasticity. The time series models in Tables 2 and 3 thus depict dynamic characteristics of the data series quite well.

5.1.2. The Markov Regime Switching Model

To further examine the return characteristics of Chinese sectoral stock indexes and the oil market, the Markov regime switching model is employed. As shown by the transition probabilities in Table 4, both the bear market and bull market after the reform generally show stronger persistence than before. After the reform, the probabilities for the bear or bull market to continue are always above 80%, with most transition probabilities being well above 90%. The return dynamics of sectoral indexes and the oil market are cyclical and asymmetric after the reform. However, the range of transition probabilities of both bear and bull markets before the reform is quite wide, and so is the range of their degree of persistence.

Table 4. Estimates for Markov regime switching model.

Market	Period	Bear Market		Bull Market		Transition Probabilities		LogLik
		μ_1	Persistence	μ_2	Persistence	p_{11}	p_{22}	
EI	Before	−0.0002	192.31	0.0009	212.77	0.9948	0.9953	2697.548
	After	−0.0019	12.18	0.0004	61.35	0.9179	0.9837	5632.8823
REI	Before	−0.0034	1.24	0.0021	2.46	0.1930	0.5929	2478.469
	After	0.0003	48.54	0.0000	16.67	0.9794	0.94	5496.9229
MI	Before	0.0049	1.39	−0.0050	1.43	0.2811	0.2996	2554.408
	After	−0.0025	13.05	0.0013	57.14	0.9234	0.9825	5488.4402
PUI	Before	−0.0048	5.98	0.0013	25.32	0.8328	0.9605	2831.619
	After	0.0006	70.92	−0.0014	13.12	0.9859	0.9238	6045.1941
TSI	Before	−0.0016	1.69	0.0005	2.67	0.4098	0.6253	2620.551
	After	0.0004	12.67	0.0001	28.09	0.9211	0.9644	5158.5537
FI	Before	−0.0006	3.83	0.0024	1.97	0.7386	0.4924	2765.0318
	After	0.0001	25.13	0.0013	8.31	0.9602	0.8796	5742.6747
HCI	Before	0.0032	3.37	−0.0024	2.38	0.7037	0.5804	2678.793
	After	0.0011	87.72	−0.0020	19.96	0.9886	0.9499	5470.766
II	Before	−0.0081	1.14	0.0035	2.61	0.1200	0.6173	2680.990
	After	0.0012	48.78	−0.0034	8.87	0.9795	0.8872	5604.7475
OCI	Before	0.0018	9.46	−0.0023	4.26	0.8943	0.7653	2661.994
	After	−0.0031	11.38	0.0012	57.47	0.9121	0.9826	5639.7799
DCI	Before	0.0009	61.73	−0.0004	16.00	0.9838	0.9375	2731.136
	After	−0.0024	15.31	0.0015	63.69	0.9347	0.9843	5577.0364
ITI	Before	0.0061	1.89	−0.0089	1.30	0.4700	0.2296	2563.181
	After	−0.0009	22.83	0.0012	84.75	0.9562	0.9882	5053.141
Oil	Before	0.0004	64.94	0.0021	13.79	0.9846	0.9275	2427.077
	After	−0.0040	6.14	0.0001	77.52	0.8371	0.9871	4752.9718

Notes: LogLik denotes the log-likelihood value. The expected persistence of a bear market and a bull market is $\frac{1}{1-p_{11}}$ and $\frac{1}{1-p_{22}}$, respectively.

The bear market tends to persist longer than the bull market for financial and health care indexes, both before and after the reform. The opposite—a stronger bull market persistence throughout the whole sample period—is true for energy, material, and telecom service indexes. As for the other sectoral indexes and the oil market, the relative persistence of bull and bear markets is reversed after the reform.

5.2. Correlations

To study the correlation between the crude oil market and the 11 Chinese sectoral stock markets, several specifications of time-varying-parameter (TVP) copula are compared, to link the marginal distributions of the oil and stock markets, including TVP-Normal copula, TVP-Student-t copula, TVP-Clayton copula, and TVP-Gumbel copula. The optimal time-varying copula is selected per the AIC criterion, and the parameter estimation results are reported in Table 5.

Table 5. Estimates of time-varying copula models.

	Before the Reform						After the Reform					
	Optimal Copula	ω	α	β	ν	τ	Optimal Copula	ω	α	β	ν	τ
Oil-EI	TVP-Clayton	0.803 (0.421)	0.239 (0.335)	−1.313 (1.118)	–	0.102	TVP-Student-t	0.002 (0.002)	0.016 (0.011)	1.980 (0.027)	15.758 (2.808)	0.072
Oil-REI	TVP-Clayton	0.571 (0.151)	0.514 (0.288)	−0.878 (0.490)	–	0.068	TVP-Student-t	0.005 (0.005)	0.025 (0.017)	1.919 (0.072)	13.765 (11.054)	0.047
Oil-MI	TVP- Normal	0.513 (0.207)	0.277 (0.222)	−1.152 (1.258)	–	0.113	TVP-Student-t	0.002 (0.002)	0.020 (0.010)	1.966 (0.025)	13.734 (1.150)	0.054
Oil-PUI	TVP- Normal	0.164 (0.127)	0.332 (0.227)	0.471 (1.006)	–	0.086	TVP-Student-t	0.003 (0.003)	0.026 (0.015)	1.934 (0.049)	19.694 (10.125)	0.045
Oil-TSI	TVP-Clayton	1.202 (2.054)	−1.278 (0.666)	−1.989 (0.333)	–	0.072	TVP-Student-t	0.006 (0.088)	0.036 (0.261)	1.866 (1.657)	15.139 (3.370)	0.044
Oil-FI	TVP-Clayton	1.172 (0.235)	−0.640 (0.404)	−1.945 (0.718)	–	0.095	TVP-Clayton	0.330 (0.209)	0.825 (0.594)	−0.227 (0.411)	–	0.067
Oil-HCI	TVP-Clayton	0.819 (0.316)	−0.698 (0.838)	−1.263 (0.952)	–	0.055	TVP-Student-t	0.282 (0.260)	−0.175 (0.369)	−1.369 (0.915)	15.528 (3.236)	0.050
Oil-II	TVP-Clayton	0.596 (0.168)	0.508 (0.295)	−0.905 (0.412)	–	0.082	TVP-Student-t	0.004 (0.022)	0.034 (0.084)	1.930 (0.421)	17.248 (0.515)	0.051
Oil-OCI	TVP-Clayton	0.760 (0.411)	−0.117 (0.955)	−1.091 (0.928)	–	0.077	TVP-Student-t	0.003 (0.025)	0.023 (0.090)	1.945 (0.221)	13.676 (4.431)	0.050
Oil-DCI	TVP- Normal	0.348 (0.198)	0.212 (0.217)	−0.780 (1.330)	–	0.086	TVP-Student-t	0.235 (0.471)	−0.040 (0.162)	−1.032 (5.972)	12.819 (5.407)	0.048
Oil-ITI	TVP-Clayton	0.335 (0.103)	0.971 (0.177)	−0.337 (0.283)	–	0.064	TVP-Student-t	0.003 (0.019)	0.026 (0.111)	1.940 (0.045)	15.566 (7.267)	0.047

The dominant optimal time-varying copula for the 11 sectoral stock indexes is the time-varying Clayton copula before the reform, and the time-varying Student-t copula after the reform. The Clayton copula is an asymmetric Archimedean copula, exhibiting greater dependence in the negative tail than in the positive. Clayton copula can better capture asymmetric tail correlation. The Normal copula and the Student-*t* copula, belonging to the Elliptical copula class, have symmetric tails. The tail correlation coefficient of the Normal Copula is 0; that is, Normal Copula assumes asymptotic independence in the tail distribution between the crude oil market and the sectoral stock market. The Student-*t* copula is suited for capturing tail changes in the oil and stock markets due to the high sensitivity in tails.

The mean values of the Kendall correlation coefficient τ indicate positive correlations between the crude oil market and the Chinese sectoral stock markets throughout the whole sample period. Due to rapid economic growth and an increase in stock market investments, the rise in crude oil price is accompanied by a boom in all stock market sectors. The positive correlation is consistent with Chen and Lv [11], but their investigation focuses on extremal dependence. It is also consistent with Zhang and Li [24], who report a stronger positive correlation between oil and equity markets after the 2008 global financial crisis in multiple countries including China. Interestingly, all correlations are weaker after the reform than before. The Chinese refined oil pricing mechanism is used to distort the relationship between the oil and stock markets, but the 2013 reform helps alleviate the distorted transmission mechanism by narrowing the adjustment window and removing the minimum change threshold, which aligns the sensitivity of Chinese companies to extreme oil price risk with expectations, thus weakening their correlation. Investors' rational expectation regarding the oil market makes the stock market operate more independently and smoothly.

It is worthwhile to note that the Kendall correlation provides a more robust estimation of the correlation in this context than the linear correlation coefficient. Foremost, the conventional linear correlation would work well if the joint distribution of the oil market and the sectoral stock market follows a bivariate normal distribution. Because the distribution of returns in the two markets typically features sharp peaks and fat tails alone with skewness—clear violations of the bivariate normal distribution—applications of the linear correlation coefficient would yield dubious results. Further, the linear correlation is sensitive to variables' marginal distribution. Variation in marginal distribution may make the linear correlation fickle [47]. In contrast, the Kendall correlation can overcome the limitations of linear correlation through the Copula function, thus providing a more reliable description on the correlation.

5.3. Tail Risk and Spillover Effects of the Extreme Oil Market

VaR indicates the maximum loss that an investor who holds a long position (lower tail risk, measured using $VaR^{down}_{0.05}$) or short position (upper tail risk, measured using $VaR^{up}_{0.05}$) may suffer over a given time frame. CoVaR indicates the value-at-risk of a sectoral stock index conditional on the oil market experiencing extreme fluctuation. Since $CoVaR^{down}_{0.05,0.05}$ is usually negative and $CoVaR^{up}_{0.05,0.05}$ is usually positive, a higher absolute value of either indicates a higher tail risk of the oil market on the Chinese sectoral stock market for long or short positions. The reduction (increase) of extreme tail risk means that when the oil market is in a state of extreme turbulence (5% in a tail), the conditional distribution of a stock sectoral index return is narrower (wider)—that is, the sectoral index would fluctuate less (more).

Figure 1 shows that the tail risk of the extreme oil market to the Chinese sectoral stock markets peaks during the 2015 stock market crash, due to the sharp drop in oil demand caused by the economic slowdown in China and other developing countries. The changing production costs and investment and financing of companies elevate the volatility of stocks.

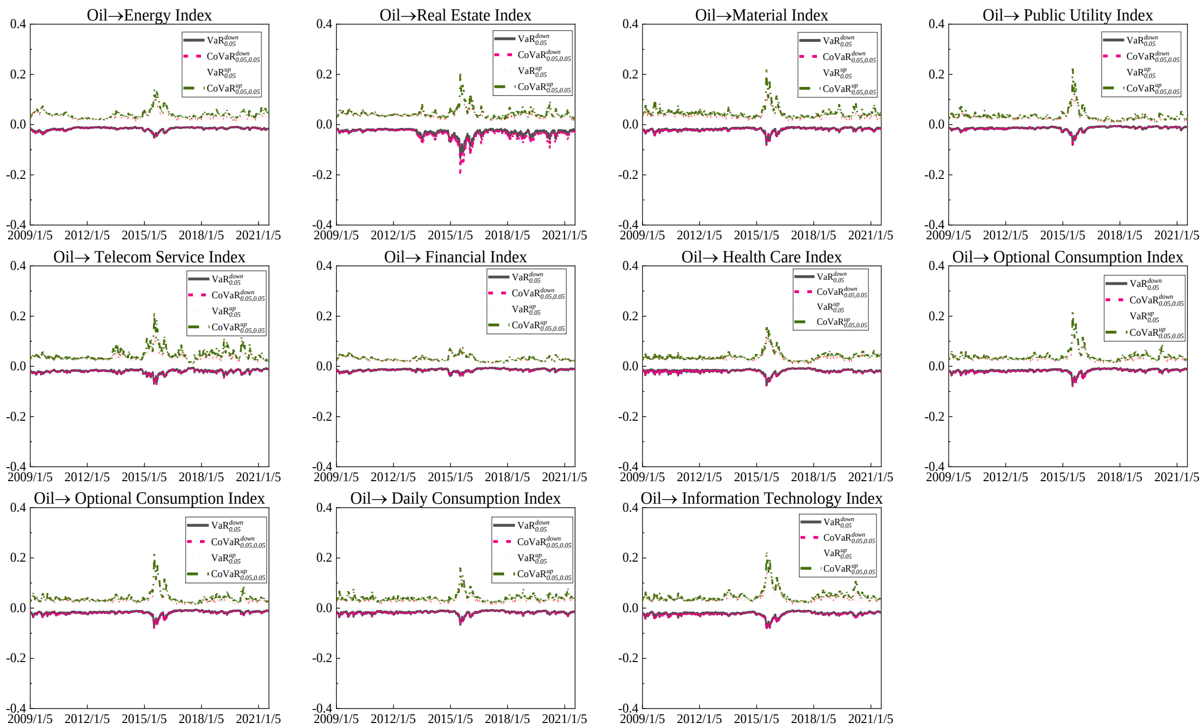

Figure 1. Tail risks of extreme oil market on Chinese sectoral stock indexes.

As indicated by the mean values of $CoVaR^{down}_{0.05,0.05}$ in Table 6, the downside tail risk of the extreme oil market on most sectoral stock markets, with the exception of real estate, telecom service, and health care, is lower after the reform than before. The changes in $CoVaR^{up}_{0.05,0.05}$ suggest that the upside tail risk of the extreme oil market on most sectoral indexes is higher after the reform. For the other sectors—including material, public utility, and financial—the upside tail risk decreases slightly after the reform. Overall, when the oil market experiences extreme fluctuations after 2013, its impact on the Chinese stock market is generally beneficial for long positions. The Chinese refined oil pricing reform has brought its domestic refined oil prices to be more closely linked to international oil prices. The closer connection reduces speculations by investors, which alleviates the downside tail risks of the extreme oil market on Chinese sectoral stock markets. The results in Table 6 are partially consistent with Bouri et al. [12], who report evidence of a much weaker causality-in-variance between the international oil and Chinese stock markets after the 2013 reform with the CCF approach. Our method explicitly differentiates upside and downside extreme risk, while CCF does not.

Table 6. Descriptive statistics of tail risk of extreme oil market on Chinese sectoral stock markets.

	$VaR^{down}_{0.05}$		$CoVaR^{down}_{0.05,0.05}$		$VaR^{up}_{0.05}$		$CoVaR^{up}_{0.05,0.05}$	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
EI	−0.017 (0.007)	−0.016 (0.007)	−0.018 (0.007)	−0.017 (0.007)	0.032 (0.012)	0.030 (0.012)	0.035 (0.013)	0.044 (0.018)
REI	−0.021 (0.003)	−0.036 (0.016)	−0.022 (0.004)	−0.047 (0.023)	0.039 (0.006)	0.036 (0.016)	0.041 (0.006)	0.047 (0.023)
MI	−0.021 (0.004)	−0.018 (0.009)	−0.023 (0.004)	−0.019 (0.01)	0.036 (0.007)	0.033 (0.016)	0.048 (0.01)	0.046 (0.026)
PUI	−0.016 (0.003)	−0.014 (0.01)	−0.016 (0.004)	−0.015 (0.01)	0.027 (0.006)	0.025 (0.018)	0.035 (0.009)	0.034 (0.026)
TSI	−0.019 (0.004)	−0.020 (0.009)	−0.020 (0.004)	−0.021 (0.01)	0.033 (0.005)	0.038 (0.018)	0.035 (0.006)	0.053 (0.028)
FI	−0.016 (0.004)	−0.013 (0.005)	−0.016 (0.004)	−0.014 (0.006)	0.029 (0.008)	0.028 (0.011)	0.031 (0.008)	0.030 (0.011)
HCI	−0.018 (0.004)	−0.018 (0.009)	−0.019 (0.004)	−0.020 (0.01)	0.032 (0.005)	0.032 (0.016)	0.034 (0.005)	0.043 (0.021)
II	−0.018 (0.003)	−0.016 (0.009)	−0.021 (0.004)	−0.017 (0.01)	0.032 (0.006)	0.031 (0.017)	0.034 (0.006)	0.043 (0.028)
OCI	−0.019 (0.004)	−0.016 (0.009)	−0.021 (0.004)	−0.018 (0.01)	0.032 (0.006)	0.030 (0.017)	0.034 (0.007)	0.043 (0.026)
DCI	−0.018 (0.004)	−0.017 (0.008)	−0.019 (0.004)	−0.017 (0.008)	0.031 (0.006)	0.031 (0.013)	0.038 (0.008)	0.043 (0.018)
ITI	−0.022 (0.004)	−0.023 (0.011)	−0.025 (0.005)	−0.024 (0.012)	0.036 (0.007)	0.040 (0.019)	0.037 (0.007)	0.054 (0.03)

Notes: Reported are mean values of the risk measures, with standard deviation in parentheses underneath.

Downside tail risk spillover effect and upside tail risk spillover effect are captured by the difference between $CoVaR^{down}_{0.05,0.05}$ and $VaR^{down}_{0.05}$, and the difference between $CoVaR^{up}_{0.05,0.05}$ and $VaR^{up}_{0.05}$, respectively. The difference between the conditional value-at-risk and the unconditional value represents the spillover effect of the event in condition, i.e., the oil market experiencing extreme fluctuations. Since it is challenging to visually gauge the difference between *VaR* and *CoVaR* in Figure 1, to ensure objectivity, the Kolmogorov–Smirnov (KS) test is employed to test the downside and upside tail risk spillover effects of the extreme oil market to Chinese sector stock markets, and the asymmetry in tail risk spillover effects. Column (1) in Table 7 tests for downside spillover effect, column (2) for upside spillover effect, and column (3) for asymmetry between the downside and upside spillover effects. The test results in Table 7 show that there are downside and upside tail risk spillover effects to all stock market sectors before and after the reform. This result is consistent with Kirkulak-Uludag and Safarzadeh [39] who report significant volatility spillover between oil futures and Chinese sectoral stock returns between 2004 and 2014. Furthermore, downside tail risks spillover effects are stronger than upside spillover effects for all sectors except real estate post reform, providing powerful evidence for asymmetric effects, consistent with Reboredo and Ugolini [46]. The asymmetric effect echoes Peng et al. [6] that negative spillover effects are of particular concern after the 2013 pricing reform.

Table 7. Hypothesis testing for tail risk spillover of extreme oil market on Chinese sector stock markets.

		(1)	(2)	(3)
	Period	$H_0: VaR^{down}_{0.05,t} = CoVaR^{down}_{0.05,0.05,t}$ $H_1: VaR^{down}_{0.05,t} > CoVaR^{down}_{0.05,0.05,t}$	$H_0: VaR^{up}_{0.05,t} = CoVaR^{up}_{0.05,0.05,t}$ $H_1: VaR^{up}_{0.05,t} < CoVaR^{up}_{0.05,0.05,t}$	$H_0: \frac{CoVaR^{down}_{0.05,0.05,t}}{VaR^{down}_{0.05,t}} = \frac{CoVaR^{up}_{0.05,0.05,t}}{VaR^{up}_{0.05,t}}$ $H_1: \frac{CoVaR^{down}_{0.05,0.05,t}}{VaR^{down}_{0.05,t}} > \frac{CoVaR^{up}_{0.05,0.05,t}}{VaR^{up}_{0.05,t}}$
Oil→EI	Before	0.105 [0.000]	0.199 [0.000]	0.664 [0.000]
	After	0.081 [0.000]	0.576 [0.000]	0.999 [0.000]
Oil→REI	Before	0.189 [0.000]	0.212 [0.000]	0.167 [0.000]
	After	0.334 [0.000]	0.333 [0.000]	0.028 [0.394]
Oil→MI	Before	0.167 [0.000]	0.664 [0.000]	0.999 [0.000]
	After	0.110 [0.000]	0.439 [0.000]	0.960 [0.000]
Oil→PUI	Before	0.103 [0.000]	0.447 [0.000]	0.883 [0.000]
	After	0.055 [0.005]	0.318 [0.000]	0.966 [0.000]
Oil→TSI	Before	0.136 [0.000]	0.201 [0.000]	0.249 [0.000]
	After	0.044 [0.043]	0.295 [0.000]	0.975 [0.000]
Oil→FI	Before	0.098 [0.000]	0.154 [0.000]	0.703 [0.000]
	After	0.070 [0.000]	0.108 [0.000]	0.861 [0.000]
Oil→HCI	Before	0.184 [0.000]	0.153 [0.000]	0.562 [0.000]
	After	0.091 [0.000]	0.331 [0.000]	1.000 [0.000]
Oil→II	Before	0.307 [0.000]	0.198 [0.000]	0.447 [0.000]
	After	0.084 [0.000]	0.398 [0.000]	0.909 [0.000]
Oil→OCI	Before	0.269 [0.000]	0.172 [0.000]	0.667 [0.000]
	After	0.080 [0.000]	0.387 [0.000]	0.981 [0.000]
Oil→DCI	Before	0.112 [0.000]	0.454 [0.000]	0.999 [0.000]
	After	0.080 [0.000]	0.425 [0.000]	1.000 [0.000]
Oil→ITI	Before	0.286 [0.000]	0.130 [0.000]	0.794 [0.000]
	After	0.082 [0.000]	0.370 [0.000]	0.943 [0.000]

Notes: Reported are Kolmogorov–Smirnov (KS) statistics, with corresponding *p* value in brackets underneath.

5.4. Tail Risk and Spillover Effects of the Moderate Oil Market

We then employ the time-varying copula model to explore the tail risk of the moderate oil market on stock markets, whose results are shown in Figure 2 and Table 8. It is found that, with the exceptions of real estate, telecom service, and information technology, the downside and upside tail risks of the moderate oil market on eight sectors are smaller or unchanged after the reform. Moreover, the tail risks of the moderate oil market on sector stock indexes are smaller than or equal to the tail risks of the extreme oil market reported in Table 6. This conclusion holds for all 11 sectoral stock markets. Moderate fluctuations in oil prices pose less tail risk to stock markets than extreme fluctuations do.

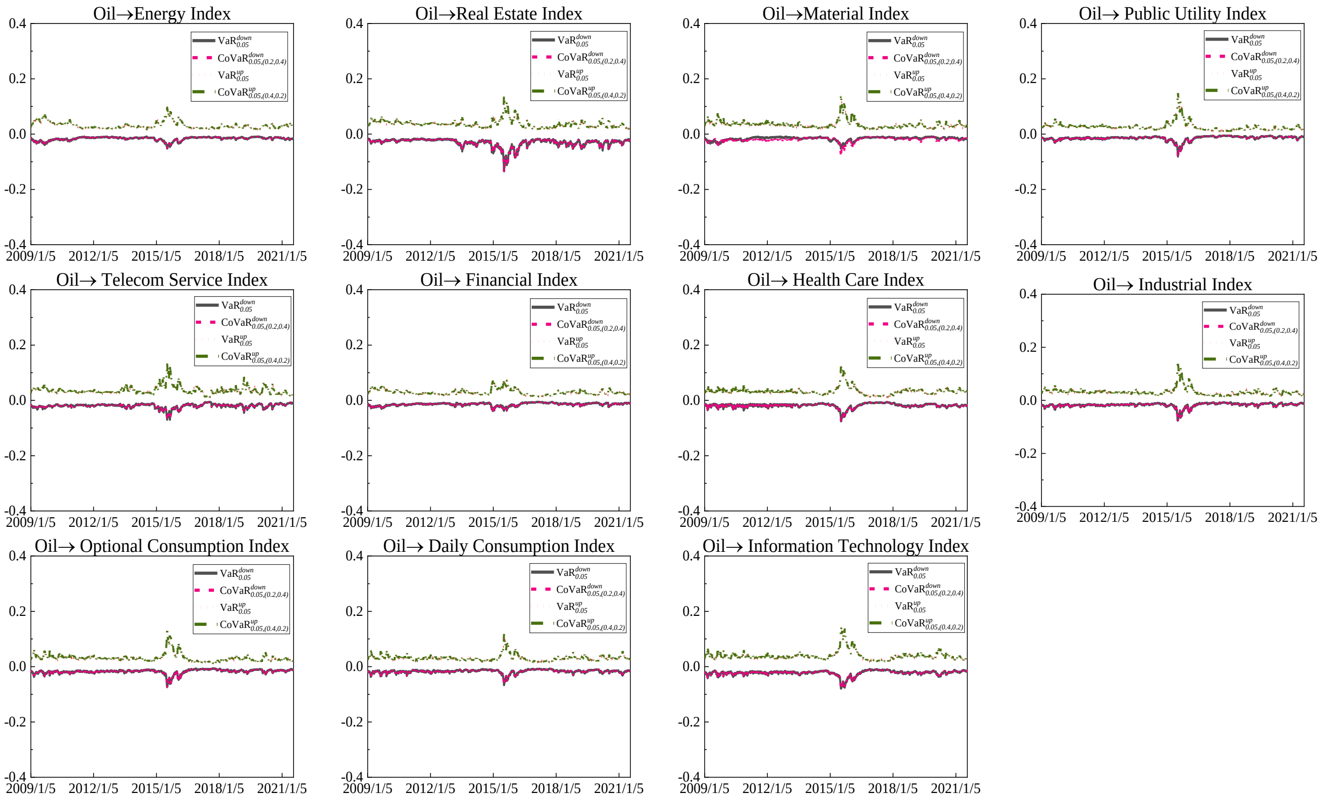

Figure 2. Tail risks of moderate oil market on Chinese sector stock markets.

Test results for the spillover effect of the moderate oil market are reported in Table 9. It shows no evidence of a downside spillover effect of the moderate oil market on any stock market sectors before the pricing reform, but evidence of upside spillover effects to all 11 sectors before the reform. In contrast, there is no upside or downside tail risk spillover effect of moderate oil market on any stock sectoral index other than the financial index after the reform. Significant asymmetry is ubiquitous that downside spillover effect exceeds upside spillover effect by the moderate oil market before and after the reform, except in the real estate sector. These findings are in contrast to Reboredo and Ugolini [46], who report no spillover effect by moderate oil price movements in eight international markets, including China, between 2000 and 2014.

Table 8. Descriptive statistics of tail risk of moderate oil market on Chinese sector stock markets.

Market	$VaR_{0.05}^{down}$		$CoVaR_{0.05,(0.2,0.4)}^{down}$		$VaR_{0.05}^{up}$		$CoVaR_{0.05,(0.4,0.2)}^{up}$	
	Before	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
EI	−0.017 (0.007)	−0.016 (0.007)	−0.017 (0.007)	−0.016 (0.007)	0.032 (0.012)	0.030 (0.012)	0.034 (0.013)	0.030 (0.012)
REI	−0.021 (0.003)	−0.036 (0.016)	−0.021 (0.003)	−0.035 (0.016)	0.039 (0.006)	0.036 (0.016)	0.040 (0.006)	0.035 (0.016)
MI	−0.021 (0.004)	−0.018 (0.009)	−0.022 (0.004)	−0.018 (0.009)	0.036 (0.007)	0.033 (0.016)	0.038 (0.007)	0.032 (0.016)
PUI	−0.016 (0.003)	−0.014 (0.01)	−0.016 (0.003)	−0.014 (0.01)	0.027 (0.006)	0.025 (0.018)	0.029 (0.006)	0.025 (0.018)
TSI	−0.019 (0.004)	−0.020 (0.009)	−0.019 (0.004)	−0.020 (0.009)	0.033 (0.005)	0.038 (0.018)	0.034 (0.005)	0.037 (0.018)
FI	−0.016 (0.004)	−0.013 (0.005)	−0.016 (0.004)	−0.013 (0.005)	0.029 (0.008)	0.028 (0.011)	0.030 (0.008)	0.029 (0.011)
HCI	−0.018 (0.004)	−0.018 (0.009)	−0.018 (0.004)	−0.018 (0.009)	0.032 (0.005)	0.032 (0.016)	0.033 (0.005)	0.032 (0.016)
II	−0.018 (0.003)	−0.016 (0.009)	−0.018 (0.003)	−0.016 (0.009)	0.032 (0.006)	0.031 (0.017)	0.033 (0.006)	0.031 (0.017)
OCI	−0.019 (0.004)	−0.016 (0.009)	−0.019 (0.004)	−0.016 (0.009)	0.032 (0.006)	0.030 (0.017)	0.034 (0.007)	0.030 (0.017)
DCI	−0.018 (0.004)	−0.017 (0.008)	−0.018 (0.004)	−0.016 (0.008)	0.031 (0.006)	0.031 (0.013)	0.032 (0.007)	0.031 (0.013)
ITI	−0.022 (0.004)	−0.023 (0.011)	−0.022 (0.004)	−0.022 (0.011)	0.036 (0.007)	0.040 (0.019)	0.037 (0.007)	0.040 (0.02)

Notes: Reported are mean values of the risk measures, with standard deviation in parentheses underneath.

Table 9. Hypothesis testing for risk spillover of moderate oil market on Chinese sectoral stock markets.

		(1)	(2)	(3)
Market	Stage	$H_0: VaR_{0.05,t}^{down} = CoVaR_{0.05,(0.2,0.4),t}^{down}$ $H_1: VaR_{0.05,t}^{down} > CoVaR_{0.05,(0.2,0.4),t}^{down}$	$H_0: VaR_{0.05,t}^{up} = CoVaR_{0.05,(0.4,0.2),t}^{up}$ $H_1: VaR_{0.05,t}^{up} < CoVaR_{0.05,(0.4,0.2),t}^{up}$	$H_0: \frac{CoVaR_{0.05,(0.2,0.4),t}^{down}}{VaR_{0.05,t}^{down}} = \frac{CoVaR_{0.05,(0.4,0.2),t}^{up}}{VaR_{0.05,t}^{up}}$ $H_1: \frac{CoVaR_{0.05,(0.2,0.4),t}^{down}}{VaR_{0.05,t}^{down}} > \frac{CoVaR_{0.05,(0.4,0.2),t}^{up}}{VaR_{0.05,t}^{up}}$
Oil→EI	Before	0.008 [1.000]	0.136 [0.000]	0.999 [0.000]
	After	0.005 [1.000]	0.021 [0.747]	0.592 [0.000]
Oil→REI	Before	0.014 [1.000]	0.139 [0.000]	0.998 [0.000]
	After	0.024 [0.616]	0.024 [0.616]	0.009 [1.000]
Oil→MI	Before	0.047 [0.216]	0.182 [0.000]	0.999 [0.000]
	After	0.011 [1.000]	0.038 [0.105]	0.357 [0.000]
Oil→PUI	Before	0.028 [0.825]	0.121 [0.000]	0.933 [0.000]
	After	0.004 [1.000]	0.010 [1.000]	0.413 [0.000]
Oil→TSI	Before	0.010 [1.000]	0.137 [0.000]	0.954 [0.000]
	After	0.006 [1.000]	0.026 [0.487]	0.515 [0.000]
Oil→FI	Before	0.007 [1.000]	0.110 [0.000]	1.000 [0.000]
	After	0.005 [1.000]	0.071 [0.000]	1.000 [0.000]
Oil→HCI	Before	0.015 [1.000]	0.105 [0.000]	0.992 [0.000]
	After	0.005 [1.000]	0.012 [0.999]	0.491 [0.000]

Table 9. *Cont.*

		(1)	(2)	(3)
Oil→II	Before	0.011 [1.000]	0.136 [0.000]	0.991 [0.000]
	After	0.005 [1.000]	0.016 [0.949]	0.446 [0.000]
Oil→OCI	Before	0.013 [1.000]	0.112 [0.000]	0.997 [0.000]
	After	0.008 [1.000]	0.031 [0.295]	0.460 [0.000]
Oil→DCI	Before	0.033 [0.643]	0.127 [0.000]	1.000 [0.000]
	After	0.008 [1.000]	0.035 [0.175]	1.000 [0.000]
Oil→ITI	Before	0.018 [0.997]	0.088 [0.001]	1.000 [0.000]
	After	0.009 [1.000]	0.020 [0.797]	0.350 [0.000]

Notes: reported are KS statistics, with the corresponding p value in brackets underneath.

6. Conclusions and Discussion

6.1. Conclusions

The Chinese refined oil pricing reform in 2013 has led to a closer linkage between its refined oil prices and the international crude oil price. This reform helps to correct the previous distorted pricing transmission mechanism, and in turn, affects the correlation, tail risk, and spillover effects between the international crude oil and Chinese sectoral stock markets. Working with the daily data of West Texas Intermediate crude oil futures prices and all 11 Chinese Wind primary sector indexes from January 2009 to August 2021, we employ the time-varying copula model to portray the correlation between the oil market and the Chinese sectoral stock market. CoVaR is adopted to measure the tail risk of the extreme and moderate oil markets on stock markets. The excess of CoVaR over the unconditional VaR indicates the spillover effect of the oil market. Besides correlation, we are interested in exploring the significance of both downside and upside tail risk and spillover effects, particularly their comparison before and after the reform.

Positive correlations prevail between the international oil market and the Chinese sector stock markets, both before and after the reform, indicating that rising oil price is usually accompanied by booming stock markets. However, the correlation is weaker after the reform than before. The pricing reform has strengthened the link between Chinese refined oil and international oil prices, which helps to alleviate the previously distorted pricing mechanism.

With few exceptions, the tail risk (especially the downside) by the extreme oil market, measured using CoVaR, is smaller after the reform than before. The extreme oil market has significant downside and upside tail risk spillover effects on all Chinese sectoral stock indexes, before and after the reform. The tail risk of the moderate oil market on all sectors except real estate, telecom service, and information technology, is reduced or unchanged after the reform. The upside tail risk spillover effect of the moderate oil market exists in all 11 sectors before the reform, but they almost all disappear after the reform. The downside spillover effect by the moderate oil market does not exist for any stock market sector, either before or after the reform. The downside tail risk spillover effect of both the extreme and moderate oil markets on the vast majority of sectoral indexes is larger than the upside spillover effect, showing significant asymmetric impacts.

This study contributes to the ongoing debate regarding the risk impact of the 2013 pricing reform by providing some fresh evidence. Due to differences in methodology and data samples, previous studies have yielded mixed results. For example, Bouri et al. [12] report evidence for diminished risk spillovers after the reform, while Wong and Zhang [2] argue that Chinese industries are more exposed to international crude oil futures volatility since the reform.

6.2. Discussion

The 2013 reform has made domestic refined oil markets more closely aligned with the international market. However, this close alignment does not necessarily carry to stock markets. The relationship between the oil and stock markets is intrinsically complex. While lower oil prices reduce costs for most industries, they often indicate a weaker demand due to an upcoming economic slowdown. Time frame is another key factor, as most effects in the economy take months or longer to realize. In contrast, stock markets are forward-looking in nature and sensitive. All these factors make the relation between the oil and stock markets a question that can be answered only through empirical investigations.

It is worthwhile to note that the data frequency in this study (daily) primarily serves the interests of stock market traders. This contrasts with the perspectives of most economists, who typically advise not paying much attention to daily fluctuations in stock markets.

The refined oil pricing reform in 2013 aims to strike a balance: it makes the pricing mechanism more market oriented, but interventions would be conducted in the case of extreme turbulence in the international oil market. Under such a pricing regime, stock traders' speculation regarding the impact of the oil market is reduced. Rational expectation with respect to the oil market would make stock markets operate more smoothly. Moreover, as conjectured in the Introduction, the 2013 reform, by enabling more timely adjustment without the 4% threshold constraint, may have mitigated the uncertainty created by the old mechanism and thus reduced the tail risk and spillover effect from the international oil market to China's refined oil market and stock market. Our empirical results support this supposition.

The findings of this study may provide a reference for future reform and regulation update on the oil market. Since the current largely market-oriented pricing mechanism seems to have worked better than the previous tightly controlled one, why not go further? For example, how about shortening the adjustment cycle to say, five days? If the occasional government intervention is beneficial, what is its optimal level, or what should be the specific condition to trigger an intervention?

The results also provide reference for stock market investors to anticipate and mitigate tail risks when formulating and adjusting their portfolios. While most sectors respond similarly to risks caused by fluctuations in the oil market, there are notable exceptions. For example, the real estate sector is an exception to several general findings: it is the only sector whose downside tail risk spillover effect of the extreme oil market is not larger than the upside spillover effect post reform, and it is one of the few sectors whose downside tail risk of the moderate oil market is higher after the reform than before. For stock investors who are concerned about the impact of the oil market, such distinct risk characteristics should distinguish the role of the real estate sector from other sectors in their portfolios.

In future studies, we plan to pursue portfolio optimization strategies based on stock market sectors' risk conjunction with the crude oil market [48,49]. The calculation of CoVaR in this study is parametric, that is, based on Copula and DCC-GARCH models. A nonparametric method such as quantile regression or its variant would allow for differentiation between oil market shocks on the basis of their causes/drivers. Results from such an exploration would provide additional insight into the risk association between oil and stock markets.

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