Extreme risk spillovers between crude oil and stock markets

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ABSTRACT

This paper investigates the spillovers of extreme risks between crude oil and stock markets using daily data of the S&P 500 stock index and West Texas Intermediate (WTI) crude oil futures returns. Based on the method of Granger causality in risk, Value at Risk (VaR) is employed to measure market risk, and a class of kernel-based tests is used to detect negative and positive risk spillover effects. Empirical results reveal that there are significant risk spillovers between the two markets. Extreme movements, past or current, in one market may have a significant predictive power for those in the other market. Prior to the recent financial crisis, there are positive risk spillovers from stock market to crude oil market, and negative spillovers from crude oil market to stock market. After the financial crisis, bidirectional positive risk spillovers are strengthened markedly. The risk spillovers may occur instantaneously, and/or with a (long) time delay. Both positive and negative risk spillover effects exhibit asymmetric correlations.

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1. Introduction

Controlling and monitoring market risk is an important issue for investors, policymakers and academic researchers. This is because huge risk usually implies extreme market movements that could lead to substantial capital changes and even economic recessions. Due to the increasing trend of economic and substantial capital changes and even economic recessions. Due to the increasing trend of economic and financial integration, it is commonplace that others are always of great concern to financial market participants.

Crude oil and stock markets play crucial roles in economic development and investment decisions. Considerable transmission of risk may exist between the two markets. In theory, crude oil returns could be derived from the implications of stock returns for real economic conditions. Meanwhile, given the nontrivial importance of oil to the world economy, the reaction of stock market to crude oil shocks could be justified by changes in real cash flows and expected returns. In addition to market fundamentals, market contagion and speculative dynamics (i.e., fads, investor sentiment, and overreaction to news) are also possible reasons for the risk spillovers.

In recent years, increasing empirical studies have found significant links between crude oil and stock market returns. However, these studies mainly focus on the conditional mean and the conditional variance which cannot disclose the whole picture of risk relations. It is well known that the mean and the variance are only two elements of an overall summary for the conditional distribution of returns. In the risk investigation, we are interested in the relations of distribution tails, either left for downside risk or right for upside risk. If the distributions involved are fat tailed as is to be expected with financial returns, a tail area relation may be quite different (Jeong et al., 2012).

Currently a few studies have used copula models to investigate the risk dependence between crude oil and stock returns. For example, Geman and Khoroubi (2008) estimate copula functions between crude oil futures and the S&P500 stock index from May 1990 to August 2006, and find that when the S&P 500 index was declining extremely,
the crude oil market was increasing extremely, and vice versa; Wen et al. (2012) find significantly increasing tail dependence between crude oil and the U.S. stock market after the occurrence of the recent financial crisis. Strong evidences are provided in favor of contemporaneous dependence of risks between crude oil and stock returns. Several important issues still remain to be solved.

First, the copula approaches do not uncover lagged effects at the risk level. In fact, there are theoretical underpinnings for risk spillovers with a time delay. Given the growing evidence of time-variation in expected returns, past price movements of crude oil could affect current expected stock returns (Jones and Kaul, 1996). Besides, it usually takes time for investors to interpret information, make decision and take action. Therefore, it appears natural to ask questions about the risk relations at (higher) lags.

Second, contemporaneous dependence is hard to specify the causality (in the Granger sense) of risk transmissions. The bridge between crude oil and stock markets is economic and financial activities. Therefore, the direction of causation can help understand how economic information is transmitted across the two markets. Of course, it also has valuable implications for predicting and monitoring risks.

Third, the prior empirical works are often concerned about downside and upside risk dependence. The downside (upside) risk dependence refers to a relation between downside (upside) risks across markets. Obviously, these two types of risk dependence stand out based on a default assumption of positive correlation between market returns. However, as often mentioned in the literature, crude oil and stock markets might be negatively correlated (See Jones and Kaul, 1996; Hammoudeh and Li, 2005; Park and Ratti, 2008; Killian and Park, 2009; Basheer et al., 2012; Mollik and Assefa, 2013 etc.). Killian and Park (2009) suggest that the response of aggregate stock returns may differ greatly depending on the cause of the oil price shock. The negative response of stock prices to oil price is found when the price of oil rises due to concerns about future crude oil supply shortfalls. Considering this situation, this paper points out that risk spillovers from crude oil to stock markets exhibit negative relations. For instance, downside (upside) risk in crude oil could spill over to the stock markets, generating upside (downside) risk in stock returns. To what extent these types of risk spillovers exist is an empirical question.

Addressing these issues, this paper comprehensively investigates both contemporaneous and lagged correlations of extreme movements, namely the risk spillovers between crude oil and stock markets. The nature of causality relations at the risk level is examined by the econometric method developed by Hong et al. (2009). Value at Risk (VaR) is employed to measure extreme market risk, and then a class of kernel-based tests is used to detect four types of Granger causality in risk between the two markets. The econometric method used in this paper has a number of appealing features. The VaR calculation nowadays is a very popular measure of price risks. Compared with those experiential measures in the literature, such as Hamilton’s (1996) normalized oil variable (NOMPI), VaR provides a standardized statistical way to capture huge price movements. Conventional tests using a large number of lags have low power because of loss of a large number of degrees of freedom. In contrast, the kernel-based statistical tests can check a large number of lags that ensures a good power.

In order to investigate the possible negative effects of risk spillovers, we first follow Fan et al. (2008) to introduce a notion of upside risk to capture extreme increase in market returns. The reason is that crude oil, as a special commodity, has its own traits of market risk. When crude oil price returns increase extremely, the crude oil buyers may incur losses, and business profits tend to decrease, which may in turn affect the stock market. Then, we define two types of negative risk spillovers in each causality direction. From stock to oil, for instance, down-to-up risk spillover captures the effects of stock downside risk on oil upside risk, and up-to-down risk spillover captures the effects of stock upside risk on oil downside risk. To the best of our knowledge, this is the first study that focuses on the dynamics of negative risk relations between crude oil and stock markets.

Our study is based on a daily-based dataset of the WTI crude oil and the S&P500 stock index from September 1, 2004 to September 11, 2012. Several interesting findings are summarized as follows.

1. Risk spillovers between crude oil and stock markets are statistically and economically significant. On one side, downside risk of the S&P500 significantly Granger causes similar risk of the WTI during normal periods. It is a positive risk spillover effect. On the other side, WTI downside (upside) risk Granger causes S&P500 upside (downside) risk, which are negative risk spillover effects. This implies that extreme movements, past or current, in one market may have a significant predictive power for those in the other market.

2. Risks are usually transmitted quickly. Substantial spillovers also occur with a time delay. Particularly, the spillover effect of upside risk in crude oil market could be significant within one month. This proves the vital necessity of investigating risk spillovers at (higher) lags.

3. After the occurrence of the financial crisis, the structure of risk spillovers is changed. Positive risk spillovers between the two markets are strengthened markedly. It indicates that the origin of oil shocks is an important determinant of the risk spillovers.

4. Asymmetric behaviors are found in both negative and positive spillover regions. Market participants are more vulnerable to downside risks in the short run. The asymmetric effects in a negative risk spillover aspect enrich findings in the literature.

Our empirical findings demonstrate the necessity of emphasizing negative correlations and lagged effects in a study of risk relationship between crude oil and stock markets. The two types of negative risk spillovers, along with the downside and the upside risk spillovers, can cover all facets of the risk relationship between the two markets. The lagged effects of risk spillovers shed light on the Granger causality relations in risk which help understand how information is transmitted between the two markets. From the perspective of actual practices, crude oil and stock markets are highly associated at the risk level. Awareness of the dynamics (or Granger causality) of risk transmissions will motivate market traders to accurately gauging and effectively guarding against extreme risks in the future, and also support the scientific decision makings of governmental departments for energy purchase and storage.

The rest of this paper is organized as follows. In Section 2, we introduce the notion of various Granger causality in risk and the methodology of econometric tests. Section 3 presents the data and their descriptive statistics. Section 4 provides empirical results, and Section 5 concludes.

2. Methodology

2.1. VaR estimation

Value at Risk (VaR) is a widely used quantitative measure of extreme downside market risk. For a given time period horizon and confidence level of 100(1 − α)%, VaR is defined as the maximum amount that can be lost with probability α. The conventional definition of VaR involves the downside risk, so it is called as downside VaR. For a given time series of returns Yt, the downside VaR, denoted by Vt(down), is written as

\[ P(Y_t < -V_t(down)|I_{t-1}) = \alpha \]

where \( I_{t-1} = \{Y_t - \mu, Y_t - \mu, \ldots\} \) is the information set available at time \( t = 1 \). Mathematically, the downside VaR is the negative of α-quantile of conditional probability distribution of \( Y_t \). What makes VaR approach...
quite appealing is its convenience. The entire price risk can be represented by a single number.

In the literature, most of the previous studies solely focus on the market risk when returns of financial assets go down (i.e., downside risk). However, as argued by Fan et al. (2008), crude oil, as a special commodity, has its own traits that differ from other financial products, and so does its market risk. Particularly, when crude oil price returns rise, crude oil consumers incur losses. Extremely high crude oil price shocks could even cause economic recessions. Therefore, both downside and upside risks need to be considered for crude oil. For this purpose, we introduce the notion of upside VaR, denoted by \( V_u \), written as:

\[
P(Y_t > V_u| Y_{t-1}) = \alpha.
\]

(2)

\( V_u \) is the upper \( \alpha \)-quantile of conditional probability distribution of \( Y_t \). In practice, commonly used \( \alpha \)-levels are 1%, 5%, and 10%.

In order to estimate VaR, the GARCH model is one of the most commonly used methods that can capture the stylized facts of financial returns such as volatility clustering, fat tails, skewness, and leverage effects (e.g., Fan et al., 2008; Hung et al., 2008). The financial return \( Y_t \) can be described in a GARCH model on the following structure:

\[
Y_t = \mu + \sum_{j=1}^{r} \phi_j Y_{t-j} + \epsilon_t,
\]

(3)

\[
\epsilon_t = \sqrt{\eta_t} z_t.
\]

(4)

\[
\eta_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j \epsilon_{t-j}^2 + \sum_{j=1}^{m} \beta_j \eta_{t-j},
\]

(5)

\[z_t \sim m.d.s.(0,1) \text{ with conditional CDF } F(\cdot).
\]

(6)

Eq. (3) decomposes the return at time \( t \) into a conditional mean and an innovation \( \epsilon_t \). Eq. (4) defines the standardized error \( z_t \). Eq. (5) determines the dynamics of the conditional variance \( \eta_t \) of \( Y_t \) given \( Y_{t-1} \). In Eq. (6), the standardized residual \( z_t \) has a conditional distribution with mean zero and variance one.

It is well known that financial returns may have leverage effects. Sometimes significant leverage effect exists in the volatility of return series, indicating that the current volatility caused by the previous increase and decrease in the returns is asymmetric. In this case, GJR models discussed in Glosten et al. (1993) are used in this paper. Thus, the conditional variance equation can be written as:

\[
\eta_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j \epsilon_{t-j}^2 + \gamma \epsilon_{t-1}d_{t-1} + \sum_{j=1}^{m} \beta_j \eta_{t-j},
\]

(7)

where indicator \( d_{t-1} = 1 \) when \( \epsilon_{t-1} < 0 \), denoting bad news; otherwise \( d_{t-1} = 0 \) and denotes good news. The coefficient \( \gamma \) measures the difference between the effects of good news and bad news on the conditional variance.

Efficient estimation of VaR is highly dependent upon the conditional distribution for the standardized error. In this paper we use the simple and flexible skewed t distribution of Hansen (1994). This distribution has two shape parameters: the degrees of freedom parameter \( \eta \) which controls the tail thickness and the skewness parameter \( \lambda \) which controls the degree of asymmetry. If \( \lambda > 0 \), the variable is skewed to the right, and vice-versa when \( \lambda < 0 \). When \( \lambda = 0 \), we obtain the standardized Student’s distribution, when \( \eta \to \infty \) we obtain a skewed normal distribution, and when \( \eta \to 0 \) and \( \lambda = 0 \) we obtain the N(0,1) distribution. The skewed t distribution allows for a rich set of behaviors of financial returns, therefore it has been widely used to be the distribution model for \( z_t \). The skewed t distribution is widely used to describe financial returns in the literate (e.g. Patton, 2013; Wen et al., 2012).

From Eq.(3) to Eq.(7), we obtain the downside VaR and upside VaR for \( Y_t \) as follows:

\[
V_d(\text{down}) = -\mu_t - \sqrt{\eta_t} Z_{\alpha}
\]

(8)

\[
V_u(\text{up}) = \mu_t + \sqrt{\eta_t} Z_{1-\alpha}
\]

(9)

where \( \mu_t = \mu_t(1) \) is the conditional mean of \( Y_t \) given \( Y_{t-1} \), \( \mu_t \) can be estimated based on the GJR-GARCH model. \( Z_{\alpha} \) is the left-tailed critical value at level \( \alpha \) of the standardized innovation in the model, and \( Z_{1-\alpha} \) is the upper \( \alpha \)-quantile.

It is necessary to test the adequacy of the VaR model for calculating extreme market risks. Kupiec (1995) has proposed a backtesting method based on likelihood ratio test. Suppose the confidence level is \( 1 - \alpha \), sample size is \( T \), the days of failure is \( N \), and hence the sample failure frequency is \( f = N/T \). Suppose the expectation of failure rate is \( \alpha \) when the VaR model is correctly specified. In order to test the null hypothesis of correct specification of the VaR model, the test statistic is

\[
LR = -2 \ln \left[ (1-\alpha)^{-N} \alpha^N + 2 \ln \left( (1-f)^{-N} f^N \right) \right].
\]

(10)

Under the null hypothesis, LR follows \( \chi^2(1) \) distribution asymptotically. If LR is larger than the critical value at a given significance level, the null hypothesis should be rejected, implying that the VaR model is inadequate.

2.2. Granger causality in risk

Between market 1 \( Y_{1t} \) and market 2 \( Y_{2t} \), we consider four types, i.e., downside, upside, down-to-up, and up-to-down risk spillovers in each direction. For each type of the risk, Granger causality in risk are examined, which is a generalization of Granger causality in mean. The main idea of Granger causality in risk is that the occurrence of a large risk in one market can help predict the occurrence of the large risk in another market.

In terms of the downside risk spillover, a downside risk indicator function is first defined as

\[
Z_{t,\text{down}} = 1(Y_{1t} < -V_{1t}(\text{down})), \quad i = 1, 2
\]

(11)

where \( 1(\cdot) \) is an indicator function, and \( i \) represents crude oil or stock market. The risk indicator \( Z_t \) takes value of 1 when actual loss exceeds VaR and takes value of 0 otherwise. For convenience, the test for Granger causality in downside risk from \( Y_{2t} \) to \( Y_{1t} \) can be stated as:

\[
H_0 : E(Z_{2t,\text{down}}|l_{1(t-1)}\text{down}) = E(Z_{2t,\text{down}}|l_{1(t-1)}\text{down})
\]

Against

\[
H_1 : E(Z_{2t,\text{down}}|l_{1(t-1)}\text{down}) \neq E(Z_{2t,\text{down}}|l_{1(t-1)}\text{down})
\]

where \( l_{i(t-1)}\text{down} = (l_{i(t-1)}\text{down}, l_{i(t-2)}\text{down}, l_{i(t-3)}\text{down}) \), while \( l_{i(t-1)}\text{down} \) and \( l_{i(t-2)}\text{down} \) are the information sets of downside risk available at time \( t - 1 \) in market 1 and market 2 respectively. If \( H_0 \) holds, there is no one-way Granger causality in downside risk from market 2 to market 1. In other words, there is no lagged effect of downside risk spillovers from market 2 to market 1. When downside risk is found in market 2, it cannot be used to forecast the downside risk in market 1 in the future. It is a type of positive risk spillover effect from market 2 to market 1. Similarly, \( H_0 : E(Z_{2t,\text{down}}|l_{1(t-1)}\text{down}) = E(Z_{2t,\text{down}}|l_{1(t-1)}\text{down}) \) is used as the null hypothesis of no downside risk spillover in the reverse direction.
With respect to the upside risk spillover, an upside risk indicator function is defined as

$$Z_{t, up} = 1 (Y_t > Y_t (up)), \quad 1.1.2.$$  

(12)

In order to test for the upside risk spillovers from market 2 to market 1, hypotheses in Granger causality in upside risk are stated as

$$H_0 : E(Z_{t, up} | I_{1(t-1), up}) = E(Z_{t, up} | I_{(t-1), up})$$

against

$$H_1 : E(Z_{t, up} | I_{1(t-1), up}) \neq E(Z_{t, up} | I_{(t-1), up})$$

where $I_{(t-1), up}$ and $I_{1(t-1), up}$ are the information sets of upside risks available at time $t-1$ in market 1 and market 2 respectively. If $H_1$ is true, we say that there is one-way Granger causality in upside risk from market 2 to market 1. That is, the upside risk spillover from market 2 to market 1 exists, and an extreme upside risk in market 2 can be used to predict the upside risk in market 1 in the future. This is a type of positive risk spillover effect from market 2 to market 1. In the reverse direction, we construct the null hypothesis as

$$H_0 : E(Z_{t, up} | I_{2(t-1), up}) = E(Z_{t, up} | I_{(t-1), up} | I_{1(t-1), up})$$

If the alternative hypothesis holds, there exists down-to-up risk spillover from market 2 to market 1. The downside risk in market 2 is useful for predicting the upside risk in market 1.

2.3. A class of kernel-based test statistics

Given two estimated series of risk indicators $\{\hat{Z}_{1t}\}$ and $\{\hat{Z}_{2t}\}$, the sample cross-covariance function is

$$\hat{C}(j) = \left\{ \begin{array}{ll} -1 \sum_{t=1}^{T-j} (\hat{Z}_{1t} - \hat{\alpha}_1) (\hat{Z}_{2t-j} - \hat{\alpha}_2), & 0 \leq j \leq T-1 \\ -1 \sum_{t=j}^{T-1} (\hat{Z}_{1t-j} - \hat{\alpha}_1) (\hat{Z}_{2t} - \hat{\alpha}_2), & 1 \leq j < 0 \end{array} \right. $$

(13)

where $j$ is the lag order, and $\hat{\alpha}_1 = T^{-1} \sum_{t=1}^{T} \hat{Z}_{1t}$. Then, the sample cross-correlation function between $\{\hat{Z}_{1t}\}$ and $\{\hat{Z}_{2t}\}$ is

$$\hat{\rho}(j) = \frac{\hat{C}(j)}{\hat{S}_{1} \hat{S}_{2}}, \quad 0, \pm 1, ..., \pm (T-1)$$

(14)

where $\hat{S}^2 = \hat{\alpha}_1 (1 - \hat{\alpha}_2)$ is the sample variance of $\{\hat{Z}_{2t}\}$. Hong et al. (2009) have proposed a class of kernel-based statistics. In order to test one-way Granger causality in risk from market 2 to market 1, the test statistic is

$$Q_1(M) = \left[ \sum_{j=1}^{M} \hat{k}(j)^2 (j) - \hat{C}_{17}(M) \right] / D_{17}(M)^{1/2}$$

(15)

where $\hat{k}(\cdot)$ is a kernel function that assigns weights to various lags. $M$ is the largest effective lag truncation order, indicating how many lags we are considering for the analysis of risk spillover. For example, $M = 30$ means we are testing if the risk spillover from one market to the other is statistically significant within 30 lags. The centering and standardization constants are

$$C_{17}(M) = \sum_{j=1}^{M-1} (1-j/T)k^2(j)/M,$$

(16)

$$D_{17}(M) = 2 \sum_{j=1}^{M-1} (1-j/T)(1-(j+1)/T)k^2(j)/M.$$  

(17)

We are also interested in testing whether there exists two-way Granger causality in risk, including instantaneous risk spillovers between the two markets. The null hypothesis is that neither market Granger causes the other in risk, nor there exists instantaneous risk spillovers. To test this hypothesis, we can use the following test statistic:

$$Q_2(M) = \left[ \sum_{j=1}^{M-1} \left( \sum_{k=j}^{M} f_{ij}^2 j \right) - \hat{C}_{27}(M) \right] / D_{27}(M)^{1/2}$$

(18)

where the centering and scaling factors are

$$C_{27}(M) = \sum_{j=1}^{M-1} (1-j/T)k^2(j)/M,$$

(19)

$$D_{27}(M) = 2 \left\{ 1 + \hat{\rho}^2(0) \right\} \sum_{j=1}^{M-1} (1-j/T)(1-(j+1)/T)k^2(j)/M.$$  

(20)

The test statistic $Q_2(M)$ takes the possible instantaneous correlation between $Z_{1t}$ and $Z_{2t}$ into account. Under the null hypothesis, $Q_1(M)$ and $Q_2(M)$ follow an asymptotically standard normal distribution. If $Q_1(M)$ or $Q_2(M)$ is greater than the right-tailed critical value at a specified significance level, the null hypothesis is rejected, meaning that there is corresponding Granger causality in risk.

3. Data

This paper uses West Texas Intermediate (WTI) recent crude oil futures price to represent the crude oil market. WTI is a dominant benchmark in the global crude oil markets. For stock markets, a composite stock index, the S&P500 index is chosen to represent the U.S. stock market, as the U.S. equity markets account for a substantial fraction of global equity markets. Daily data are derived from the Wind Database and the U.S. Energy Information Administration (EIA). Observations cover the period from September 1, 2004 to September 11, 2012. The sample period covers the last worldwide financial crisis which is generally thought to erupt on September 15, 2008 when Lehman Brothers filed for Chapter 11 protection (Wen et al., 2012). Daily Returns are defined as the first difference in the natural logarithm of the daily closing price.

Fig. 1 describes the dynamics of WTI crude oil and S&P500 returns. Dashed line indicates the first day after the financial crisis outbreak. We can see that after the occurrence of the recent financial crisis, both crude oil and stock returns experienced sharp drops and became more volatile. Meanwhile, noticeable clustering emerged as soon as the financial crisis began. Existing studies have shown that the recent financial crisis seems to have impacts on the relationship between oil and stock markets (Filis et al., 2011; Wen et al., 2012; Mollick and Assefa, 2013).

1. There are two reasons to use the crude oil futures price rather than the spot price. First, the futures exchange provides a forum for establishing and disseminating price information. It brings much desired transparency of market price signals which are essential for risk monitoring. Second, the NYMEX WTI futures is one of the most actively traded commodity in the world. The trading volumes in crude oil futures market are much higher than the spot market. The risk in the futures price is a matter of great concern to various types of market participants.

2. Based on time-varying copula models, Wen et al. (2012) find a significant change in the tail dependence between crude oil and stock markets after the failure of Lehman Brothers. Therefore, this paper uses the data September 15, 2008 to break the sample into two sub-sample periods.
Considering possible structural change in the risk spillovers between the two markets, the whole sample is divided into two parts by the date September 15, 2008 when Lehman Brothers filed for Chapter 11 protection. The first subsample is from September 1, 2004 to September 14, 2008, which is the period prior to the recent financial crisis. It is a normal period. The second subsample is from September 15, 2008 to September 11, 2012, which is right after the start of the financial crisis, representing a period of recession and recovery in the world economy.

Table 1 gives the descriptive statistics of WTI crude oil and S&P500 stock returns. Several stylized facts of financial returns are observed. Generally speaking, skewness is negative, and kurtosis is greater than three. Hence, distributions of both asset returns are skewed to the left and have heavy tails. The Jarque–Bera test statistics show that the two return series are nonnormal. Volatility clustering can be seen from significant serial correlations in the squared returns. In addition, crude oil prices are much more dispersed than stock prices.

From a comparison of the two subsample periods, we find that both market returns become more volatile after the financial crisis in 2008. Skewness and kurtosis are also increased, indicating that large extreme returns have higher probability to occur in both markets during the second sample period. With respect to the linear relationship between the two markets, the linear correlation is weakly negative before the financial crisis, while after the financial crisis the linear correlation increases markedly and becomes positive.

4. Empirical results

4.1. VaR estimation

The estimation of upside and downside risk is very crucial for the tests of risk spillovers across markets. GJR-GARCH models based on the skewed t distribution are used to capture stylized features of financial returns, such as volatility clustering, kurtosis (i.e., tail thickness) and skewness.

Table 2 presents the estimation results of GJR-GARCH models for oil and stock returns. First, we can see that the coefficients of lagged conditional variance, \( \beta \), are all significant, indicating that the conditional variance depends on its previous values. Volatility clustering is evident. Second, a significant leverage effect, captured by \( \gamma \), exists in the U.S. stock market but not in crude oil market. For the stock market, the estimated \( \gamma \) is positive, implying that bad news has stronger impact than good news. Third, the estimates of degrees of freedom \( \nu \) are all greater than 4 (i.e., kurtosis exist) and all significant, which again indicates that the two market returns are fat-tailed. Further, the asymmetric parameter \( \lambda \) are all significant except for that of WTI crude oil price returns in the pre-crisis period.

Based on the estimated GARCH models presented in Table 2, upside and downside VaR are calculated for WTI and S&P500 returns. For internal risk management within the firm, typical risk level is 5%. Therefore, we consider 5% VaR in this paper. That is, the confidence level of risk is set to be 95%. Table 3 provides summary statistics for the estimated VaRs. We can see that the VaR means of WTI crude oil is larger than those of the S&P500 stock index, implying that the former has a larger market risk. The GARCH model can be evaluated by computing the failure rate which is the number of times the value of returns exceeds the estimated VaR. As shown in Table 3, the failure rates are very close to the VaR level 5%, implying that the GJR-GARCH-skewed-t models are doing well. Furthermore, Kupiec’s (1995) LR test statistics are insignificant at the 5% significance level, indicating that the VaR models are adequate for both markets.

Different GARCH models might result in different testing results of Granger causality in risk, because VaR values estimated from GARCH

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**Table 1** Descriptive statistics.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>J-B</th>
<th>Q(30)</th>
<th>Q2(30)</th>
<th>Cor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before the crisis (September 1, 2004–September 14, 2008)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WTI</td>
<td>0.09</td>
<td>1.90</td>
<td>-0.07</td>
<td>4.22</td>
<td>59.53***</td>
<td>41.02*</td>
<td>63.28***</td>
<td>-</td>
</tr>
<tr>
<td>S&amp;P500</td>
<td>0.01</td>
<td>0.88</td>
<td>-0.27</td>
<td>5.09</td>
<td>183.07***</td>
<td>67.77***</td>
<td>455.28***</td>
<td>-0.03**</td>
</tr>
<tr>
<td>After the crisis (September 15, 2008–September 11, 2012)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WTI</td>
<td>0.00</td>
<td>2.50</td>
<td>-0.61</td>
<td>9.37</td>
<td>1648.00***</td>
<td>80.25*</td>
<td>521.89***</td>
<td>-</td>
</tr>
<tr>
<td>S&amp;P500</td>
<td>0.01</td>
<td>1.81</td>
<td>-0.53</td>
<td>12.00</td>
<td>3218.03***</td>
<td>88.90***</td>
<td>1162.1***</td>
<td>0.55</td>
</tr>
</tbody>
</table>

Note: J-B is the Jarque-Bera test for normality. Q(30) is the Ljung-Box Q test of serial correlation of up to 30 lags in the returns. Q2(30) is the Ljung-Box Q test of serial correlation of up to 30 lags in the squared of returns. ‘Cor.’ is the linear correlation with WTI crude oil.

*** Statistical significance at the 1% level.
** Statistical significance at the 5% level.
* Statistical significance at the 10% level.
models are crucial inputs for the tests. The estimation accuracy of VaR mainly depends on the distribution of standardized innovation in a GARCH model. Sometimes the standardized innovation is assumed to mainly depend on the distribution of standardized innovation in a GARCH model. Testing results of spillovers involving upside risks are slightly different from those based on the skewed t distribution. This is the reason why GARCH models with GED distribution tend to underestimate upside market risk. In summary, it is more acceptable to use VaR models with skewed t distribution rather than Student’s t or GED distribution.

Different performance of the three distributions arises from their quantiles close to those of the skewed t distribution. Even though, the skewed t distribution in Table 3 appears more accurate to the extent that all of them formally pass the Kupiec test. Nonetheless, the VaR models are acceptable at the conventional significance level in the post-crisis period. They are roughly correct to the extent that all of them formally pass the Kupiec test. Even though, the skewed t distribution in Table 3 appears more accurate to the extent that all of them formally pass the Kupiec test.

Table 4 provides the summary statistics of the VaRs estimated by GJR-GARCH-t models. The failure times are much less than the given time (about 47) as expected with the convergence level in the post-crisis period. They are roughly correct to the extent that all of them formally pass the Kupiec test.

Table 5 provides the summary statistics of the VaRs estimated by GED models. The failure times are much less than the given time (about 47) as expected with the convergence level in the post-crisis period. They are roughly correct to the extent that all of them formally pass the Kupiec test.

Testing results of risk spillovers before the recent financial crisis are reported in Table 7. In order to overcome the difficulty of presenting large tables with numbers we use simplified notions to present the corresponding p-values of Granger causality in risk. It can be seen that the statistics for several types of risk spillovers are significant at the 10% significance level. Risk spillovers between crude oil and stock markets.

4.2. Empirical results of risk spillovers

Testing results of risk spillovers before the recent financial crisis are reported in Table 7. In order to overcome the difficulty of presenting large tables with numbers we use simplified notions to present the corresponding p-values of Granger causality in risk. It can be seen that the statistics for several types of risk spillovers are significant at the 10% significance level. Risk spillovers between crude oil and stock markets.

5 Analogous tests for risk spillovers could be conducted based on GJR-GARCH-GED models. Testing results of spillovers involving upside risks are slightly different from those based on the skewed t distribution. It is reasonable because different GARCH models results in different estimation of VaR and risk indicator functions.
markets exist before the financial crisis. The two markets are significantly associated at the risk level.

In the causality direction from stock to crude oil, the downside risk spillover is significant at the 10% significance level. Large falls of stock returns have a significant predictive power for large falls of oil returns in the future. This is a significantly positive risk spillover effect. Note that the risk spillover from stock to crude oil occurs with a time delay. This may be due to a process of news dissemination among market participants and portfolio position adjustments based on updated information by investors.

In the reverse causality direction, there are mainly negative risk spillover effects. Both types of negative risk spillovers from crude oil to stock market are found to exist. Current and past information of downside (upside) risk in crude oil market Granger causes upside (downside) risk in the stock market.

In addition to the existence of risk spillovers, the dynamics of risk transmissions are also of interest. Fig. 2 plots three test statistics \(Q_2(M), Q_{11}(M)\) and \(Q_2(M)\) at different values of M. \(Q_2(M)\) and \(Q_{11}(M)\), defined in Eq. (15), measure the one-way risk spillovers in the stock-to-oil and the oil-to-stock direction respectively, while \(Q_2(M)\), defined in Eq. (18), measures the two-way risk spillovers between crude oil and stock returns. A larger value of test statistic indicates a stronger cumulative spillover effect within M days.

Fig. 2(a) describes the downside risk spillovers in the two causality directions. \(Q_2\) is significant at the 1% significance level at the beginning. Then it strictly diminishes. After about 9 days, it becomes insignificant even at the 10% significance level. It appears that the downside risk running from stock market to crude oil market spills shortly and keeps decreasing.

In the oil-to-stock direction, there exist two types of negative risk spillover effects. For the down-to-up risk spillovers, Fig. 2(c) shows that \(Q_{11}\) is significant at the 10% significance level within 4 days. It indicates that extremely loss news in crude oil market is transmitted into stock market quickly, then starts decaying and after 4 days the cumulative effect becomes insignificant even at 10% significance level. The transmission of downside risk is very fast but diminishes quickly.

In terms of the up-to-down risk spillovers, Fig. 2(d) demonstrates that the lagged effects of extremely positive news in crude oil market keeps accumulating over time and becomes significant at the 10% significance level after 25 days. It is well known that today's financial markets are often more influenced by most recent events than remote past ones (Hong et al., 2009). The long-lagged risk spillover effect found in this paper is a special characteristic of crude oil market.

Based on Table 7 and Fig. 2, we find that either positive or negative risk spillovers between the two markets are asymmetric in the sense of magnitudes and dynamics over time. Take the Granger causality in risk from oil to stock for an example. The cumulative effect \(Q_2\) of down-to-up risk spillover attains 6.62, while the cumulative effect \(Q_{11}\) of up-to-down risk spillover attains 2.11 within 2 days. Asymmetry may be due to the fact the bullish and bearish markets behave differently. Market participants may respond in different ways to increase and decrease of financial returns. Our results of asymmetric effects in a negative spillover aspect enrich findings in the literature.

Similarly, we investigate the risk spillovers between crude oil and stock markets for the period after the recent financial crisis. Testing results are reported in Table 8.

Table 8 shows that bidirectional causalities exist between the two markets after the occurrence of the financial crisis. However, the structure of risk transmissions changes a lot compared with the pre-crisis period. During the post-crisis period, positive risk spillovers stand out. Instantaneously negative risk spillovers disappear, while instantaneously positive risk spillovers become statistically significant. Moreover, both types of positive risk spillovers from oil to stock returns are also significant at lags.

Fig. 3 plots the three test statistics \(Q_2\), \(Q_{11}\) and \(Q_2\) over different values of M. We can see that the value of \(Q_2(M)\) is very large within 30 days. The instantaneously positive risk spillover effects are rather strong during the post-crisis period.

4.3. Further discussions

During the pre-crisis period, downside risk spillover is found from the stock to crude oil market. This finding is consistent with economic theories. As it is well known, global economic activity is one of the most important drivers of crude oil prices (Kilian, 2009; He et al., 2010). Since stock values reflect the market's expectation of the future business, an extreme crash in the stock market implies decrease in aggregate demand in the economic system and dramatic decline in the demand for energy products, which in turn results in extremely low oil prices.

After an extreme downturn occurs in stock market, the strongest spillover effect on crude oil returns appears the next day. The cross-correlation at lag 1 between the two market downside indicators is 0.08. During the pre-crisis period, there are totally 50 times of downside risks occurring in the crude oil market, of which 6 times can be exactly predicted by yesterday's downside risk in stock market and 13 times can be predicted by those occurring within 5 days. A small correlation between the downside risk indicators actually implies a relatively high probability of co-occurrence of extreme losses in both markets. The lagged effects of risk spillovers from stock to crude oil market are much stronger than the contemporaneous one, which proves the vital necessity of emphasizing risk spillovers at lags.

Our finding has important implications for investors and policymakers. Extremely low stock returns are possibly followed by extremely low oil price returns. When extremely low stock returns occur, crude oil importing countries could consider buying crude oil at an extremely low price in the next few days. In contrast, traders who take long positions in crude oil futures markets may be exposed if they do not have enough cash to meet the margin calls. Awareness of the dynamics of risk transmissions can motivate market traders to accurately gauging and effectively guarding against extreme risk in the future.

### Table 7: Results of Granger causality in risk before the financial crisis.

<table>
<thead>
<tr>
<th>Null hypothesis</th>
<th>Panel A: Positive risk spillovers</th>
<th>Panel B: Negative risk spillover</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Down-to-down</td>
<td>Up-to-up</td>
</tr>
<tr>
<td>Oil ≠ stock</td>
<td>***</td>
<td>***</td>
</tr>
</tbody>
</table>

Notes: ***, ** and *** denote p-value statistical significance at the 10%, 5% and 1% levels. \(\neq\) represents there is no one-way Granger causality in risk from the former to the latter. ‘Inst.’ is the instantaneous risk spillover, and ‘Lagged’ represents the risk spillover occurring at lags.

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6 Note that we also find one type of positive risk spillover effect, i.e., the downside risk spillover effect, from crude oil to stock market. A possible explanation for this finding is that sometimes crude oil market risk delivers global economic information which has a positive correlation with stock markets.
In addition, we find that the positive risk spillover effect of stock on crude oil market is asymmetric. The downside risk spillover is significant but the upside risk spillover is insignificant. It is widely agreed that people react differently to a positive shock compared to a negative one of the same absolute magnitude in financial markets. The asymmetric character of returns and the underlying correlations in financial markets are investigated by Longin and Solnik (2001), Patton (2006) and Garcia and Tsafack (2011) among others. The asymmetric behavior shows that participants in crude oil market are very vulnerable to extremely loss news in the stock market in the short run.

In the reverse direction, we find that the causality effects from crude oil to stock market are very strong, spill quickly and could last for several days. Between the oil downside risk and the stock upside risk, the contemporaneous correlation is 0.11. It is higher than the correlation (0.03) at the mean level. In total, 11 out of 36 times of stock upside risk can be exactly predicted by the oil downside risk in 2 days. Between the oil upside risk and the stock downside risk, the largest cross-correlation is 0.11 (at lag 11). 8 out of 59 times of downside risk in stock market are associated with the upside risk in crude oil market occurring 11 days ago. The stock market is very vulnerable to the news of crude oil, making very quick response to both bad news and good news. Moreover, the long-lagged up-to-down spillover effects from crude oil to stock market demonstrate that impact of crude oil price rises on economic variables is relatively drawn out.

The risk spillovers from crude oil to stock markets are not just a statistical coincidence. As suggested by Kilian and Park (2009), there are three structural components of crude oil shocks, i.e., oil supply shock, aggregate economic demand shock and oil-market specific demand shock. Different oil shocks have very different effects on stock returns. Negative response of stock prices to oil price rises is due to oil-market specific demand shocks such as increases in precautionary demand driven by concerns about future crude supply shortfalls. Crude oil shortage tends to result in higher production costs, lower consumption spending, and higher inflation among others. Stock market would react negatively in such cases. In contrast, oil prices driven by an aggregate demand of global economic expansion have positive effects on stock returns. A positive innovation to the global business cycle will stimulate the economy directly, while at the same time driving the oil price up. Because the stimulating effect is very strong in the short run, stock returns will increase. These effects are fed through expected dividends and cash flows of firms. If one of the three shocks is more prevalent, it will dominate the average responses to crude oil market for that period.

![Fig. 2. Risk spillovers between crude oil and stock markets before the financial crisis.](image-url)

Table 8

Results of Granger causality in risk after the financial crisis.

<table>
<thead>
<tr>
<th>Null hypothesis</th>
<th>Panel A: Positive risk spillovers</th>
<th>Panel B: Negative risk spillovers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Down-to-down</td>
<td>Up-to-up</td>
</tr>
<tr>
<td>Stock ≠ oil</td>
<td>***</td>
<td>***</td>
</tr>
<tr>
<td>Oil ≠ stock</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: * and *** denote p-value statistical significance at 10% and 1% levels. ≠ represents there is no one-way Granger causality in risk from the former to the latter. ‘Inst.’ is the instantaneous risk spillover, and ‘Lagged’ represents the risk spillover occurring at lags.
In the early 21st century, rapid economic growth has been accompanied with crude oil price booms. Since high oil prices sustained for several years, oil product shortages have frequently caught the attention of the world. An extreme increase in the oil price is interpreted by markets as an indicator of shocks of oil supply shortfalls which will reduce business profits in the future. Therefore, extremely high oil returns cause extremely low stock returns. The reverse is also true. An extreme decrease in the oil price eases the pressure on economic crash, and thus causes extremely high stock returns. This down-to-up risk spillover does not manifest themselves from stock to oil market, because there is no upside risk spillovers from stock to oil returns.

Before the start of financial crisis, it is agreed that the U.S. stock market has been resilient to higher oil prices for several years. From an economic view, Kilian and Park (2009) explain that this is due to the direct stimulating effect of positive aggregate demand shocks. Statistically, stock and crude oil returns are found to be positively cointegrated in a long-run equilibrium (Zhu et al., 2011). However, in this paper, we find evidences of substantially opposite reactions of stock returns to crude oil returns in the short run. First, the instantaneously negative risk transmission from crude oil to stock returns may also imply that, during the normal period, if an investor diversifies his or her portfolio by holding assets in both the oil and stock markets, there would be benefits of diversification in the short run. Second, the upside risk of crude oil is found to be transmitted to stock markets with a long time delay. After an extremely positive return occurs in the oil market, investors in the stock markets, if hold very well portfolios, have to be concerned with the whole market risk in the following month. A hedge using stock index futures might be a good choice to remove the subsequent risk in stock markets.

In addition, we find that both positive and negative risk spillovers between crude oil to stock markets exhibit asymmetric correlations in absolute magnitudes and dynamics over time. This finding is in contrast to the conclusions of symmetric risk dependence in Wen et al. (2012). Copula models are used in Wen et al. (2012) to estimate the probability of risk co-occurrence. Instead the risk correlations are calculated in our paper. This is one reason for the different results. Another reason is that Wen et al. (2012) do not consider the dynamics of risk transmissions over time which is a major source of asymmetry. It is useful for investors to know the asymmetric risk dependence. Incorporating assets’ asymmetric characteristics can lead to substantial economic value in portfolio decisions (Patton, 2001).

After the financial crisis, changes in the risk transmission mechanism are observed. An interpretation for that involves a switch of the origin of oil price movements. As the crisis spread around the world, investors realized that economic news was affecting markets more widely. In contrast to the pre-crisis time period, sizable movement in crude oil prices does not imply precautionary shortage of power of economic growth, but often carry the information of recovery in world economic activities (Vo, 2011). Therefore, stock returns positively react to extreme movements in the oil price during the recession and recovery.

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7 The regularity in the timing between extreme movements in crude oil and stock markets may be partly attributed to their common dependence on some third set of economic factors, such as exchange rates. To what extent the third economic variables take effects is an open question in the future research.
period. The essence of oil price shocks has a significant impact on the risk relationships between oil and stock returns. This means that effects of diversification diminish during the economic downturn.

After the financial crisis, the instantaneous linkage in risk increases markedly. The instantaneous correlation of upside risks varies from 0.01 for the pre-crisis period to 0.18 for the post-crisis period, and the instantaneous correlation of downside risks varies from 0.03 to 0.33. As many as 16 out of about 50 times of downside risk occur simultaneously in both markets. This is partly in line with Wen et al. (2012) which find that the positive (tail) dependence between crude oil and stock markets increases after the failure of Lehman Brothers. This is owing to both fundamental and contagion effects (such as financial panics and herding behaviors of investors).

The lagged risk spillover effects between the two markets are non-trivial. Regardless of the contemporaneous correlation, more than 12% downside (upside) risk in one market can be exactly predicted by the same risk occurred in the other market within 5 days.

5. Conclusions

Using daily samples of WTI crude oil futures prices and the S&P500 stock index, we investigate the risk spillovers between crude oil and stock markets. Our aim is to study the contemporaneous and lagged correlations of extreme movements comprehensively, from which Granger causality relations in risk can be disclosed. We use the econometric method proposed by Hong et al. (2009). A large risk is said to have occurred at a pre-specified level if actual loss exceeds VaR at the given level. The estimation of VaRs is carried out by GJR-GARCH type models. Then a class of kernel-based statistical tests is used to detect risk spillovers that occurs a large number of lags.

One unique contribution of this study is to consider four types of risk spillovers. They are downside and upside risks in stock markets associated with those in crude oil markets. Downside and upside risk spillovers represent two types of positive relations at the risk level, while down-to-up and up-to-down risk spillovers represent two types of negative risk relations. The four types of risk spillovers can describe all facets of the risk relationship between crude oil and stock markets.

We find that significant risk spillovers exist between crude oil and stock markets. Current and/or past information of extreme movements in one market may be able to predict extreme movements in the other market. Before the recent financial crisis, there are positive risk spillovers from stock to crude oil market, and negative spillover effects from crude oil to stock market. Risk spillovers occur instantaneously, and/or last for several days. We find a long-lagged transmission of crude oil upside risk. This proves the vital necessity of concern with risk spillovers at lags. After the financial crisis, the structure of risk transmissions is changed. Bidirectional positive spillovers are strengthened markedly. The origin of oil shocks is an important determinant of the risk spillovers between the two markets. Moreover, there are drastic asymmetries in both negative and positive risk spillovers. Generally speaking, market participants are more vulnerable to the downside risk than the upside risk in the short run.

The empirical findings have important implications. Academically, it is shown that negativity and lagged effects are important aspects of the risk relationship between crude oil and stock markets. The two types of negative risk spillovers, along with the downside and the upside risk spillovers, should be addressed simultaneously. Substantial lagged effects can reveal the Granger causality relations in risk. This will help understand how information is transmitted between the two markets.

Crude oil and stock markets are found to be highly associated at the risk level. From the perspective of actual practices, awareness of the dynamics (or Granger causality) of risk transmissions will motivate market traders to accurately gauging and effectively guarding against extreme market risks. For example, the positive risk spillover from stock to crude oil market means that long traders in crude oil futures markets might meet huge margin calls right after an extreme crash occurs in the stock market; the negative risk spillover from crude oil to stock market implies that, after an extremely positive return occurs in the oil market, investors in the stock markets, if hold very well portfolios, could consider to hedge the whole market risk in the following month. Neglecting of the asymmetric characteristics may lead to substantial economic loss in portfolio decisions. Besides, governments can use the past risk information of stock markets to make suitable decisions of purchase and storage of energy, especially for large oil importing countries in the world.

The bridge between crude oil and stock markets is economic and financial activities of firms and investors. There are theoretical grounds for claiming that the risk relations between the two markets cannot explained as just a coincidence. That is not to say some third macroeconomic variable was not responsible for both extreme movements in the two markets. To what extent the risk relations can be systematically attributed to other common variables remains an open question.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2015.08.007.

References