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Investigating the risk-return trade-off for crude oil futures using high-frequency data

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HIGHLIGHTS

- The contemporaneous relation between risk and return of crude oil futures is significantly negative.
- The contemporaneous negative relation between downside risk and return is stronger than volatility/jump risk.
- The intertemporal volatility/jump risk-return relationship is insignificant.
- There is weak negative correlation between downside risk and excepted return in the crude oil futures market.
- There is not the risk–return trade-off in the crude oil futures market.

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ABSTRACT

This paper comprehensively examines the existence and significance of a contemporaneous/intertemporal risk-return trade-off for crude oil futures using high-frequency transaction data. The results reveal that the contemporaneous relation between risk (volatility risk, downside risk or jump risk) and return in the crude oil futures market is negative and statistically significant and that the contemporaneous negative relation between downside risk and return is stronger than the two others. However, the intertemporal volatility/jump risk-return relationship is insignificant, and there is weak negative correlation between downside risk and expected return in the crude oil futures market. These findings can be explained by the asymmetric effect of risk on returns. The findings are robust across different samples and different measures of volatility, downside and jump risks. Thus, there is no risk-return trade-off in the crude oil futures market.

1. Introduction

The crude oil market plays an important role in the economic system [1]. Crude oil is one of the most important energy sources for a nation's economic development [2–4]. Thus, analyzing crude oil futures has attracted considerable attention from academics, governments and investors.

Among the various research topics on crude oil futures, estimating the risk-return relationship in the crude oil futures market is of special interest for energy researchers. Notably, the empirical evidence is mixed. Some researchers find that there is a risk-return trade-off for crude oil futures (see, e.g., [5–7]). However, some studies support the contention that the relation between risk and return in the crude oil futures market is negative (see, e.g., [8–11]).

Thus, the research results are inconsistent, and accurately estimating the risk-return relationship in the crude oil futures market is a challenging task. In this paper, we comprehensively analyze the relationship between contemporaneous/intertemporal risk and return in the crude oil futures market. Compared with the existing literature, our study offers the following advantages and contributions. First, existing studies focus mainly on the correlation between volatility risk and return of crude oil futures (see, e.g., [10,11]). However, we not only estimate the volatility risk-return relationship but also investigate the downside/jump

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risk-return relationship in the crude oil futures market. Second, some studies show that the contemporaneous risk-return relationship and intertemporal risk-return relationship is different (see, e.g., [5,8]). Thus, our analysis is more comprehensive and examines both the contemporaneous risk-return relationship and intertemporal risk-return relationship in the crude oil futures market. Third, the overwhelming majority of studies use low-frequency data to measure risk when investigating the risk-return trade-off for crude oil futures (see, e.g., [7,10]). We use high-frequency transaction data to measure the volatility, downside and jump risks of crude oil futures. The high-frequency transaction data contain far more information than the low-frequency transaction data, which more accurately measure the risks (see [12–14]). Thus, our empirical results are more reliable than the results based on low-frequency transaction data. Finally, we find that the failure of both contemporaneous and intertemporal risk-return tradeoffs in the crude oil futures market and the asymmetric effect of risk on returns are important reasons for the lack of evidence of contemporaneous and intertemporal risk-return tradeoffs. Our findings can be utilized to enhance risk management and portfolio diversification, and help investors to make better choices under uncertainty in the crude oil futures market.

The remainder of this paper is organized as follows. The next section offers a literature review that addresses studies on the risk-return relationship in energy markets, in particular the oil market. In Section 3, we measure the volatility, downside and jump risks. Section 4 describes the data. In Section 5, we estimate the relationship between contemporaneous risk and return for crude oil futures using high-frequency transaction data. Section 6 examines the existence and significance of an intertemporal risk-return trade-off in the crude oil futures market through high-frequency data. Section 7 concludes.

2. Literature review

The risk-return trade-off in energy markets is a hot topic. In recent years, many researchers have paid close attention to the relation between risk and return in the energy project investment and the energy futures markets.

Many studies analyze the risk and return relationship in energy project investment, for example, carbon capture and storage (CCS) technologies in power generation plant investment [15], wind energy investment [16], coal-fired electricity investment [17], and community-based photovoltaic investment [18]. Generally, there is a risk-return trade-off in energy project investment.

However, the findings do not appear to be consistent, in particular in the crude oil futures market. Some studies show that the relation between the risk and return of crude oil futures is positive. Kolos and Ronn [5] found that the market price of risk estimates in US markets (Pennsylvania–New Jersey–Maryland forwards, Cinergy, Gas and Oil) is positive, but most are not statistically significant. In the European Energy Exchange market, they found that the commodity market price of risk is significantly positive. Cotter and Hanly [6] estimated a time-varying measure of risk aversion by applying a GARCH-M model and found that the coefficient of relative risk aversion was positive, indicating that the relationship between volatility and expected return of NYMEX New York Harbor (HU) Unleaded Gasoline was positive. Cifarelli and Paladino [7] used a univariate GARCH(1,1)-M model to estimate the relation between volatility risk and return. The evidence suggested that there is a positive feedback trading and positive volatility risk and return relationship in the oil market.

However, some studies found that the risk and return relationship in the crude oil futures market was negative. Following Cifarelli and Paladino [7], Li et al. [8] found an intertemporal negative relation between the return on the price of oil futures and volatility components. In addition, Miffre et al. [19] indicated that there is a negative relationship between idiosyncratic volatility risk and expected returns in commodity futures markets (including the crude oil market) under traditional benchmarks. Kristoufek [9] also found that the correlation between returns and the volatility risk of both Brent and WTI crude oils is negative. Chatrath et al. [10] showed that the relation between crude oil futures returns and implied volatility risk is negative. Chiarella et al. [11] used a continuous time stochastic volatility model to study the relationship between return and volatility risk in commodity futures markets. Their empirical results indicated a negative relation in the crude oil futures market, in particular during periods of high volatility risk driven mainly by market-wide shocks.

In summary, it must be noted that the literature provides a number of good references for understanding the relationship between risk and return in the crude oil futures market. However, it is necessary to further analyze certain issues, such as the downside/jump risk-return relationship, the contemporaneous and intertemporal risk-return relationship, and the relationship between risk and return using high-frequency transaction data. In this paper, we study the above mentioned issues and investigate the risk-return trade-off in the crude oil futures market based on high-frequency data.

3. Alternative risk measures

3.1. Volatility risk

Volatility risk denotes the fluctuation in financial asset prices and is used to measure uncertainty in return on assets and reflect the risk level of financial assets. Volatility risk in financial markets cannot be observed, and thus a method is required to measure it (see, e.g., [20,21,12]). There are many methods to measure volatility risk, such as GARCH-class models (see, e.g., [20,22–26]) and SV-class models (see, e.g., [21,27,28]), among others (see, e.g., [29]). However, GARCH-type and SV-type models do not adequately describe whole-day volatility information as they use low-frequency data to measure volatility. In the last few decades, computers have greatly reduced the cost of recording and storing high-frequency data, which are now important in the study of volatility in financial markets. Andersen and Bollerslev [12] first used high-frequency data to propose a new method of measuring volatility (i.e., realized volatility, RV). Compared with GARCH-type and SV-type models, realized volatility has two main advantages. On the one hand, it is based on model-free measures and can be calculated directly. On the other hand, realized volatility is computed using high-frequency transaction data, which contain more fluctuation information. Thus, it is a more accurate proxy variable for volatility risk in financial markets. Many studies (see, e.g., [30,31,32]) have therefore used realized volatility to measure volatility risk. Therefore, we choose realized volatility to measure the volatility risk of crude oil futures.

Daily realized volatility can be written as

$$RV_{t'}^{d0} = \sum_{i=1}^{N} r_{t',i}^2 \tag{1}$$

where $r_{t',i}$ is the ith return ($i = 1, \ldots, N$) in day t', i.e., $r_{t',i} = 100(\ln P_{t',i} - \ln P_{t',i-1})$. $P_{t',i}$ is the ith closing price in day t'.

However, Eq. (1) does not consider the overnight return variance, and it is not the consistency estimation of integrated volatility [33]. Therefore, following Andersen et al. [34], Gong et al. [35] and Huang et al. [36], we obtain the new daily realized volatility.

$$RV_{t'}^{d} = RV_{t}^{d0} + r_{t',n}^{2} = \sum_{j=1}^{M} r_{t',j}^{2} \tag{2}$$

where $r_{t',n}$ is the overnight return.

Corsi [37] used average realized volatility between day t' and $t'+H$ (where H is the number of days in a month) to measure monthly realized volatility. Following Corsi [37], monthly volatility risk VR_t is defined as

$$VR_t = RV_t^m = \frac{RV_{t',1}^d + RV_{t',2}^d + \cdots + RV_{t',H}^d}{H} \tag{3}$$

3.2. Downside risk

Downside risk in financial markets cannot be observed. Downside variance (see, e.g., [38,39]), downside deviation (see, e.g., [38]), gain-confidence limit (see, e.g., [40]), downside beta (see, e.g., [41,42]), shortfall probability [43], value at risk (VaR; see, e.g., [44,45]), expected shortfall (see, e.g., [43,46,47]), and downside realized semivariance (see, e.g., [13,48]) are used as a proxy for downside risk. Unlike other proxies, downside realized semivariance is computed based on high-frequency data, which contains more information and is more accurate for measuring downside risk. Therefore, we apply downside realized semivariance as a proxy for downside risk in the crude oil futures market.

Referring to Barndorff-Nielsen et al. [13], on the basis of Eq. (2), downside realized semivariance (RSV^-) can be expressed as

$$RSV_{t'}^{-} = \sum_{j=1}^{M} r_{t',j}^{2} I(r_{t',j} \leqslant 0) \tag{4}$$

where $I(\cdot)$ is the indicator function taking the value 1 if the argument I is true. In this paper, we use monthly downside realized semivariance to measure monthly downside risk. Thus, we obtain the expression for monthly downside risk (DR_t)

$$DR_t = RSV_t^{-(m)} = \frac{RSV_{t',1}^{-(d)} + RSV_{t',2}^{-(d)} + \cdots + RSV_{t',H}^{-(d)}}{H} \tag{5}$$

3.3. Jump risk

We assume that the logarithmic price of crude oil futures ($p_{t'} = \ln(P_{t'})$) within the trading day follows a standard jump-diffusion process

$$dp_{t'} = \mu_{t'} dt' + \sigma_{t'} dW_{t'} + \kappa_{t'} dq_{t'}, \quad 0 \leqslant t' \leqslant T' \tag{6}$$

where $\mu_{t'}$ is the drift term with a continuous variation sample path. $\sigma_{t'}$ denotes a strictly positive stochastic volatility process. $W_{t'}$ denotes a standard Brownian motion. $\kappa_{t'} dq_{t'}$ is the pure jump part.

For the discrete prices process, the log return volatility at time t includes jump volatility and is not an unbiased estimator of integrated volatility. The log return from $t'-1$ to t' is quadratic variation

$$QV_{t'} = \int_{t'-1}^{t'} \sigma_s^2 ds + \sum_{t'-1 < s \leqslant t'} \kappa_s^2 \tag{7}$$

where $\int_{t'-1}^{t'} \sigma_s^2 ds < \infty$ is an integrated variation and denotes the continuous component of the total variation. $\sum_{t'-1<s\leqslant t'} \kappa_s^2$ is the cumulative jump variation in $[t'-1, t']$.

Andersen and Bollerslev [12] found that the quadratic variation could not be observed directly and could be estimated based on discrete data. When $M \to \infty$, the daily realized volatility $RV_{t'}^d$ can be used as a consistent estimator of $QV_{t'}$.

$$RV_{t'}^{d} \xrightarrow{M\to\infty} QV_{t'} = \int_{t'-1}^{t'} \sigma_s^2 ds + \sum_{t'-1 < s \leqslant t'} \kappa_s^2 \tag{8}$$

In addition, integrated volatility IV_t can be estimated by the realized bipower variation RBV_t (see [49,50]). When $M \to \infty$, realized volatility $RV_{t'}^d$ can be used as a consistent estimator of $QV_{t'}$. $RBV_{t'}$ can be used as a consistent estimator of the continuous sample path variation.

$$RBV_{t'} = z_1^{-2} \frac{M}{M-2} \sum_{j=3}^{M} |r_{t',j-2}||r_{t',j}| \tag{9}$$

where $z_1 = E(Z_{t'}) = \sqrt{\pi/2}$, Z_t is a random variable that follows a standard normal distribution. $M/(M-2)$ denotes an adjustment for sample size. According to Barndorff-Nielse and Shepherd [49,50] and Huang and Tauchen [51], we use Z-statistics to identify the discontinuous jump variation

$$Z_{t'} = \frac{(RV_{t'} - RBV_{t'})RV_{t'}^{-1}}{\sqrt{(\mu_1^{-4} + 2\mu_1^{-2} - 5)\frac{1}{M}\max\left(1, \frac{RTQ_{t'}}{RBV_{t'}^2}\right)}} \to N(0,1) \tag{10}$$

where $\mu_1 = \sqrt{2/\pi}$, $RTQ_{t'}$ is realized tri-power quarticity, $RTQ_{t'} = M\mu_{4/3}^{-3}\left(\frac{M}{M-4}\right)\sum_{j=4}^{M}|r_{t',j-4}|^{4/3}|r_{t',j-2}|^{4/3}|r_{t',j}|^{4/3}$, $(\mu_{4/3} = E(|Z_T|^{4/3}) = 2^{2/3}\Gamma(7/6)\Gamma(1/2)^{-1})$

Daily discontinuous jump variation $J_{t'}^d$ can be defined by

$$J_{t'}^d = I(Z_{t'} > \phi_\alpha)(RV_{t'} - RBV_{t'}) \tag{11}$$

where $I(\cdot)$ is an indicator function. α equals 0.99 (see [14,34]).

In this paper, we use monthly discontinuous jump variation to measure the monthly jump risk of the crude oil futures market. Similar to Eqs. (3) and (5), monthly jump risk can be written as

$$JR_t = J_t^{-(m)} = \frac{J_{t',1}^d + J_{t',2}^d + \cdots + J_{t',H}^d}{H} \tag{12}$$

4. Data description

The choice of sampling frequency of intraday high-frequency data greatly influences the accuracy of the risk measure. On the one hand, low sampling frequency does not adequately reflect the volatility information of that day. On the other hand, high sampling frequency may lead to microstructure noise. Therefore, following Clements and Todorova [52], Haugom et al. [53], Souček and Todorova [54], Wen et al. [55], Žikeš and Baruník [56], we take both influences into consideration and compute risk using the widely used 5-min high-frequency transaction data from the NYMEX-CME for the front-month WTI crude oil futures contract. The full sample period is from January 1998 to April 2014, which contains 196 monthly observations.

To demonstrate the properties of the monthly return and different risk components, we provide a plot in Fig. 1. The figure shows the dynamic dependencies in different components. The change trends of volatility, downside and jump risks are almost the same. Obviously, the volatility, downside and jump risks during the period from July 2008 to June 2009 are higher than those in other periods because the global financial crisis increased the price changes in the crude oil futures market.

The resulting summary statistics are reported in Table 1. The return of crude oil futures shows negative skewness and a fat tail, and the volatility, downside and jump risks all have the property of positive skewness and a fat tail. In addition, the Ljung-Box Q-statistics reported in the table show that the volatility, downside and jump risks of crude oil futures indicate significant

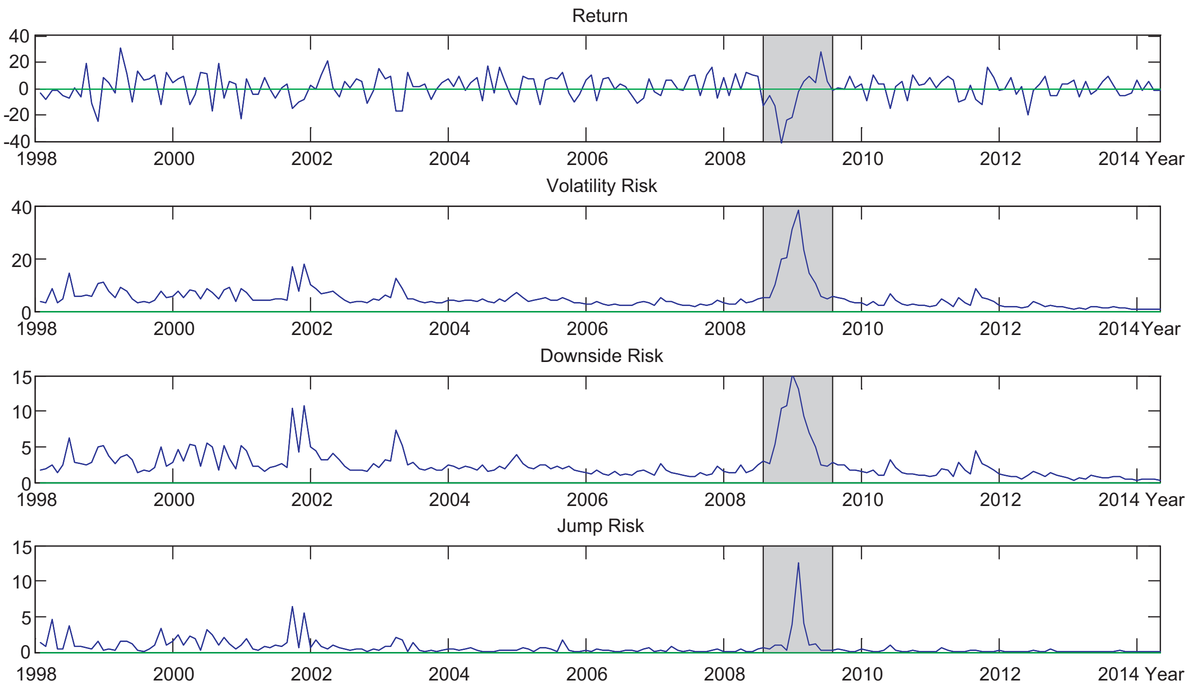

Fig. 1. Monthly returns and three risk components for crude oil futures.

Table 1
Summary statistics for all variables.

	Mean	Std.Dev.	Skewness	Kurtosis	Q(5)	Q(10)	Q(15)	Q(20)	t-statistic
R_t	0.8618	9.6718	−0.5114	4.6432	4.5950	13.845	31.709***	35.016**	−12.724***
VR_t	4.9353	4.6107	3.7780	22.271	286.39***	292.45***	292.56***	293.45***	−4.7833***
DR_t	2.4966	2.1937	2.8440	13.076	276.00***	285.57***	287.19***	289.39***	−4.7900***
JR_t	0.6910	1.2687	5.4728	43.949	52.684***	54.863***	58.248***	66.080***	−9.3837***

Note: Asterisks indicate statistical significance at the 5% (**) or 1% (***) level.

dependencies. According to the t-statistics, we find that all variables refuse the null hypothesis that there is a unit root.

5. Contemporaneous relation between risk and return

5.1. Econometric model

We investigate the contemporaneous risk-return relationship in the crude oil futures market. The econometric model that we analyze the contemporaneous risk-return relationship at the monthly frequency is written as follows:

$$R_t = \alpha + \beta X_t + \varepsilon_t \tag{13}$$

where R_t is the monthly return of crude oil futures. X_t represents VR_t, DR_t or JR_t. VR_t is the monthly volatility risk as defined in Eq. (3). DR_t is the monthly downside risk as defined in Eq. (5); and JR_t is the monthly jump risk as defined in Eq. (12). β is a slope coefficient. A positive value for β implies that the return of crude oil futures is higher as the risk level for the market increases. However, a negative value for β indicates that the return is lower as the risk level for the crude oil futures market increases.

5.2. Empirical results

Table 2 presents the parameter estimates of Eq. (13). For volatility risk, β is negative and statistically significant, which shows that the return of crude oil futures is lower as the volatility risk level of the market increases. This is consistent with results reported in Kristoufek [9], Chatrath et al. [10], etc. For downside risk, we observe that β is significantly negative. This result indicates that the contemporaneous downside risk-return relationship is negative in the crude oil futures market. Similarly, the result of Column 6 implies that the contemporaneous relation between jump risk and returns on crude oil futures is negative and statistically significant. In addition, comparing the coefficient and t-statistic of all β, we find that the contemporaneous negative relation between downside risk and return is stronger than the other two.

To analyze the reason why the contemporaneous relationship between the risk and return of crude oil futures is significantly negative, we propose a new model.

$$R_t = \alpha + \beta_1 X_t + \beta_2 D_t X_t + \varepsilon_t, \tag{14}$$

where D_t is a dummy variable, $D_t = I(R_t < 0)$.

Table 3 reports the estimation results for Eq. (14). In this table, all β_1 are significantly positive, but all β_2 are significantly negative. Moreover, the absolute values of β_2 are obviously larger than β_1. The above results show that negative returns produce higher volatility, downside and jump risks than positive return. Thus, the contemporaneous relationship between risk and return is asymmetric, and this asymmetric effect bring about the result that the contemporaneous relationship between the risk and return of crude oil futures is negative.

Table 2
Estimated results for the contemporaneous risk-return relationship.

	Volatility risk		Downside risk		Jump risk	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
α	3.9182***	4.0365	5.1466***	5.3171	1.7828**	2.2945
β	−0.6193***	−4.3039	−1.7163***	−5.8863	−1.3329**	−2.4734
Adj. R^2	0.0825		0.1472		0.0256	

Note: Asterisks indicate statistical significance at the 5% (**) or 1% (***) level.

Table 3
Estimated results of Eq. (14).

	Volatility risk		Downside risk		Jump risk	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
α	0.3460	0.4663	1.2237*	1.6661	−0.0133	−0.0181
β_1	1.2395***	7.2593	2.2573***	6.4910	6.3526***	5.4486
β_2	−2.1829***	−13.6442	−4.4634***	−14.1406	−8.5622***	−7.2310
Adj. R^2	0.5305		0.5790		0.2293	

Note: Asterisks indicate statistical significance at the 10% (*) or 1% (***) level.

5.3. Robustness test

5.3.1. Sub-samples

To test the robustness of results in Table 2, we use sub-samples to estimate Eq. (13). We divide the full sample into two sub-samples, sub-sample 1 with 98 items of data from January 1998 to February 2006 and sub-sample 2 with 98 data from March 2006 to April 2014. The estimated results are presented in Tables 4 and 5. In Table 4, all values of β are negative and statistically significant, which is consistent with the results of the full sample. This shows that the contemporaneous relation between risk (i.e., volatility, downside and jump risks) and return is negative. In Table 5, the results indicate that the contemporaneous volatility risk-return relationship and downside risk-return relationship are negative and statistically significant in the crude oil futures market. However, the contemporaneous jump risk-return relationship is negative and insignificant, which shows that the contemporaneous relationship between jump risk and return is weak in sub-sample 2. In addition, the results also show that the contemporaneous negative relation between downside risk and return is stronger. These findings are similar to those in Section 5.2. Thus, the results of Eq. (13) are robust under different samples, which provide further evidence that the contemporaneous risk-return relationship is negative.

5.3.2. Different proxy variables

In this section, we choose other proxy variables to measure the monthly volatility, downside and jump risks. Following [57] [58], monthly volatility risk is measured by the GARCH (1,1) model. The GARCH (1,1) model can be written as follows:

$$R_t = \mu_{t-1} + \varepsilon_t, \tag{15}$$

$$\varepsilon_t = \sqrt{h_t} \cdot \upsilon_t, \tag{16}$$

$$h_t = \omega + \xi_i \varepsilon_{t-1}^2 + \theta_1 h_{t-1} \tag{17}$$

where h_t represents the monthly volatility risk of crude oil futures.

Barndorff-Nielsen et al. [13] applied the daily downside realized semivariance as a proxy of daily downside risk. The daily downside realized semivariance is determined by summing the high-frequency intradaily squared negative returns of the day. Thus, we argue that monthly downside risk can be measured by the sum of daily negative returns of the month. It can be written in the following form:

$$DR_t = \frac{1}{H}\sum_{i=1}^{H}[R_{t,i}^d I(R_{t,i}^d \leqslant 0)]^2 \tag{18}$$

where H is the number of days in the tth month; $R_{t,i}^d$ is the ith daily return of crude oil futures in month t; and $I(\cdot)$ is the indicator function.

Tauchen and Zhou [59] and Zhang et al. [60] indicated that jump frequency can be used to measure jump risk in financial markets. Thus, following Tauchen and Zhou [59] and Zhang et al. [60], we define jump frequency as a proxy variable of monthly jump risk, which is written as follows.

$$JR_t = \frac{1}{H}\sum_{i=1}^{H}[1 \times I(J_{t,i}^d > 0)] \tag{19}$$

where $J_{t,i}^d$ is the ith daily discontinuous jump variation of crude oil futures at month t.

Table 6 reports the estimated results for the contemporaneous relation between risk and return in the crude oil futures market. In this table, β for each risk is significantly negative, which shows that the return is lower as the volatility, downside or jump risk level for the crude oil futures market increases. Moreover, the table shows that the contemporaneous negative relation between downside risk and return is stronger than the other two, which is consistent with the results in Section 5.2. Therefore, the results of Eq. (13) are robust when using different proxy variables to measure volatility risk, downside risk, and jump risk.

Based on the empirical results in Section 5.2 and the robustness test results in Section 5.3, we reach the conclusion that the contemporaneous relation between risk (volatility risk, downside risk or jump risk) and return in the crude oil futures market is negative and statistically significant. The results suggest the failure of the risk-return tradeoff in the crude oil futures market, which is similar to other studies on the contemporaneous risk-return tradeoff; see, e.g. Chiarella et al. [11] for one such study. In addition, the contemporaneous negative relation between downside risk and return is stronger than downside risk and jump risk.

Table 4
Estimated results for the contemporaneous risk-return relationship under sub-samples 1.

	Volatility risk		Downside risk		Jump risk	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
α	6.8647***	3.1498	8.2224***	4.3422	3.4291***	2.6757
β	−1.0012***	−2.8895	−2.3651***	−4.2410	−2.3406***	−2.6603
Adj. R^2	0.0704		0.1490		0.0590	

Note: Asterisks indicate statistical significance at the 1% (***) level.

Table 5
Estimated results for the contemporaneous risk-return relationship under sub-samples 2.

	Volatility risk		Downside risk		Jump risk	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
α	2.8784**	2.6016	3.7502***	3.4002	0.8663	0.8719
β	−0.5622***	−3.6446	−1.5991***	−4.7006	−0.8430	−1.2160
Adj. R^2	0.1124		0.1786		0.0048	

Note: Asterisks indicate statistical significance at the 5% (**) or 1% (***) level.

Table 6
Estimated results for the contemporaneous risk-return relationship using other proxy variables.

	Volatility risk		Downside risk		Jump risk	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
α	1.3904	0.9083	5.0929***	6.8586	1.7828**	2.2945
β	−0.7020***	−10.781	−1.7744***	−9.1143	−1.3329**	−2.4734
Adj. R^2	0.0144		0.2962		0.0256	

Note: Asterisks indicate statistical significance at the 5% (**) or 1% (***) level.

6. Intertemporal relation between risk and return

6.1. Econometric models

To investigate the intertemporal risk-return relationship, we propose the following two econometric models.

$$R_t = \alpha + \beta X_{t-1} + \varepsilon_t \tag{20}$$

$$R_t = \alpha + \beta E_t(X_t) + \varepsilon_t \tag{21}$$

where X_{t-1} is the lagged monthly volatility risk VR_{t-1}, lagged monthly downside risk DR_{t-1} or lagged monthly jump risk JR_{t-1}. $E_t(X_t)$ denotes the predicted value of volatility risk, downside risk or jump risk at time t. The predicted value is obtained by using the AR(1), AR(3) or HAR(3) model.[1]

The AR(1) model is written as follows:

$$X_t = a + bX_{t-1} + \varepsilon_t \tag{22}$$

The AR(3) model is written as follows:

$$X_t = a + bX_{t-1} + cX_{t-2} + dX_{t-3} + \varepsilon_t \tag{23}$$

The HAR(3) model is written as follows:

$$\bar{Y}^d_{t'+21} = a + bY^d_{t'-1} + c\bar{Y}^d_{t'-5} + d\bar{Y}^d_{t'-22} + \varepsilon_{t'} \tag{24}$$

where $\bar{Y}^d_{t'+21}$ is the average volatility/downside/jump risk between day t' and $t'+21$. If t' is the first day of the tth month, $\bar{Y}^d_{t'+21}$ approximately equals risk X_t as computed in Eq. (3), Eq. (5) or Eq. (12) at time t. We extract all $\bar{Y}^d_{t'+21}$ at the first day of all months and obtain all predicted values of monthly risks. In addition, $Y^d_{t'-1}$ is the daily risk; $\bar{Y}^d_{t'-5} = (Y^d_{t'-1} + Y^d_{t'-2} + \cdots + Y^d_{t'-5})/5$ is the weekly risk; and $\bar{Y}^d_{t'-22} = (Y^d_{t'-1} + Y^d_{t'-2} + \cdots + Y^d_{t'-22})/22$ is the monthly risk.

6.2. Empirical results

Table 7 reports the results for the intertemporal relation between the risk and return of crude oil futures. The table indicates that all β are negative, but they are non-significant. The results suggest that the intertemporal risk-return relationship is weak in the crude oil futures market.

In addition, we develop an econometric model on the basis of Eq. (20) for explaining the results of Table 7.

$$R_t = \alpha + \beta_1 X_{t-1} + \beta_2 D_t X_{t-1} + \varepsilon_t \tag{25}$$

where D_t is a dummy variable, $D_t = I(R_t < 0)$.

Estimated results of Eq. (25) are reported in Table 8. All β_1 are significantly positive, but all β_2 are significantly negative in this table. We argue that the positive effect and negative effect cancel each other out; as a result, the intertemporal risk-return relationship is weak in the crude oil futures market.

Table 9 lists the results for the intertemporal risk-return relationship as defined in Eq. (21). The predicted values of risk $E_t(X_t)$ are obtained by using the rolling window prediction method. In this section, five years are used as the rolling window length. That is to say, the rolling window length for the AR(1) and AR(3) models is 60, and that of the HAR(3) model is 1296. In Columns 3 and 7 of Table 7, all β are not significant, which shows that both the intertemporal volatility risk-return relationship and the intertemporal jump risk-return relationship are weak. In Column 5, β in the AR(3) and HAR(3) models are negative and statistically significant. The results indicate there is a negative intertemporal relation

[1] The AR(1) model is the simplest time-series forecasting model. The HAR(3) model is a good risk forecasting model, and the AR(3) model is a match with the HAR(3) model, whose independent variable include three lag variables.

Table 7
Estimated results for the intertemporal risk-return relationship as defined in Eq. (20).

	Volatility risk		Downside risk		Jump risk	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
α	1.5128	1.4816	1.8531*	1.7578	0.9133	1.1513
β	−0.1271	−0.8417	−0.3869	−1.2215	−0.0438	−0.0798
$Adj.\ R^2$	−0.0015		0.0025		−0.0051	

Note: Asterisks indicate statistical significance at the 10% (*) level.

Table 8
Estimated results of Eq. (25).

	Volatility risk		Downside risk		Jump risk	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
α	1.5408**	1.9947	0.7127	0.9130	1.5478**	2.1361
β_1	0.6731***	5.0946	1.7860***	6.1999	1.6711***	2.9800
β_2	−1.8947***	−12.0509	−3.9598***	−12.8307	−6.2925***	−6.5952
$Adj.\ R^2$	0.4268		0.4602		0.1762	

Note: Asterisks indicate statistical significance at the 5% (**) or 1% (***) level.

Table 9
Estimated results for the intertemporal risk-return relationship as defined in Eq. (21).

		Volatility risk		Downside risk		Jump risk	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
AR(1)	α	1.5422	1.4867	2.1477	1.9066	0.6798	0.8196
	β	−0.1367	−1.0244	−0.5208	−1.6033	0.2174	0.7079
	$Adj.\ R^2$	0.0004		0.0115		−0.0037	
AR(3)	α	1.5448	1.5156	2.1696**	1.9837	0.7308	0.8931
	β	−0.1409	−1.0729	−0.5525*	−1.7271	0.1508	0.6043
	$Adj.\ R^2$	0.0011		0.0145		−0.0047	
HAR(3)	α	1.7721*	1.6981	2.3797**	2.0948	0.5457	0.5907
	β	−0.1864	−1.3424	−0.6401*	−1.8549	0.4553	0.6494
	$Adj.\ R^2$	0.0059		0.0178		−0.0043	

Note: Asterisks indicate statistical significance at the 10% (*) or 5% (**) level.

between downside risk and expected return in the crude oil futures market.

To account for the results in Table 9, we propose an econometric model based on Eq. (21).

$$R_t = \alpha + \beta_1 E_t(X_t) + \beta_2 D_t E_t(X_t) + \varepsilon_t \quad (26)$$

where D_t is a dummy variable and $D_t = I(R_t < 0)$.

Table 10 presents estimated results for Eq. (26). Most of β_1 in this table are positive and statistically significant. However, all β_2 are negative and statistically significant. The values of β_1 are smaller than the absolute values of β_2. If the negative effect is significantly stronger than the positive effect, β in Table 9 are negative and statistically significant. If the difference between the negative effect and positive effect is non-significant, β in Table 9 are not significant. Thus, β in the AR(3) and HAR(3) models are significantly negative when testing the intertemporal relation between downside risk and expected return. However, in most cases, the intertemporal relation between risk and expected return is weak.

6.3. Robustness test

6.3.1. Different samples

We use sub-samples 1 and 2 of Section 5.3.1 to test the robustness of results in Table 7. The test results are presented in Tables 11 and 12. In these tables, all values of β are negative but statistically insignificant, indicating that the negative intertemporal relation between risk and expected return is very weak in the crude oil futures market. The results are consistent with those of Table 7, which suggests that the results of Eq. (20) are robust under different samples.

As robustness tests, we use two years as the rolling window length in this section. Table 13 reports the estimated results of Eq. (21). The results are similar to those in Table 7. That is to say, the intertemporal volatility/jump risk-return relationship is very weak. However, the intertemporal relation between downside risk and expected return is negative in the crude oil futures market. The results are similar to those in Table 9, which shows the estimated results of Eq. (21) are robust.

6.3.2. Different proxy variables

In this section, volatility risk is also measured by Eqs. (15)-(17); downside risk is measured by Eq. (18), and jump risk is measured by Eq. (19). Table 14 presents the estimated results of Eq. (20). In this table, β of volatility risk and jump risk are statistically insignificant, but β of downside risk is statistically significantly negative. The results show that the intertemporal volatility/jump risk-return relationship is weak and that the intertemporal downside risk-return relationship is strongly negative in the crude oil futures market. It furthermore indicates that the estimated results of Eq. (20) are robust when using different proxy variables to measure risk in the crude oil futures market.

The HAR(3) model cannot be estimated because of the proxy variables. Thus, Table 15 only presents the results for the intertemporal risk-return relationship as defined in Eq. (21) of the AR(1)

Table 10
Estimated results of Eq. (26).

		Volatility risk		Downside risk		Jump risk	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
AR(1)	α	1.2264	1.4679	−0.1040	−0.1186	4.9980***	6.4995
	β_1	0.5343***	4.0267	1.9970***	5.7408	0.1294	0.5522
	β_2	−1.4139***	−8.6013	−3.6210***	−10.1755	−19.0296***	−9.8725
	Adj. R^2	0.0004		0.4400		0.4164	
AR(3)	α	1.2021	1.4290	−0.3156	−0.3545	5.5974***	7.6196
	β_1	0.5160***	3.8001	2.1145***	5.6124	0.0204	0.1127
	β_2	−1.3500***	−8.0142	−3.5949***	−9.4225	−24.6513***	−11.1433
	Adj. R^2	0.3213		0.4046		0.4765	
HAR(3)	α	1.2720	1.5376	0.4487	0.5289	0.6731	0.7807
	β_1	0.5718***	4.1332	1.8863***	5.5038	2.3387***	3.0267
	β_2	−1.4996***	−9.0098	−3.8797***	−10.8753	−5.3493***	−4.5782
	Adj. R^2	0.3780		0.4762		0.1259	

Note: Asterisks indicate statistical significance at the 1% (***) level.

Table 11
Estimated results for the intertemporal risk-return relationship as defined in Eq. (20) under sub-samples 1.

	Volatility risk		Downside risk		Jump risk	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
α	1.6037	0.6986	1.5246	0.7306	1.9159	1.433
β	−0.0579	−0.1592	−0.0835	−0.1364	−0.6773	−0.7414
Adj. R^2	−0.0103		−0.0103		−0.0047	

Table 12
Estimated results for the intertemporal risk-return relationship as defined in Eq. (20) under sub-samples 2.

	Volatility risk		Downside risk		Jump risk	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
α	1.1899	1.0100	1.7272	1.4261	0.3705	0.3700
β	−0.1631	−0.9941	−0.6020	1.4261	0.2743	0.3911
Adj. R^2	−0.0001		0.0163		−0.0088	

Table 13
Estimated results for the intertemporal risk-return relationship as defined in Eq. (18) under the other rolling window length.

		Volatility risk		Downside risk		Jump risk	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
AR(1)	α	2.0806	1.6316	1.5855	1.1495	0.4360	0.3686
	β	−0.2527	−1.2200	−0.3150	−0.6740	0.5303	0.3761
	Adj. R^2	0.0028		−0.0032		−0.0050	
AR(3)	α	2.2924*	1.9438	2.2081*	1.7941	0.4538	0.3839
	β	−0.3010	−1.5954	−0.5718	−1.4117	0.5029	0.3577
	Adj. R^2	0.0090		0.0058		−0.0051	
HAR(3)	α	1.8671*	1.9049	2.6585**	2.4760	0.6831	0.8286
	β	−0.2125	−1.5941	−0.7452**	−2.3059	0.1419	0.2619
	Adj. R^2	0.0089		0.0246		−0.0055	

Note: Asterisks indicate statistical significance at the 10% (*) or 5% (**) level.

Table 14
Estimated results for the intertemporal risk-return relationship as defined in Eq. (20) using other proxy variables.

	Volatility risk		Downside risk		Jump risk	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
α	−0.1633	−0.0469	2.0384**	2.3097	0.9133	1.1513
β	0.1096	0.3068	−0.4826**	−2.0909	−0.0438	−0.0798
Adj. R^2	−0.0023		0.0171		−0.0051	

Note: Asterisks indicate statistical significance at the 5% (**) level.

Table 15
Estimated results for the intertemporal risk-return relationship as defined in Eq. (21) using other proxy variables.

		Volatility risk		Downside risk		Jump risk	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
AR(1)	α	4.0024	0.9290	1.8568	1.4762	1.3863	1.5657
	β	−0.3288	−0.7434	−0.3121	−0.8179	−0.3616	−1.1028
	Adj. R^2	−0.0033		−0.0025		0.0016	
AR(3)	α	4.2539	0.9943	1.5005	1.2757	2.1696**	1.9837
	β	−0.3550	−0.8086	−0.1680	−0.4960	−0.5525*	−1.7271
	Adj. R^2	−0.0026		−0.0056		0.0145	

Note: Asterisks indicate statistical significance at the 10% (*) or 5% (**) level.

and AR(3) models. The table shows that most values of β are statistically insignificant, which indicates that the intertemporal relation between risk and expected return of crude oil futures is weak. The above results are similar to those in Table 9, which shows that the results of Eq. (21) are robust under different proxy variables.

According to Sections 6.2 and 6.3, we find that the intertemporal volatility/jump risk-return relationship is insignificant and that there is little negative correlation between downside risk and expected return in the crude oil futures market. The results are robust when using different samples and different proxy variables, which indicates the failure of intertemporal risk-return tradeoff in the crude oil futures market.

7. Conclusion

We comprehensively investigate the contemporaneous risk-return relationship and intertemporal risk-return relationship in the crude oil futures market. In this paper, we use realized volatility as a measure of volatility risk, downside realized semivariance as a measure of downside risk, and discontinuous jump variation as a measure of jump risk. Then, we use a simple linear regression model to examine the relation between volatility/downside/jump risk and return by applying high-frequency transaction data from the NYMEX-CME for the front-month WTI crude oil futures contract.

We find that the contemporaneous relation between risk (volatility risk, downside risk or jump risk) and return in the crude oil futures market is statistically significantly negative. In addition, the contemporaneous negative relation between downside risk and return is stronger than the other two. However, the intertemporal volatility/jump risk-return relationship is insignificant, and there is little negative correlation between downside risk and expected return in the crude oil futures market. Moreover, we find that the empirical results are robust across different samples and different measures of volatility risk, downside risk and jump risk. Our empirical results also demonstrate the failure of both contemporaneous and intertemporal risk-return tradeoffs in the crude oil futures market. Further empirical analysis shows that the asymmetric effect of risk on returns is an important reason that there is no evidence of contemporaneous and intertemporal risk-return tradeoffs.

The crude oil futures market is different from the stock market, where market participants mainly buy assets and are risk averse. However, the effect of buyers and sellers in the crude oil futures market is relatively even. Investors do not exhibit risk aversion, and the risk-return tradeoff fails in the crude oil futures market. Our results suggest that market participants should take into account the asymmetric effect factor when they seek to explain and/or understand the return-risk relation in the crude oil futures market. Additionally, the results can be utilized to enhance risk management and portfolio diversification under uncertainty in the current context of the crude oil futures market. When price fluctuation (or market risk) is large in the crude oil futures market, market participants should sell crude oil futures for rational asset allocation.

In future work, we will investigate the risk-return relationship in other energy markets based on high-frequency transaction data. It will also be interesting to analyze the dynamic relationship between risk and return and the economic underpinnings of a negative risk price in the crude oil futures market.

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