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Measuring contagion effects between crude oil and Chinese stock market sectors

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Highlights

- We investigate extreme events in the return process of the Chinese stock market at the sectoral level.
- A multinomial logit model is applied to evaluate the contagion effect from the international crude oil market.
- Our empirical findings suggest that the explanatory power of oil returns for synchronous tail events across sectors is relatively weak but never negligible.
- The results indicate that the contagion from the oil market to China's stock market is significantly different across categories and between positive co-exceedances and negative co-exceedances.

Abstract:

The role of cross-market linkages in the occurrence of tail events in stock and energy markets has not yet been fully understood in the contagion literature. This paper investigates the contagion from oil prices to Chinese stock sectors by considering differences between extreme positive returns and extreme negative returns. We compute time-varying cut-offs by employing a generalized Pareto distribution (GPD) function to estimate excess returns. We then use a multinomial logit (MNL) model to examine the probability of Chinese stock sector co-exceedances associated with oil price exceedances. Our results indicate that, compared to common domestic factors, the contagion between oil price and stock sectors is relatively weak, but never negligible. We argue that faced with volatile oil prices during turbulent periods, the existence of any contagion weakens the benefits of portfolio diversification related to oil and Chinese stock sector investment. Based on our findings, investors holding a portfolio of oil and Chinese sector stocks should pay special attention to the extreme changes in crude oil prices and adopt hedging measures to protect their portfolio from extreme shocks to oil markets.

***Key words*:** Contagion; Oil market; Chinese stock sectors; Extreme returns; Co-exceedances

JEL classification: C32; G12; G15

1. Introduction

Investors seek a well-diversified portfolio in which the degree of correlation across asset classes is low. In addition, they allocate their capital across both developed and developing economies in order to diversify their investments internationally. The development of global economic integration means that the returns from stock markets across countries tend to commove however, reducing the benefits of international diversification. Over the past two decades, investors have therefore begun to pay special attention to the crude oil market, due to the low correlation between oil and stock prices.

The aim of this paper is to investigate the contagion effect from the crude oil market to the Chinese stock market at a sectoral level using a multinomial logit model (MNL). Our paper differs from existing literature in the area in that it evaluates the probability of Chinese stock sectors being contemporaneously influenced by fluctuations in the price of international crude oil on a given day. We believe our approach to be a more robust method than a sector by sector based analysis which may ignore the cross-sectoral link in response to extreme changes in oil prices.

As an increase in the price of crude oil is deemed a negative shock, it is intuitively considered to be negatively correlated with both the real economy and the stock market. This analysis is based on the "commodity attribute" of oil, i.e., rising oil prices will increase operating costs of listed companies, and thus depress stock prices. In addition, however, oil also has a "financial attribute". For example, Kilian and Park (2009) find that higher oil prices, driven by unanticipated global economic expansion, have persistent positive effects on cumulative stock returns within the first year of the expansionary shock. In the presence of extreme circumstances however, the "financial attribute" of oil may dominate the impact of oil price changes on stock returns[①]. There is also considerable evidence that the normal distribution is too thin-tailed to adequately fit financial data from many different markets (Rocco, 2014). It is also widely acknowledged that fat tails in financial time series make investors underestimate systematic risk. Furthermore, when assets have heavy tails, diversification may be suboptimal, and individually optimal diversification may differ from social optimality, since investors undervalue systemic risk (Chollete et al., 2012).

Several papers have focused on the extreme returns and dependence between oil prices and stock markets. Sukcharoen et al. (2014) find evidence of weak tail dependence between oil prices and stock indices[②] while Ding et al. (2016) consider the causal relationship between oil price changes and five stock index returns (S&P 500,

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[①] This can be defined as the contagion from the perspective of extreme returns as described by Bae et al. (2003).

[②] The authors exclude oil and gas stock companies from the stock indices used in their estimations.

Nikkei, Hang Seng, Shanghai, and KOSPI) within a quantile causality framework. Mensi et al. (2014) examine the dependence between the emerging stock markets of BRICS countries and oil prices. The authors find that the level of dependence differs across countries and quantiles. In recent years, a number of papers have emerged which examine this relationship with regard to Chinese stock markets. Chen and Lv (2015) use Extreme Value Theory (EVT) and find a positive extreme dependence between Chinese stock market returns and the global crude oil market. The authors also find that tail dependence increased dramatically during the global financial crisis and decreases considerably after the crisis. Wen et al. (2012) apply a time-varying copulas approach to investigate whether contagion effects exist between energy and stock markets during financial crises. The authors find evidence to support this relationship in both Chinese and US markets. Nguyen and Bhatti (2012) on the other hand, applying a similar technique, do not find any tail dependence between international oil price changes and China's stock market.

It is clear that the majority of the literature in this area has focused on the linkages between the oil and stock market at an aggregate level, but very few deal with this linkage at industry level[③]. This is despite the fact that there exists huge heterogeneity in the response of stock sectors to oil price changes. This paper will attempt to fill this gap in the literature by investigating the contagion from fluctuations in oil prices to the Chinese stock market at the sectoral level while also allowing for contemporaneous effects. The occurrence of multiple sectors experiencing extreme returns on a given day has been labelled co-exceedance. The term "co-exceedance" introduced by Bae et al. (2003) is defined as the joint occurrence of two exceedances, i.e. large absolute returns above a certain threshold of two financial market returns at a certain point of time *t* (Baur & Schulze 2005). Our paper will measure the effect of

③ There are a few exceptions. For example, Zhu et al. (2015) investigate the relationship between crude oil price changes and the Chinese stock market at the industry level and Zhang & Cao (2013) investigate the relationship between international oil shocks and the sectoral dynamics of the Chinese stock market. The authors do not however examine the different sectors being contemporaneously influenced by international crude oil price fluctuations on a particular day.

extreme changes in oil prices on the number of co-exceedances across stock sectors in China. To our knowledge, this form of contagion has not been applied to the Chinese stock market in this way and is the key motivation for our paper.

The paper is structured as follows. Section 2 describes the methodology, Section 3 is devoted to explaining the data and our preliminary analysis, Section 4 presents the empirical results while Section 5 concludes.

2. Methodology

This paper uses a multinomial logit (MNL) model to examine the probability of Chinese stock sector co-exceedances associated with oil price exceedances. This technique will allow us to examine the cross sectional link between Chinese stock sectors and extreme changes in international oil prices. We believe that this will improve on previous studies which have focused on linkages at an aggregate level analysis as well as those which have undertaken sector by sector based analysis. Our MNL approach also allows us to control for other important variables that contemporaneously affect the stock markets and the crude oil market.

The difficulty in using the MNL model is how to quantify the extreme returns or exceedances. The threshold differentiating ordinary returns from extreme returns varies over time, for example, it may vary across different financial crises. Therefore, before introducing our MNL model, we first present the estimation procedure for the time-varying cut-offs. For this, we adopt an Extreme Value Theory (EVT) technique which will distinguish the center from the tail of the distribution of oil price changes and Chinese stock sector returns. If the return exceeds the upper cut-off on a certain day, it is referred to as a positive exceedance. If it is below the lower cut-off, it is referred to as a negative exceedance. If the exceedance occurs contemporaneously in i sectors on a particular day, we assume that there exists i sector co-exceedances.

2.1 Time-varying cut-offs[4]

A constant cut-off ignores the effect of potentially updated information on extreme returns and volatilities. We therefore use the EVT technique to calculate time-varying cut-offs which assimilates the latest volatility information. Consider that $X_1, X_2, ..., X_n$ are daily observations which are independent and identically distributed (*i.i.d*). Let u denote the cut-off or threshold value. Excess returns are given by $y_i = x_i - u$ for $i = 1,..., N$, where N is the total number of observation above the threshold u. Y may approximate to the generalized Pareto distribution (GPD) as the threshold u gets larger (Pickand, 1975).

$$G_{\xi,\psi}(y) = \begin{cases} 1-(1+\frac{\xi y}{\psi})^{-1/\xi} & if\ \xi \neq 0 \\ 1-e^{-y/\psi} & if\ \xi = 0 \end{cases} \tag{1}$$

In equation (1), $\xi = 1/\alpha$ is the tail index, α is the shape parameter, and ψ is the scale parameter. Also, $\psi > 0$ and $y \geq 0$ when $\xi > 0$, the GPD takes the form of the ordinary Pareto distribution (heavy-tailed). $0 \leq y \leq -\psi / \xi$ when $\xi < 0$, it follows a Pareto II type distribution (short-tailed); And when $\xi = 0$, it corresponds to the exponential distribution. So the probability of returns over threshold u is as follows;

$$F_u(y) = \Pr(X - u \leq y \mid X > u) = \frac{F(y+u) - F(u)}{1 - F(u)} \tag{2}$$

The following equality holds for $x > u$ in the tail of F

$$F(x) = [1 - F(u)]F_u(y) + F(u) \tag{3}$$

$F(u)$ represents the probability of returns less than the threshold u. By using the method of Historical Simulation (HS), the estimate of $F(u)$ equals $(n - N)/n$, where

[4] In this section, we give the process for estimating the upper cut-offs. For the lower cut-off, we simply take the negative of the raw time series and apply the same process.

n is the sample size. Since y is the excess returns, it follows that the GPD $F_u(y) = G_{\xi\psi}(y)$. Plugging the estimate of $F(u)$ and $F_u(y)$ into equation (3), we get

$$F(x) = \begin{cases} 1 - \dfrac{N}{n}[1 + \xi \dfrac{(x-u)}{\psi}]^{-1/\xi} & if \ \xi \neq 0 \\ 1 - \dfrac{N}{n} e^{-(x-u)/\psi} & if \ \xi = 0 \end{cases} \tag{4}$$

where ξ and ψ can be estimated by a maximum likelihood method for $X > u$. For the preset confidence level q, let $F(x) = q$. The inverse of equation (4) is

$$x_q = \begin{cases} u + \dfrac{\psi}{\xi}[(\dfrac{1-q}{N/n})^{-\xi} - 1] & if \ \xi \neq 0 \\ u - \psi In(\dfrac{1-q}{N/n}) & if \ \xi = 0 \end{cases} \tag{5}$$

This represents the upper cut-off for *i.i.d* time series.

As financial time series possess characteristics of leptokurtosis, fat tails, clustering and serial correlation however, we use an ARMA-GARCH model to filter the raw time series for GPD estimates of standardized residuals. The upper time-varying cut-off of the raw time series for a 1-day horizon is

$$x_{up}^t = u_t + \sigma_t x_{z,q}^{up} \tag{6}$$

Where u_t is the mean of the raw time series at time t; σ_t is the conditional volatility, and $x_{z,q}^{up}$ is the upper-cut-off of standardized time series.

2.2 The Multinomial Logit (MNL) Model

To investigate the existence of contagion from the crude oil market to Chinese stock sectors, we classify co-exceedances into different categories (*m* categories) using polychotomous variables. The multinomial logit (MNL) model can be used to analyze the category of co-exceedances. If we let $P(Y = i)$ be the probability associated with a category *i* of *m* possible categories, our MNL is given by

$$P(Y=i\,|\,X)=e^{\beta_i'X}\,/[1+\sum_{j=1}^{m-1}e^{\beta_j'X}]\qquad i=0,1,\ldots,m \tag{7}$$

Where X is the vector of covariates and β_i is the vector of coefficients on the covariates. $Y=0$ can be viewed as the reference or baseline outcome, indicating that there is no sector experiencing exceedance at time t. The probability of $Y=i$ is then gauged against the baseline outcome. Equation (7) is estimated using a maximum likelihood method whose log function for a sample of n independent observations is as follows:

$$\begin{aligned} LogL &= \sum_{i=1}^{n}\sum_{j=1}^{m} y_{ij} LogP_i(Y=j) \\ &= \sum_{i=1}^{n}(y_{ij}\sum_{j=1}^{m}\beta_j X_i - Log(1+\sum_{j=1}^{m}e^{\beta_j X_i})) \end{aligned} \tag{8}$$

Where y_{ij} is an indicator variable equal to 1 if the *i*th observation falls into the *j*th category, and zero otherwise, $\sum_{j=1}^{m} y_{ij}=1$. There in total $k\times m$ parameters to be estimated in the model, including the constant term, where k is the number of independent variables. Due to the non-linear nature of the logistic model, it is not easy to interpret coefficients as in a linear regression. Therefore, we calculate the marginal change in the probability for a given unit change in independent variables to test whether this change is statistically significantly different from zero,

$$\tau_{ij}=\frac{\partial P(Y=i)}{\partial x_j}=\beta_{ij}\frac{\partial P(Y=i)}{\partial X}\,|\,X=X^*\qquad i=1,2,\ldots,m-1;\quad j=1,2,\ldots,k \tag{9}$$

Where X^* is the unconditional mean value of independent covariate X.

3. Data and preliminary analysis

The sample period is January 1st 1997 to September 30th 2015. We use Brent daily spot prices as a representative of international crude oil prices. Brent prices are chosen as it is the leading global price benchmark for Atlantic Basin crude oil, which accounts for two thirds of the world's internationally traded crude oil supplies. The series is denominated in dollars per barrel and accessed from the U.S. Energy Information Administration (EIA). Following the Global Industry Classification Standard (GICS), Chinese listed companies are sorted into ten sectors: Energy, Materials, Industrials, Consumer Discretionary (Consumer_D), Consumer Staples (Consumer_S), Health Care (Health), Financials, Information Technology (IT), Telecommunication Services (Telecom) and Utilities. Chinese sector stock prices were obtained from Wind Information Co., Ltd.[⑤]. It should be noted that B shares, or Domestically Listed Foreign Investment Shares, are excluded from our sample. There are two main reasons for this. Firstly, the B share market has been historically quite volatile. Secondly, because B shares are expressed in US dollars it is difficult to differentiate changes in market value due to oil price or other shocks and changes due to the US/RMB exchange rate. Crude oil price changes and stock returns are given as the difference of logarithm closing prices, $R_t = 100 \times \log(P_t / P_{t-1})$, where P_t is the closing price at time t.

Table 1 presents summary statistics for both crude oil prices and Chinese stock sector returns. Of the ten stock sectors, four sectors show a negative mean for daily returns: Energy, Materials, Financials, Utilities. The mean of crude oil price changes is also negative. All series are negatively skewed and leptokurtic. The non-normality of distributions is confirmed by the Jarque-Bera statistic, which strongly rejects the null hypothesis at the 1% significance level. On the basis of the Ljung-Box Q statistic, the null hypothesis that autocorrelations of returns and squared returns up to 20 lags are jointly zero is rejected for all time series with the exception of Financials and Telecom.

Insert Table 1 here

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⑤ Wind Information Co., Ltd (Wind info) is the market leader in China's financial data services industry.

By fitting an ARMA(*m*,*n*)-EGARCH(*p*,*q*) model, we can extract the standardized residuals from the raw time series. The number of *m*, *n*, *p* and *q* varies across sectors, depending on the information criteria such as AIC, SC and log-likelihood. Minimizing the information criteria, following the procedure above, we select an ARMA(0,0)-GARCH(1,1) model for Energy and Financials, an ARMA(0,0)-EGARCH(1,1) model for Telecom, an ARMA(1,0)-EGARCH(1,1) model for Consumer_S, Utilities and Brent, an ARMA(1,1)-GARCH(1,1) model for Health, and finally an ARMA-EGARCH(1,1) model for Materials, Industrials, Consumer_D and IT. Jarque-Bera and Ljung-Box Q are also tested for the standardized residuals. The result shows that the autocorrelation is eliminated or effectively alleviated.

4. Empirical results

4.1 The time-varying cut-offs

To calculate the time-varying cut-offs for each stock sector and crude oil prices, the first step is to choose an appropriate threshold u which distinguishes ordinary returns from extreme returns for standardized residuals. This choice is an important one as a high u (fewer observations) may lead to a larger variance of parameter estimates while reducing the bias. On the other hand, a lower u (more observations) may make the estimates more efficient but include more values around the center of the distribution. We select the optimal threshold by considering a combination of the Empirical Mean Excess Function (EMEF), the Hill Estimator (HE) and the Moment Estimator (ME). The Empirical Mean Excess Function is given as $EMEF = \sum_{i=1}^{N}(X_i - u)/N$, where N is the number of returns above the threshold u. The Hill Estimator is given as $\hat{\xi}^{(H)} = \sum_{i=1}^{N}[Log(X_i) - Log(u)]/N$, but HE is only valid for heavy-tailed distribution ($\xi > 0$); Finally, the Moment Estimator is given as $\hat{\xi}^{(M)} = 1 + M^{(1)} + \frac{1}{2}[\frac{(M^{(1)})^2}{M^{(2)}} - 1]^{-1}$, where $M(s) = \sum_{i=1}^{N} [Log(X_i) - Log(u)]^s / N$, ME is valid for all ξ. The rule of thumb for determining the optimal threshold for the EMEF method is that the EMEF statistics should be linear in the best threshold u_0. In other words, if the slope of the EMEF approximation is constant when u exceeds a certain level u_0, then the optimal threshold is u_0.

The same rule can be applied for the HE and ME statistics. Firstly, we select a threshold u based on the EMEF statistics, and then repeat the procedure until the threshold is confirmed by the HE and ME statistics. Table 2 reports the choice of optimal thresholds for the standardized residuals. There are significant differences in the optimal thresholds for crude oil and stock sector returns, ranging from 1.23% to 1.57% for top tails, and from -1.65% to -1.32% for bottom tails. The ratio of the number of time series over optimal threshold to sample size fluctuates roughly between 5% and 10%, in accordance with the findings of Karmakar and Shukla (2015). Using a maximum likelihood method, equation (1) can be applied to estimate returns of oil price and stock sectors in excess of their optimal thresholds. The tail index (ξ) and scale parameters (ψ) of GPD for top and bottom tails are shown in Table 2. The upper tail indices are not significantly different from zero at the 10% level for four sectors: Health, Financials, IT and Telecom, suggesting that the tails of their standardized residuals follow an exponential distribution. The upper tail indices of the remaining sector returns are significantly positive, which implies that the tails of their standardized residuals are characterized by a Pareto distribution. The lower tail indices of four sectors (Materials, Consumer_D, Consumer_S and IT) are insignificant at the 10% level, while others are significantly positive.

Insert Table 2 here

It is worth mentioning that the technique for calculating the cut-offs is piecewise, depending on whether or not the tail index ε is significantly equal to zero. On the basis of equation (5) and the estimate of optimal thresholds, tail indices and scale parameters, we can calculate the cut-off of the standardized residuals for oil prices and stock sectors. Inserting the related estimates into equation (6), we can obtain time-varying cut-offs of the raw time series for crude oil prices and stock sectors. The mean ($\bar{x}$) of the time-varying cut-offs is also given in Table 2. By comparing the mean of time-varying cut-offs of top tails and bottom tails, we can see that the lower cut-off is greater than the upper cut-off in absolute terms for all sectors, with the exception of the Telecom sector.

4.2 Multinomial logit regression

4.2.1 Descriptive statistics of (co-)exceedances

We define returns that lie above (below) the top (bottom) cut-off of raw returns as positive (negative) exceedances or extreme positive (negative) returns. A co-exceedance is defined as exceedance occurring in more than two sectors on a particular day. The ratio of returns above (below) our top (bottom) cut-offs to total sample size varies across oil prices and stock returns, but hovers roughly around 5%[⑥]. By comparing negative (positive) exceedance based on the EVT methodology with that based on the 5^{th} (95^{th}) quantile truncation for bottom (top) tails, we find that there is mean overlap of 61%, but this differs across sectors/markets[⑦].

Table 3 presents the number of joint occurrences of extreme returns i.e. how many sectors in China experience contemporaneously exceedances over the sample period.

[⑥] Energy sector is 4.95% (5.14%) for positive (negative) exceedance, Materials 4.91% (4.91%), Industrials 4.84% (5.23%), Consumer_D 5.05% (4.95%), Consumer_S 4.89% (4.75%), Health 4.91% (4.77%), Financials 5.00% (5.14%), IT 4.95% (5.00%), Telecom 4.86% (4.98%), Utilities 5.07% (5.11%).

[⑦] Energy is 62.44% (64.44%) for positive (negative) exceedance, Materials 60.18% (65.61%), Industrials 57.92% (63.35%), Consumer_D 61.99% (66.52%), Consumer_S 60.18% (63.80%), Health 61.09% (66.06%), Financials 64.70% (64.71%) , IT 63.80% (69.68%), Telecom 64.25% (66.52%), Utilities 58.37% (64.25%).

Co-exceedances are divided into five groups which are also shown in Table 3. We not only count the total number of days when co-exceedances occur during the sample period for group i , but also identify which sectors experience exceedances and how often this occurs. For example, of the 4,420 trading days, there are 3,643 days when no sector experience positive exceedances. If we examine this in more detail we see that of 506 occurrences of one or two sectors contemporaneously experiencing positive exceedances in total, there are 71 occurrences across Group 2 for the Energy sector. The same analysis holds for other categories, and also true for negative (co-) exceedances. Also, the distribution of (co-)exceedances is generally asymmetric between positive and negative returns. The number of positive co-exceedances across Group 1, Group 2 and Group 3 dominate negative co-exceedances while in Group 5 (7+ sectors), positive co-exceedances are less frequent than negative ones. In the case of Group 3, the number of positive co-exceedances is greater than that of negative co-exceedances, with the exception of the Financial sector. The opposite is the case for Group 4 with the exception of Energy and Consumer_S sectors. This indicates that seven or more sectors are more likely to experience contemporaneously extreme negative returns, rather than extreme positive returns on a particular day. This would seem to indicate a certain level of asymmetry with respect to higher (co-)exceedances. It is also interesting to note that the more co-exceedances across stock sectors, the more each of the ten stock sectors participate in the tail of the distribution, irrespective of positive or negative co-exceedances. This suggests that there is strong contagion within sectors when co-exceedances are high.

Insert Table 3 here

Table 3 also reports the average returns for positive (negative) co-exceedances for each of the ten stock sectors as well as the total for all stock sectors. Not surprisingly, the absolute average return for negative co-exceedances across ten sectors (-4.41%) is greater than that of positive co-exceedances (3.83%). This result is also true for each individual sector. The Telecom sector has the highest absolute average extreme returns among the ten sectors in terms of top and bottom tails. If we define the exceedances based on the 5th (95th) quantile of returns, the cutoff is constant during the sample periods with a large number of (co-)exceedances occurring around financial crisis in 2008. We must note however, that the psychology of investors as well as the environment they face are changing over time. This is particularly true with respect to the Chinese stock market which has experienced many reforms in recent years (see for example Beltratti et al. 2016). Therefore, the cut-off should also vary with time. Our time-varying cut-off is modeled and adjusted based on the volatility of the Chinese stock market, which is high during the financial crisis. This leaves us with reason to wonder if co-exceedances of stock sectors are the result of high volatility and not a result of changes in the oil market. The fact that the distribution of our (co-) exceedances is relatively flat during the entire sample period eases these concerns however.

4.2.2 Regression Results of MNL

We sort co-exceedances into five categories: base category, category 1, 2, 3 and 4, in line with group 1, 2, 3, 4 and 5 from Section 4.2.1 respectively. Based on the MNL model, any estimated coefficients are gauged against the base category, which has no estimated coefficients. Therefore, we have four estimated coefficients on each of covariates, denoted as $\beta_{i,1}$, $\beta_{i,2}$, $\beta_{i,3}$, $\beta_{i,4}$, where i denotes the covariate i , representing one or two sectors contemporaneously experiencing exceedances, three or four sectors, five or six sectors, and seven or more sectors, respectively.

We select two covariates, oil price exceedance and oil conditional volatility, to investigate the contagion from the crude oil market to Chinese stock sectors. We do so by separately estimating equation (9) for top and bottom tails. The results are shown in

Table 4 and indicate that there is a striking difference in the level of contagion between positive and negative co-exceedances. For positive co-exceedances, the regression coefficients on exceedances of crude oil prices are significantly positive for all but seven or more sector co-exceedances at the 10% significance level, while the marginal effect of oil exceedances is only significant for positive co-exceedances associated with category 1 and 2. For negative co-exceedances, the coefficient is significant only for category 4 (seven or more sector co-exceedance). This indicates that one or two sectors and three or five sectors are more likely to experience contemporaneously positive exceedances when extreme positive returns occur in oil market. This is in contrast to seven or more sectors experiencing contemporaneously negative exceedances when extreme negative returns occur in the oil market. In addition, we find that the estimated coefficients for Group 1 and Group 2 are greater for top tails than for bottom tails while the opposite is true for Group 5. These results are consistent with the summary statistics in Section 4.2.1.

Insert Table 4 here

The conditional volatility of crude oil prices (Brent) reduces the probability of one or two sector co-exceedances at the 5% significance level but increases the probability of seven or more co-exceedances for top tails at the 10% significance level. By comparison, the effect of Brent conditional volatility on negative co-exceedances is not significant for all categories. The pseudo R^2 tells us that the absolute explanatory power of crude oil factors is relatively weak for upper and lower co-exceedances. The R^2 is 0.41% for top tails while it is 0.21% for bottom tails. Log-likelihood statistics demonstrate that the overall model is significant for positive co-exceedances at the 1% level but it is insignificant for negative co-exceedances.

As mentioned in Section 4.2.1, if exceedances tend to occur jointly in more than two sectors, it implies that co-exceedances of stock sectors are mostly driven by unknown common factors. A survey of the literature (for example Bae et al., 2003; Cong et al., 2008; Cao, 2012), would suggest that domestic factors such as SMB (Small

Minus Big effect), HML (High Minus Low effect), the conditional volatility of A shares, interest rate and exchange rate may affect Chinese stock markets. It is important to point out that the contagion model estimations shown in Table 4 only considers factors relating to oil prices. Therefore, it may suffer from the problem of endogeniety and may omit important variables relevant to Chinese stock sector co-exceedances. In the interest of robustness, we add the aforementioned common domestic factors as well as crude oil factors to the MNL model[8]. Data for SMB and HML are obtained from the RESSET database[9]. The interest rate is given as the three-month deposit rate before May 24, 2004, after which it is the average overnight inter-bank lending rate. The exchange rate is USD against RMB, measured as continuously compounded returns[10]. The results are depicted in Table 5.

Insert Table 5 here

The pseudo R^2 suggests that the inclusion of common factors can significantly improve the explanatory power of the model, increasing from 0.41% to 1.24% for positive co-exceedances, and from 0.21% to 5.87% for negative co-exceedances. This indicates that sector co-exceedances are mainly influenced by common domestic factors. Even controlling for common domestic factors, the positive exceedances of oil prices can significantly improve the probability prediction of positive co-exceedances of stock sectors for category 1, 2 and 3 at 10% significance level. Negative exceedances of oil prices on the other hand only significantly improve the probability prediction of negative co-exceedances of stock sectors in category 4. This

[8] Before considering these factors, we regress common domestic factors on Chinese sector co-exceedances using the MNL model and find that Chinese A-share volatility is insignificant for top tails while the interest rate is not significant for bottom tails. Therefore, we remove the conditional volatility of Chinese A-shares for positive co-exceedances and interest rate for negative co-exceedance in this estimation.

[9] Beijing Gildata RESSET Data Tech Co., Ltd (RESSET) is China's leading provider of financial databases and software solutions for financial and investment research: http://www.resset.cn:8080/en/about/about_resset.jsp.

[10] Data for both the interest rate and exchange rate were sourced from WIND info.

result is highly consistent with our model that considers only oil price factors (see Table 4). The log-likelihood test shows that our MNL model encompassing common domestic factors are significant for positive co-exceedances and negative co-exceedances. Therefore, we can suggest that contagion exists from oil prices to Chinese stock sectors, but differs across top tails and bottom tails and across categories of co-exceedances. This result also confirms that the "financial attribute" of crude oil dominates Chinese stock markets in the face of extreme changes in international oil prices. It must be noted however that the estimated coefficients on oil exceedances are smaller than many domestic factors such as SMB and HML. This suggests that while contagion from oil prices to Chinese stock sectors does exist, the effect is weak compared to domestic factors. What is interesting is that our findings would appear to complement the existing literature on the contagion between the oil and stock market. For example in a study of Central and Eastern European (CEE) transition economies, Aloui et al. (2013) argue that the lower tail dependence is stronger than the upper tail across oil and stock markets.

4.2.3 Robustness Tests

To add credence to our empirical results we also conduct two robustness tests. Firstly, we test if the choice of model selection effects our findings in any significant way. We therefore adopt a Multinomial Probit (MNP) model in our estimation of Equation 7 rather than the MNL model applied in Section 4. The results of the MNP estimations can be seen in Table A. The corresponding size of our coefficients and their levels of significance are in accordance with our original MNL model, allowing us to maintain the same conclusions as before. Secondly, we examine any significant change in our findings resulting from an adjustment in the control variables of equation 7. For example, we include the conditional volatility of Chinese A shares to our positive co-exceedances regression and the interest rate to our negative co-exceedance regression. Once again, the results remain consistent with the results of our estimations from Section 4. It would therefore appear that our results are fairly robust.

5. Conclusion

It is immensely popular among investors to hold portfolios consisting of oil and stock sectors in order to diversify risk. Therefore, the contagion from the oil market to stock markets has become an important topic for economists, investors and policy makers. It has been shown that the effect of oil price changes on the stock market is stronger under extreme circumstances than under normal circumstances. However, the literature on the relationship between oil and stock markets in terms of extreme returns is scant. This paper investigates extreme events in the return process of the Chinese stock market at the sectoral level during the period 1997 to 2015. We compute time-varying cut-offs distinguishing the center from the tails of the distribution by employing a GPD function to estimate excess returns. We then use a multinomial logit model to examine the probability of Chinese stock sector co-exceedances, associated with defined categories, when the crude oil market experiences exceedances. Our empirical findings show that the explanatory power of extreme oil returns for synchronous tail events across Chinese stock markets sectors is relatively weak in contrast to common domestic factors, but it is never negligible. Also, our empirical results indicate that the contagion effect from the oil market to Chinese stock market is significantly different across categories and between positive co-exceedances and negative co-exceedances.

The findings of our paper have important implications for Chinese stock market investors. Faced with volatile oil prices during turbulent periods, the existence of contagion weakens the benefits of portfolio diversification related to oil and Chinese stock sector investment. Investors holding a portfolio of oil and Chinese sector stocks should pay special attention to extreme changes in crude oil prices and adopt hedging measures to protect their portfolio from extreme shocks to oil markets. Their response should differ between extreme positive and negative oil price changes however. For example, investors should consider adjusting a position covering seven or more sectors in the presence of negative exceedances in oil prices, while they need only adjust four or less stock sectors in extreme positive exceedances. Our findings also have important policy recommendations for Chinese regulatory authorities. Regulators should attach more importance to the co-movement between oil prices and Chinese stock sectors, especially during turbulent periods. Moreover, policy makers should guard against the systematic risk brought about by extreme changes in oil prices.

Finally, the asymmetric effect of oil price changes on stock markets is a popular topic in the finance literature. While we touch on the area of asymmetry in this paper, our analysis is far from adequate. It does however provide us with an initial insight into the asymmetric effect of contagion between the oil market and Chinese stock markets. A more detailed and sophisticated asymmetric examination is beyond the scope of this paper and will be the focus of the author's future work.

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Table 1

Summary statistics for daily Chinese stock sector and oil price changes

Sectors	Mean(%)	Skew.	Kurt.	J.B.	Q(20)	Q2(20)
Energy	-0.0039	-0.6042	13.7041	21371***	68.06***	235.59***
Materials	-0.0029	-0.5222	6.4064	2338***	60.81***	1807.77***
Industrials	0.0041	-0.5388	6.7881	2857***	54.66***	1928.68***
Consumer_D	0.0059	-0.5347	6.5574	2541***	55.96***	1730.92
Consumer_S	0.0069	-0.3720	6.9975	3045***	60.50***	1362.16***
Health	0.0160	-0.4687	6.4056	2298***	64.98***	1583.96***
Financials	-0.0097	-1.9083	36.1504	2E+05***	47.35***	22.71
IT	0.0121	-0.4337	5.6201	1403***	50.41***	1406.24***
Telecom	0.0005	-11.0724	408.7400	3E+07***	13.90***	0.02
Utilities	-0.0059	-0.4972	7.3442	3658***	67.02***	2268.74***
Brent	-0.0029	-0.2088	7.7263	4146***	31.37*	659.80***

Note: *** and * denote the significance at 1% and 10% level.

Table 2

Optimal thresholds and GPD parameter estimates for Brent and stock sectors

	Top tails (q=95%)				Bottom tails (q=95%)			
	u	ξ	ψ	$\bar{x}$	u	ξ	ψ	$\bar{x}$
Energy	1.566	0.214*** (2.63)	0.490*** (9.52)	2.935	-1.324	0.253*** (3.88)	0.511*** (11.95)	-2.969
Materials	1.429	0.181** (2.34)	0.422*** (9.96)	2.662	-1.521	0.081 (1.29)	0.630*** (11.82)	-3.088
Industrials	1.477	0.133* (1.73)	0.399*** (9.73)	2.584	-1.352	0.118** (2.12)	0.607*** (13.38)	-2.982
Consumer_D	1.303	0.115* (1.91)	0.407*** (12.17)	2.545	-1.321	0.002 (0.04)	0.698*** (14.59)	-2.999
Consumer_S	1.412	0.139** (2.10)	0.470*** (11.28)	2.511	-1.474	0.065 (1.08)	0.616*** (11.93)	-2.695
Health	1.401	0.063 (1.06)	0.477*** (11.84)	2.635	-1.645	0.145* (1.84)	0.566*** (9.90)	-2.940
Financials	1.562	0.031 (0.44)	0.583*** (10.38)	2.851	-1.561	0.238*** (3.54)	0.553*** (10.82)	-2.878
IT	1.336	0.096 (1.49)	0.433*** (11.73)	2.991	-1.381	0.069 (1.19)	0.596*** (12.89)	-3.389
Telecom	1.290	0.057 (0.92)	0.638*** (12.21)	3.973	-1.472	0.351*** (4.38)	0.474*** (9.87)	-3.759
Utilities	1.399	0.124** (1.99)	0.450*** (11.73)	2.546	-1.568	0.189** (2.50)	0.501*** (10.49)	-2.866
Brent	1.226	0.106** (1.97)	0.443*** (13.84)	3.313	-1.595	0.200*** (2.59)	0.465*** (10.15)	-3.586

Notes: *t* values are given in parentheses. ***, **, * denote the significance at 1%, 5%, 10% levels, respectively.

Table 3

Summary statistics for of (co-)exceedances for stock sectors

	Mean return (%)	Number of positive (co-)exceedances					Number of negative (co-)exceedances					Mean return (%)
		Group 5 (7+)	Group 4 (5-6)	Group 3 (3-4)	Group 2 (1-2)	Group 1 (0)	Group 1 (0)	Group 2 (1-2)	Group 3 (3-4)	Group 4 (5-6)	Group 5 (7+)	
Energy	4.05	79	33	36	71	3643	3806	64	29	28	106	-4.41
Materials	3.58	91	43	42	41	3643	3806	23	23	46	125	-4.30
Industrials	3.40	93	46	50	25	3643	3806	20	33	49	129	-4.09
Consumer_D	3.42	94	45	45	35	3643	3806	18	26	46	129	-4.17
Consumer_S	3.39	89	35	38	54	3643	3806	36	21	27	126	-3.92
Health	3.47	79	29	39	66	3643	3806	39	24	30	118	-4.21
Financials	3.92	83	29	34	82	3643	3806	53	35	32	107	-4.24
IT	3.97	79	29	41	70	3643	3806	48	24	33	116	-4.79
Telecom	5.70	51	21	27	116	3643	3806	96	17	22	85	-5.97
Utilities	3.38	88	38	31	67	3643	3806	39	27	41	119	-3.95
Total	3.82	94	64	113	506	3643	3806	324	76	64	132	-4.40

Note: Co-exceedance of *i* indicates that *i* sectors have an exceedance on the same day. Co-exceedances are reported for *i*=1-2, 3-4, 5-6 and 7 or more (7+), respectively for positive and negative tails. Mean return denotes average return of (co-)exceedances.

Table 4

Contagion from the oil market to Chinese stock sectors

	Positive co-exceedances		Negative co-exceedances	
	Coeff.	Δprob		
β_{01} (constant)	-1.8315***		-2.3983***	
β_{02}	-3.7078***		-3.9785***	
β_{03}	-3.8726****		-3.8700***	
β_{04}	-3.9224***		-3.5200***	
β_{11} (Brent)	0.4418**	0.0404**	0.2279	0.0137
β_{12}	0.7108**	0.0159*	0.1239	0.0013
β_{13}	0.7726*	0.0099	0.2823	0.0034
β_{14}	0.3576	0.0057	0.8862***	0.0249***
β_{21} (volatility)	-0.0338**	-0.0035**	-0.0045	-0.0003
β_{22}	0.0347	0.0010*	0.0112	0.0002
β_{23}	-0.0451	-0.0006	-0.0474	-0.0007
β_{24}	0.0446*	0.0010**	0.0178	0.0005
Log-likelihood	23.49***		10.42	
Pseudo R2	0.41%		0.21%	

Note: Volatility is the conditional variance of Brent returns, from ARMA(1,0)-EGARCH(1,1) model. ***, **, * denote significance at 1%, 5% and 10% level, respectively.

Table 5

Contagion results with the inclusion of common domestic factors

	Positive co-exceedances		Negative co-exceedances	
	Coeff.	Δprob		
β_{01}(constant)	-1.8753***		-2.3057***	
β_{02}	-3.1727***		-3.8407***	
β_{03}	-4.0883***		-3.9590***	
β_{04}	-3.9445***		-3.7856***	
β_{11}(SMB)	-12.5007*	-1.2391*	-70.6125***	-4.2155***
β_{12}	-14.5371	-0.3275	-94.9744***	-1.3214***
β_{13}	21.7139	0.3376	-149.4972***	-1.7906***
β_{14}	-4.4959	-0.0610	-127.2677***	-3.0707***
β_{21}(HML)	24.3964***	2.1669**	-27.5151**	-1.3834*
β_{22}	25.7962	0.5175	-54.2065**	-0.7433**
β_{23}	59.2445**	0.7776**	-93.9926***	-1.1242***
β_{24}	42.4736**	0.7878**	-108.6266***	-2.7747***
β_{31}(Interest/Volatility-A)	0.0009	0.0007	-0.0517**	-0.0032**
β_{32}	-0.2423	-0.0060*	-0.1019**	-0.0016*
β_{33}	0.0637	0.0010	-0.1189**	-0.0015**
β_{34}	-0.0040	0.0000	-0.0187	-0.0002
β_{41}(Exchange)	-2.0502***	-0.1988***	0.6997	0.0377
β_{42}	-2.4769**	-0.0551**	1.8511	0.0277
β_{43}	0.4184	0.0105	2.5094**	0.0312**
β_{44}	-0.2162	0.0019	1.6147	0.0384
β_{51}(Brent)	0.4572**	0.0414**	0.2206	0.0121
β_{52}	0.7245**	0.0160*	0.1302	0.0010
β_{53}	0.8066*	0.0103*	0.3178	0.0031
β_{54}	0.3879	0.0062	0.9156***	0.0242***
β_{61}(volatility-Brent)	-0.0305**	-0.0032**	0.0031	0.0002
β_{62}	0.0260	0.0007	0.0255	0.0004
β_{63}	-0.0424	-0.0006	-0.0314	-0.0005
β_{64}	0.0459*	0.0010**	0.0253	0.0007
Log-likelihood	70.69***		292.08***	
Pseudo R2	1.24%		5.87%	

Note: The conditional volatility of Chinese A shares has been excluded in positive co-exceedances regression, and interest rate has been removed in negative co-exceedances. ***, **, * denote significance at 1%, 5% and 10% level, respectively.

Appendix

Table A1: Multinomial Probit Model

	Positive co-exceedances		Negative co-exceedances	
	Coeff.	Δprob		
β_{01}(constant)	23.73***		-1.8937***	
β_{02}	-2.5778***		-2.7573***	
β_{03}	-2.6587***		-2.7116***	
β_{04}	-2.6978***		-2.5286***	
β_{11}(Brent)	0.3492**	0.0416**	0.1855	0.0142
β_{12}	0.4536**	0.0162*	0.1224	0.0014
β_{13}	0.4754**	0.0104	0.2017	0.0035
β_{14}	0.2520	0.0053	0.5451***	0.0261***
β_{21}(volatility)	-0.0219**	-0.0034**	-0.0030	-0.0003
β_{22}	0.0161	0.0009	0.0055	0.0002
β_{23}	-0.0235	-0.0006	-0.0214	-0.0006
β_{24}	0.0233*	0.0011**	0.0096	0.0006
Log-likelihood	23.73***		10.96	

Note: Volatility is the conditional variance of Brent returns, from ARMA(1,0)-EGARCH(1,1) model. ***, **, * denote significance at 1%, 5% and 10% level, respectively.

Table A2: Multinomial Logit (MNL) model including all control variables

	Positive co-exceedances		Negative co-exceedances	
	Coeff.	Δprob		
β_{01} (constant)	-1.8706***		-2.3040***	
β_{02}	-3.1026***		-4.1130***	
β_{03}	-3.9422***		-3.7115***	
β_{04}	-4.0230***		-4.2108***	
β_{11} (SMB)	-12.5235*	-1.2428*	-70.6201***	-4.2168***
β_{12}	-15.6862	-0.3571	-94.6468***	-1.3147***
β_{13}	23.0631	0.3569	-149.9762***	-1.7988***
β_{14}	-3.4282	-0.0384	-127.1084***	-3.0627***
β_{21} (HML)	24.4063***	2.1649**	-27.5364**	-1.3863*
β_{22}	26.5411	0.5358	-53.9921**	-0.7388**
β_{23}	61.8373***	0.8146**	-93.9604***	-1.1250***
β_{24}	40.9876**	0.7557*	-108.4167***	-2.7663***
β_{31} (volatility-A)	-0.0018	-0.0001	-0.0518**	-0.0033**
β_{32}	-0.0269	-0.0007	-0.1003*	-0.0015*
β_{33}	-0.0571	-0.0008	-0.1226**	-0.0016**
β_{34}	0.0274	0.0006	-0.0153	-0.0001
β'_{31} (Interest)	0.0007	0.0007	-0.0005	-0.0005
β'_{32}	-0.2459*	-0.0061*	0.1038	0.0017
β'_{33}	0.0600	0.0009	-0.0943	-0.0015
β'_{34}	0.0000	0.0001	0.1579*	0.0044*
β_{41} (Exchange)	-2.0667***	-0.2004***	0.6998	0.0376
β_{42}	-2.5336***	-0.0565**	1.8697	0.0280
β_{43}	0.4409	0.0109	2.4954**	0.0310**
β_{44}	-0.1816	0.0027	1.6471*	0.0393
β_{51} (Brent)	0.4580**	0.0414**	0.2203	0.0376
β_{52}	0.7376**	0.0164**	0.1206	0.0280
β_{53}	0.8205*	0.0105*	0.3207	0.0310**
β_{54}	0.3752	0.0060	0.9031***	0.0393
β_{61} (volatility-Brent)	-0.0303**	-0.0032**	0.0031	0.0001
β_{62}	0.0297	0.0008	0.0319	0.0005
β_{63}	-0.0368	-0.0005	-0.0374	-0.0006
β_{64}	0.0422*	0.0009*	0.0354	0.0010
Log-likelihood	73.29***		295.79***	
Pseudo R2	1.29%		5.95%	

Note: Volatility is the conditional variance of Brent returns, from ARMA(1,0)-EGARCH(1,1) model. ***, **, * denote significance at 1%, 5% and 10% level, respectively.