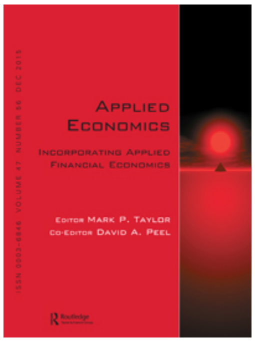

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An empirical research of crude oil price changes and stock market in China: evidence from the structural breaks and quantile regression

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This article investigates the relationship between real crude oil price changes and the Chinese real stock market at the industry level. Our study uses monthly data over the period 1994:03 to 2013:12. Based on input–output (IO) tables, this article will explore more details for the driving factors of sensitivity to oil price changes. We divide these driving factors into cost- and demand-side dependence. Empirical results reveal that sensitivity varies across different industries and periods based on structural breaks and asymmetric effects of oil price changes. Furthermore, some industries seemingly not directly affected by oil are sensitive to the real oil price changes. Finally, using a penalized quantile regression for panel data, we find that these two factors significantly affect lower, but not upper, quantile of sensitivity.

Keywords: crude oil; industry stock market; input–output tables; structural breaks; penalized quantile regression

JEL Classification: R15; Q43

I. Introduction

Crude oil is a natural and nonrenewable resource that plays a critical role in modern economic activity. Plenty of theoretical and empirical research has focused on the relationship between oil prices and economic activity, including Hamilton's (1983) seminal study. Kilian and Park (2009) demonstrate that oil should be considered an important indicator for the rate of national economic development. As the stock market is commonly seen as an economic barometer, oil's impact is likely to be reflected in the stock market. Furthermore, oil price changes can affect stock, particularly due to their high fluctuations (Arouri *et al.*, 2012). Oil prices have changed with sequences of very large increases and decreases in recent years, as shown in Fig. 1. Thus, policy-makers should attach great importance to the oil market, as oil price changes can affect economic growth, industrial productivity, inflation and the stock market (Tang *et al.*, 2010; Khalifa *et al.*,

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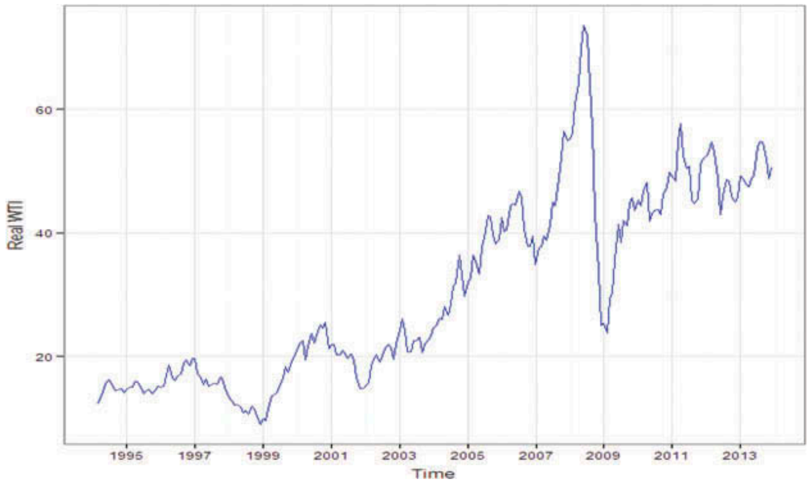


Fig. 1. Real crude oil price in dollars (West Texas Intermediate (WTI))

2014). For investors, oil price changes imply that they may face greater uncertainty as a result of large losses or gains, since oil price changes may cause fluctuations in stock market. Therefore, we conclude that either the government or profit-maximizing investors are keen to oil price changes.

The stock market can be affected by oil price changes through multiple channels. Firstly, stock value theoretically equals the discounted value of expected future cash flows. The expected future cash flows of firms may be affected by oil price changes, as oil is an important input in the production of many goods. A rise in oil price increases cost, reduces profits and tampers stock prices (Sadorsky, 1999; Arouri and Nguyen, 2010). Secondly, oil price changes may affect the discount rate by triggering expected inflation and interest rates (Huang *et al*., 1996; Miller and Ratti, 2009). When other conditions are held constant, the decline of the discount rate may trigger a rise in stock. Thirdly, oil shocks may cause macroeconomic events, or at least changes in the macroeconomy (Hamilton and Herrera, 2004; Cologni and Manera, 2009). The stock market may be influenced by oil price changes through this macroeconomic variation.

As opposed to research in developed nations, relatively few studies have investigated the relationship between oil prices and stock market in developing countries. In an earlier study, Basher and Sadorsky (2006) find that oil price changes greatly affect whole stock return in emerging markets. According to the International Energy Agency (IEA) and International Monetary Fund (IMF), oil prices have produced greater shocks in developing than developed economies. Crude oil consumption of developing economies increases dramatically. Developing economies are experiencing rapid urbanization and modernization with oil as a vital input. Furthermore, developed countries are more energy efficient due to technological innovation and greater diversity of energy sources. Developing ones, however, tend to be more dependent on energy, and therefore more sensitive to oil prices. Finally, developed countries can implement more effective monetary and fiscal policy to reduce substantial adjustment costs by oil price changes.

As the largest oil importer and second-largest oil consumer (Energy Information Administration, EIA, 2014), China plays an important role in the global oil market. Furthermore, with increasing energy demand caused by rapid growth, Chinese markets are probably more susceptible to oil prices. Thus, Chinese oil-stocks have received increased attention (Cong *et al*., 2008; Zhang and Chen, 2011; Li *et al*., 2012; Nguyen and Bhatti, 2012; Wang *et al*., 2013; Wang and Zhang, 2014). Additionally, Arouri *et al*. (2012) argue, ‘the use of equity sector indices is, in our opinions, advantageous because market aggregation may mask the characteristics, not necessarily uniform, of various sectors’. Nevertheless, research has only recently studied the effects of oil prices on industrial stock markets in China (Cong *et al*., 2008; Li *et al*., 2012; Wang and Zhang, 2014).

These studies, however, have ignored the importance of structural changes or asymmetric effects. The changing relationship between oil and stock prices has received increased attention (Ciner, 2001; Reboredo, 2010; Lee and Zeng, 2011; Moya-Martínez *et al*., 2014). All of these papers indicate that oil price exposure remains inconstant over time. Moreover, sophisticated analysis has assessed whether oil price changes can cause asymmetric effects on stock markets or economic performance (Mork, 1989; Ferderer, 1996; Brown and Yücel, 2002; Hooker, 2002; Hamilton and Herrera, 2004; Basher and Sadorsky, 2006; Arouri and Nguyen, 2010; Ramos and Veiga, 2013). One possible explanation is that governments more stringently tighten policy in response to increasing oil prices than they loosen policy against oil price decreases. Other possible explanations include interest rates, adjustment costs, asymmetry in petroleum product prices and investment uncertainty. To the best of our knowledge, no study has yet investigated this issue in China considering both of these aspects. Thus, one purpose of our article is to fill this void by examining the link between oil and stock in China from an industry perspective, in a structural break framework and considering asymmetric effects.

Another purpose of our article is to explore the driving factors behind oil price change sensitivities from a cost- and demand-side dependence perspective. Cost-side dependence measures the extent to which industry is exposed to oil in its production process. Demand-side dependence evaluates the indirect action of oil price volatility through the main oil-intensive customer industries. This provides a new perspective to understand why and how oil impacts industries, especially for those indirectly affected by oil. Gogineni (2010) conducted a similar study. However, this author studied only the US, and we focus on China. China's net imports of oil exceeded those of the US, making it the largest net importer of crude oil in September 2013, which probably impacts future oil price from demand, thereby affecting the world economy. We have documented that behaviours between the two markets differ significantly. Furthermore, Gogineni (2010) performed a check on the asymmetric reaction to oil price changes, and did not find asymmetric effects. We consider the structural breaks caused by big events, such as 2008 crisis, finding an asymmetric reaction.

Additionally, Gogineni (2010) argues that effects of the factors on sensitivities are heterogeneous, varying across oil-intensive and non-oil-intensive industries. It is useful to not merely identify factors that increase or decrease the correlation but also to judge whether the roles of these factors differ in high- and low-correlation cases. Therefore, we use penalized quantile regression to explore driving factors behind sensitivities for Chinese industrial stock markets. The motivation to use this approach is twofold. Firstly, we can explore the impacts of independent variables on dependent variable in the centre, as well as upper and lower tails of the conditional distribution of dependent variable. In our case, we can explore the main factors behind industries that are negatively (corresponding to the low quantiles of the distribution of sensitivities) and positively affected by oil (corresponding to the high quantiles). From a policy perspective, it is often more important to understand differences among industries. A policy might be acceptable for some industries but not for others. Therefore, it is useful to assess how factors affect industries according to their position on the conditional sensitivities distribution. In fact, we expect it depends on industry specifics, such as whether oil is an essential input. Through analysing the relative effects of cost- and demand-side dependence across industries, we can categorize industries as oil-intensive and non-oil-intensive. Secondly, compared with panel quantile regression with a dummy variable, a penalized approach to estimate parameters has some advantages. We are effectively reducing the number of parameters to be estimated and, hence, reducing the incidental parameters problem (Koenker, 2004). Furthermore, by shrinking the individual effect to a common value, the penalized shrinkage models can reduce panel bias and increase the estimation efficiency (Galvao and Montes-Rojas, 2010).

Thus, this article links two strands of the literature in an effort to reveal some rather important findings. Overall, we conduct the research motivated by the following reasons. Firstly, little research has explored the impact of oil price changes on the Chinese equity market at the industry level. Further, literature has not fully considered both structural break and asymmetric effects. We consider the two important features. Secondly, we only analyse the period in which China has become a net oil-importing country. This has often been overlooked in previous studies, despite its importance (Park and Ratti, 2008; Wang *et al*., 2013). Thirdly, we explore different responses across industries towards oil price shocks. Understanding this relationship from an industry perspective is important for investors and portfolio managers. Finally, to the best of our knowledge, many papers investigate the relationship between oil and stock, though none have explored driving factors behind the correlation between Chinese industry markets and oil price changes.

This article is organized as follows: Section II briefly reviews literature. The data and methodology are presented in Section III. Section IV contains a discussion on the results and Section V provides the conclusion.

II. Literature Review

Abundant literature has studied the relationship between oil price changes and stock market returns, but this research has mainly concerned developed economies and findings are inconclusive. In earlier studies, Jones and Kaul (1996) showed that oil price increases have a significant inverse correlation with stock market returns. Some scholars have found a negative relationship between oil and stock prices (e.g. Nandha and Faff, 2008; Miller and Ratti, 2009). Huang *et al*. (1996), however, find that oil futures do not influence stock returns, indicating there is no significant relationship between these variables. Some scholars have found a positive relationship between oil and stock prices, such as Faff and Brailsford (1999), Sadorsky (2001), El-Sharif *et al*. (2005) and Managi and Okimoto (2013). Moreover, McSweeney and Worthington (2008) find that the impacts of oil on the stock market vary across industries. Furthermore, Cunado and Perez De Gracia (2014) argue that oil price shocks affect the European real stock differently depending on the causes of the oil price changes.

With the rise of emerging economies, the economic position of developing countries is becoming increasingly important. Although research of developing countries is far less than for developed ones, increased attention has been given to the former in recent years. Basher and Sadorsky (2006) investigate that oil price changes greatly affect stock market returns in emerging markets. Bhar and Nikolova (2009) explore the extent that oil prices affect stock returns and volatility in Brazil, Russia, India and China (BRIC). Ono (2011) examines whether oil prices affect stock returns for BRIC, showing that oil prices have a significant impact on the stock market, but not in Brazil. Aloui *et al*. (2012) examine the effects of oil on emerging markets, demonstrating that oil price risk is priced significantly. Arouri and Rault (2012) employ the panel co-integration method to compare differences in the Gulf Cooperation Council (GCC) countries. Ajmi *et al*. (2014) investigate the relationship between 2 major oil prices (WTI and Brent) and 11 Middle East and North Africa stock markets.

With continued growth, China plays an increasingly influential role in the global economy and inevitably attracts global investors. Additionally, the relationship between oil prices and Chinese stock markets has received increased research attention. For example, Zhang and Chen (2011) argue that China's stock returns are positively affected by oil prices and only correlated with expected volatilities (the volatilities are separated into expected, unexpected and negatively unexpected ones). Nguyen and Bhatti (2012) find no evidence of tail dependence between China's stock market and global oil prices.

Very few studies have investigated the relationship between oil price changes and Chinese stock market returns from industry perspective. Li *et al*. (2012) argue that oil prices and the Chinese industry stock market have a panel co-integration correlation. Broadstock *et al*. (2012) show that the relationship between Chinese energy-related stock markets and oil prices is time-variant, having a tremendous increase after the 2008 financial crisis. Wang and Zhang (2014) study how Chinese fundamental industries are differently affected by oil price changes, finding this influence varies across industries. These papers, however, have ignored the importance of structural breaks or asymmetric effects in investigating the oil–stock nexus.

This article aims to enhance our understanding of global oil market impacts on China's stock market by paying particular attention to industry oil price sensitivity. Therefore, we study the relationship between the Chinese stock market and oil prices at the industry level by taking the asymmetric effect and structural breaks into account. We then apply penalized quantile regression to make a depth analysis of the reasons causing this sensitivity.

III. Data and Methodology

Data description

We investigate the impact of real oil price changes on industry stock returns based on the monthly data. Park and Ratti (2008) study the relationship between oil price and stock markets, showing that oil price shocks have a significantly different impact on the real stock market. This is partly due to whether the country imports or exports oil. According to the EIA, we observe that China has become an oil-importing country since 1993. However, we cannot determine the precise turning month. Considering the data availability, we choose monthly data from 1994:03 to 2013:12.

Stock returns come from the Resset Financial Database (www.resset.cn). Both the market return and industry returns are weighted by the market capitalization of the largest Chinese companies in this industry. In keeping with industries of the input–output (IO) tables, some industries are merged with a weighted average industrial market value. There are 15 industries, and Table 1 lists the nomenclature and full name. We deflate the nominal stock returns by the Chinese CPI, which are obtained from the OECD database.

For oil, we use the monthly Cushing, WTI Spot Price free on board (dollars per barrel) obtained from the EIA. The WTI is one of the major international oil price benchmarks. We then use the US PPI to adjust nominal price to obtain the real oil price. We calculate oil price changes by $\ln(p_t / p_{t-1})$, where p_t is the real oil price in time t. Interest and exchange rates are from the OECD. We deflate the interest rate by the Chinese CPI. The real exchange rate is calculated by $\textit{the nomnial exchange rate} \times \textit{US PPI Chinese CPI}$.

Finally, we have collected the annual IO tables for the Chinese economy from the National Bureau of Statistics of China, and consumption of energy by industry from the Chinese Stock Market Accounting and Research database. The IO tables detail how the supplier industry's output is consumed as input by the customer industry. These tables are published at an industry level, including 17 industries. Due to limited data availability, we combine the three industries (Real Estate, Leasing and Business Services; Financial Intermediation; Other Services). Therefore, we have 15 total industries.

Table 1. Nomenclature and full name of each industry

Nomenclature	Full name
AFAF	Agriculture, Forestry, Animal Husbandry and Fishery
MINI	Mining
MFBT	Manufacture of Foods, Beverage and Tobacco
MTWL	Manufacture of Textile, Wearing Apparel and Leather Products
OTMA	Other Manufacture
EHW	Production and Supply of Electric Power, Heat Power and Water
CGPP	Coking, Gas and Processing of Petroleum
CHIN	Chemical Industry
MNM	Manufacture of Nonmetallic Mineral Products
MMM	Manufacture and Processing of Metals and Metal Products
MME	Manufacture of Machinery and Equipment
CONS	Construction
TSPIC	Transport, Storage, Post, Information Transmission, Computer Services and Software
WRTH	Wholesale and Retail Trades, Hotels
FIOS	Financial Intermediation and Other Services

Descriptive statistics of these variables are summarized in Table 2. Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests are applied to investigate the order of integration. From the SD we see that Chinese stock returns are more volatile than real oil price changes, indicating great instability of the Chinese stock market in recent years. The series are all nonnormal, with sharp peak and fat tail distributions from skewness and kurtosis. The ADF and PP test results demonstrate the rejection of the null hypothesis at 1% significance level. Hence, the variables are stationary.

Methodology

A multi-factor market model is widely used to study the relationship between various risk factors and the stock market. An earlier model including two factors (the investigated risk factor and entire stock market

Table 2. Descriptive statistics of returns and factors

Variables	Mean	Med.	SD	Skew.	Kurt.	ADF	PP
AFAF	0.171	0.170	0.243	4.747	50.770	−10.753***	−14.996***
MINI	0.170	0.181	0.214	1.888	14.948	−6.893***	−14.224***
MFBT	0.176	0.178	0.233	4.400	44.997	−10.384***	−15.084***
MTWL	0.169	0.173	0.227	3.371	32.318	−9.880***	−13.878***
OTMA	0.170	0.175	0.210	2.991	28.331	−10.212***	−14.476***
EHW	0.170	0.181	0.220	3.037	27.578	−10.014***	−15.130***
CGPP	0.171	0.174	0.254	4.694	48.431	−11.257***	−16.109***
CHIN	0.169	0.176	0.229	3.598	34.893	−9.656***	−13.671***
MNM	0.168	0.187	0.209	2.308	22.300	−9.062***	−14.082***
MMM	0.170	0.180	0.246	4.814	53.594	−6.462***	−15.674***
MME	0.170	0.179	0.215	2.984	28.535	−9.785***	−14.513***
CONS	0.167	0.168	0.256	5.687	63.633	−15.145***	−15.165***
TSPIC	0.171	0.186	0.224	3.725	36.749	−10.047***	−15.263***
WRTH	0.166	0.177	0.223	3.439	33.256	−10.028***	−14.074***
FIOS	0.168	0.174	0.227	3.930	38.920	−10.467***	−14.748***
R_{m}	0.169	0.180	0.204	1.687	13.431	−6.591***	−13.904***
OIL^{+}	0.032	0.013	0.042	1.466	4.991	−14.512***	−14.537***
OIL-	−0.027	0.000	0.048	−2.596	11.498	−10.961***	−10.961***
I	−0.004	−0.003	0.012	−1.404	7.383	−5.931***	−10.465***
EX	−0.002	−0.002	0.011	−0.522	3.774	−3.897**	−10.859***

Notes: This table provides the basic descriptive statistics of industry returns, market return, oil price and interest rate. The statistics include mean, median (Med.), standard deviations (SD), skewness (Skew.), kurtosis (Kurt.), augmented Dickey–Fuller test (ADF), Phillips–Perron test (PP), real market return (R_{m}), real interest rate change (I) and real exchange rate change (EX). *** and ** denote the statistical significance at 1% and 5% levels, respectively.

return) was developed to facilitate the related research, such as in Jorion (1990), Khoo (1994) and Faff and Brailsford (1999). Furthermore, the multi-factor model can be justified either from arbitrage pricing theory or a multi-beta capital asset pricing model perspective. Using regression diagnostic tests and recursive estimation techniques, Sadorsky (2001) demonstrates that the model will be more appropriate by adding interest and exchange rates. This model has recently been used by Sadorsky and Henriques (2001), El-Sharif *et al*. (2005), Basher and Sadorsky (2006), and many others. Therefore, the following model is applied in this article:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_i OIL_t + \delta_i I_t + \varsigma_i EX_t + \varepsilon_{it} \tag{1}$$

where R_{it} is the stock market return of the ith industry at time t, R_{mt} represents the stock market return and regulates the macro environment, OIL_t, I_t and EX_t represent the first natural logarithm difference of real crude oil price, real interest rate and real exchange rate, respectively. ε_{it} refers to a random error term. β_i, γ_i, δ_i and ς_i represent the sensitivity of ith industry return to the real stock market return, real crude oil price, real interest rate and real exchange rate, respectively.

The stock market return is used to control the macro environment. We expect the coefficient to be positive since a higher value indicates a better macroeconomic condition. What we are most interested in is the sign and significance of γ_i, which we expect to change across industries. This change depends on whether oil is input or not, and the industry's ability to shift oil price to the consumers. Industries that are oil-intensive will benefit from oil price decreases and suffer from increases. Conversely, for industries which comprise companies that profit from oil price increases, stock markets may be positively affected by oil price changes. Interest rate is included to capture monetary policy instruments. The coefficient is expected to be negative because it can dampen stock market returns by reducing capital expenditures and changing investors' portfolios (e.g. selling stocks and buying bonds). Exchange rate has often been used to examine stock with the belief that corporate earnings are significantly affected by fluctuations in currency value (Kim, 2003). Generally, exchange rate may be important for multinationals and the energy industry. We expect the exchange rate to negatively affect the stock market.

Considering the importance of asymmetric effects of oil price changes on real stock returns, we divide the real oil price changes into oil price increases ($OIL^+ = \max(OIL_t, 0)$) and decreases ($OIL^- = \min(OIL_t, 0)$). Equation 1 is improved to the following model:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_i{}^+ OIL_t{}^+ + \gamma_i{}^- OIL_t{}^- + \delta_{\mathrm{i}} I_t + \varsigma_i EX_{\mathrm{t}} + \varepsilon_{it} \tag{2}$$

Furthermore, the structural break has received increased attention in recent research (Andrews *et al.*, 1996; Li *et al.*, 2012; Moya-Martínez *et al.*, 2014). The method proposed by Bai and Perron (1998, 2003) is applied to the models with m structural breaks ($m + 1$ regimes). We transform Equation 2 to

$$R_{it} = \alpha_{ij} + \beta_{ij} R_{mt} + \gamma_{ij}{}^+ OIL_t{}^+ + \gamma_{ij}{}^- OIL_t{}^- + \delta_{ij} I_t + \varsigma_{ij} EX_t + \varepsilon_{it} \tag{3}$$

where $t = T_{j-1} + 1, \ldots, T_j, j = 1, \ldots, m + 1, j$ is the segment index, the break points $(T_1, \ldots, T_m)$ are treated as unknown and by convention $T_0 = 0$, $T_{m+1} = T$. F-statistic (Andrews, 1993; Andrews and Ploberger, 1994) is designed to choose a specific alternative and test against the null hypothesis of one break with unknown timing. With breakpoint i, we need to make a comparison between the OLS residuals $\hat{e}_i$ from one regression for each subsample and the residuals $\hat{e}$ from the whole model via

$$F_i = \frac{\hat{e}^T \hat{e} - \hat{e}_i{}^T \hat{e}_i}{\hat{e}_i{}^T \hat{e}_i / (n - 2k)}, \quad i = n_h, \ldots, n - n_h (n_h \geq k) \tag{4}$$

This method has been extended by Bai and Perron (1998, 2003) to test for 0 versus L breaks and L versus $L + 1$ breaks. As to confirm the number of breaks for empirical application, they advise that we should first check if at least one break exists on the base of $UD\max$ and $WD\max$ tests, then to decide the accurate number of breaks using a sequential examination of the $\sup F_T[(L + 1)/L]$ statistics.

Few studies have assessed how oil prices affect industry stock markets. Like Gogineni (2010), we divide factors into cost- and demand-side dependence. Shahrur (2005) proposes that for every pair of customer–supplier industries, the customer input coefficient is the consumption of the supplier industry's output by the customer industry divided by the customer industry's output. The takeover percentage is the percentage of the customer industry that buys the supplier industry's output. Meanwhile, the main customer industries of an industry have high supplier percentage sold. Considering that there are 15 industries in our study, all customer industries are taken into account without identifying the main customer industries. Therefore, we define cost- and demand-side dependence of industry i in year t on oil as

$$CSD_{it} = \frac{oil\ used\ as\ input_{it}}{industry's\ output_{it}}, \quad i = 1, \cdots, 15 \tag{5}$$

$$DSD_{it} = \sum_{j=1}^{15} supplier\ percentage\ \ output_j \times CSD_j \tag{6}$$

where CSD_{it}, and DSD_{it} represent the cost- and demand-side dependence of industry i on oil in year t, respectively. The *supplier percentage output*$_j$ is the percentage of the customer industry j buys the supplier industry $i's$ output.

The panel data consist of the 15 industries' sensitivity to oil price changes. The OLS regression can only summarize the average relationship between the response variable and regressors. Binder and Coad (2011) report that only focusing on mean effects may inaccurately estimate coefficients, or even fail to examine important relationships. Furthermore, unobserved heterogeneity likely exists among industries. Quantile regression can fully depict information and is less susceptible to the influence of heterogeneity, outlier observations and skewness (Koenker and Hallock, 2001). Quantile regression, as firstly proposed by Koenker and Bassett (1978), has been extended for panel data by Koenker (2004). We consider a conditional quantile model:

$$Q_{y_{it}}(\tau_j|x_{it},\alpha_i) = x'_{it}\beta(\tau_j) + \alpha_i \tag{7}$$

where $0 < \tau_j < 1, \beta(\tau_j)$ is the estimated parameter in the equation, and α_i represents the unobserved effect. $\beta(\tau_j)$ is estimated as follows:

$$\hat{\beta}(\tau_j) = \arg\min \sum_{i=1}^{N} \rho_{\tau_j}\left(y_{it} - x'_{it}\beta(\tau_j) - \alpha_i\right) \tag{8}$$

where $\rho_{\tau_j}(u) = u\left(\tau_j - I(u \le 0)\right)$ is the check function, and $I(\cdot)$ is the indicator function. The main problem of this method is the inclusion of plentiful fixed effects (α_i). Koenker (2004) addresses this problem by adding a penalty term called the shrinkage method. This method is advantageous in controlling the variability introduced by large numbers of estimated individual parameters. Furthermore, by shrinking the fixed effects we are effectively reducing the number of estimated parameters and, hence, ameliorating the incidental parameters problem. Specifically, parameter is estimated by

$$\min \sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{i=1}^{N} \omega_j \rho_{\tau_j}(y_{it} - x'_{it}\beta(\tau_j) - \alpha_i) + \lambda \sum_{i=1}^{N} |\alpha_i| \tag{9}$$

where ω_j is the tau weight, which controls for the influence of the jth quantile on the estimation of the quantile effects. The last term is called the penalty term and λ is a tuning parameter. The degree of shrinkage caused by penalty is regulated by λ. Although this author reported how to choose the optimal λ, this must satisfy the unknown Gaussian distribution of the error and individual effects. This assumption may relate to ideals, but lack practical value. Many scholars report different methods for choosing the optimal λ (Schwarz, 1978; Akaike, 1998; Lamarche, 2010). However, there is no general agreement. To verify our study, we choose different λ and τ weights to check whether the results are robust.

IV. Empirical Analysis

The structural breaks

The method proposed by Bai and Perron (2003) is applied to detect structural breaks in our study. This article sets the maximum number of breaks allowed as five (i.e. $M = 5$), with a trimming parameter of 0.10. We first examine whether there exists at least one break based on the $UD\max$ and $WD\max$ tests. The numbers of breaks are then selected by using the sequential examination $\sup F_T[(L+1)/L]$ statistics. Table 3 presents the multiple structural breaks in the relationship between crude oil price and industry returns. We can see from the table that all industries have two or more breaks, whereas heterogeneity exists in different industries to the breaks. Five breaks are estimated in EHW and TSPIC industries. For the MINI, CHIN and CONS industries, four breaks are present. There are three breaks in MFBT, MMM and FIOS industries. There are two breaks for the others.

From Table 3, the breaks concentrate in the period 1996:02 to 1998:03. The cause of this finding is complicated. In addition to the influence of the 1997 Asian crises, Chinese events

Table 3. Multiple structural breaks in the relationship between crude oil price and industry returns

Industry	Number of breaks	Break date
AFAF	2	1996:03, 1998:03
MINI	4	1997:11, 2003:04, 2007:11, 2009:11
MFBT	3	1996:02, 1998:02, 2011:12
MTWL	2	1996:02, 1998:01
OTMA	2	1996:02, 1998:02
EHW	5	1996:02, 1998:01, 2006:06, 2008:12, 2012:02
CGPP	2	1996:02, 1998:01
CHIN	4	1996:02, 1998:03, 2007:09, 2010:04
MNM	2	1996:04, 1998:03
MMM	3	1996:02, 1998:03, 2007:06
MME	2	1996:03, 1998:02
CONS	4	1996:02, 1998:01, 2008:12, 2011:05
TSPIC	5	1996:03, 1998:03, 2000:03, 2003:08, 2008:01
WRTH	2	1996:02, 2000:02
FIOS	3	1996:02, 2007:01, 2011:11

Notes: Bai–Perron tests of $L + 1$ versus L sequentially are used to determine the number and timing of breaks. The break test options include trimming 0.10, Max. breaks 5, Sig. Level 0.05. Test statistics employ HAC covariances (Prewhitening with lags from AIC, Bartlett kernel, Newey–West automatic bandwidth). The heterogeneous error distributions across breaks are allowed.

(e.g. a soft landing for its economy in 1996, privatization and restructuring in 1997–2000, further deregulation of the domestic oil pricing mechanism in 1998) also have a significant impact on the stock market. Due to entry into the WTO, further deregulation of Chinese petroleum products in 2000 and the SARS epidemics, several breaks occurred in 2000:02–2003:08. Another major special break point in 2007:06–2007:11 may have been caused by the up-regulating of stamp duty in 2007:05. The stock markets are also impacted by the 2008 financial crisis and Beijing Olympic Games, so some industries have breaks in 2008–2009. Finally, the last break point in 2011:05–2012:01 is the result of the Europe's debt trouble in 2010, which has inflicted a severe impact on China's exports.

Industry market sensitivity to oil price changes

We estimate Equation 3 for subsamples, with results exhibited in Table 4. The adjusted R^2 values vary from 0.84 to 0.97, indicating a good fit. As expected, all industries are significantly and positively affected by market returns. This finding is normal because market return represents fluctuation of the overall market. However, for oil, there is a more complicated reaction to what we expect. We are amazed to find that almost all industries are sensitive to oil price changes, even those seemingly unaffected by oil. Only AFAF, MMM and WRTH industries are not affected by oil price changes. Additionally, the large variance across industries and over time can be easily observed.

According to the consumption of energy by industry, we can regard MINI, CGPP, CHIN and TSPIC as the energy-intensive industries. It is easy to understand that these sectors are affected by oil prices, as presented in Table 4. Industry MINI has a negative sensitivity to oil increases, and a positive sensitivity to oil decreases. This is because the rise of oil prices increases cost, resulting in decreased industry; the fall of oil prices reduces cost and improves returns. The CGPP industry is negatively affected by oil price increases. This finding is intuitive, as a high oil price increases the cost of materials and leads to a reduction in the stock price. Interestingly, this effect only occurred from 1996:02 to 1997:12. This may be because companies within the industry are state-owned. The public are blindly optimistic, without considering industry return. Since the soft landing of the Chinese economy in 1996, China's economic development has slowed. The people who blindly trusted in the government fell slightly and began to more rationally view the stock market. CHIN has a negative response to oil price increases from 1994:03 to 1996:01 and oil decreases from 2010:04 to 2013:11. When oil price increases, the cost of TSPIC also increases, so there exists an inverse relationship between increasing oil prices and returns. The situation becomes complicated when oil prices drop. The industry returns first appear negative and then positive. Because the market value of Information Transmission, Computer Services and Software, seemingly unrelated to oil, was higher than Transport, Storage, Post in 1996:03–1998:02, the industry stock return had a negative sensitivity to oil at only 10% significance. At the turn of the century, entry into WTO, the successful bid for the Beijing Olympic and the SARS epidemics all occurred. These events may have facilitated or hindered achievement of industry stock market returns in 2000:03–2003:07. Therefore, significance is still under 10% but with a weak negative impact of oil decrease. With the development of Transport, Storage, Post, market value surpassed the Information Transmission, Computer Services and Software during 2008:01–2013:11. The relationship between the TSPIC industry and oil price decreases is significantly positive.

The other industries, except AFAF, MMM and WRTH industries, are seemingly unaffected by oil but also sensitive to oil price changes. For instance, MTWL, OTMA, MNM, MME and CONS industries all have significantly negative sensitivities to oil price increases and OTMA, CHIN and CONS show the negative sensitivity to oil price decreases. Additionally, the complicated changes in sensitivity to oil price changes exist in some industries. For example, the sensitivity of the EHW industry to falling oil price is first negative, then positive and finally positive. These industries consume little oil in their production process, but the estimation results of the regression show relatedness.

To check the robustness of the results, we re-estimate the relationship by adding some

Table 4. Estimation results of the industry stock with breaks

Industry	Subsamples	Intercept	R_m	OIL^+	OIL^-	I	EX	Adj. R^2
AFAF	1994:03–1996:02	−0.20***	1.75***	−0.65	0.37	−5.94	12.94	0.94
	1996:03–1998:02	0.08**	0.57***	0.62	−0.09	3.42	−9.88**	
	1998:03–2013:12	−0.00	1.00***	−0.10	−0.04	−0.80*	0.29	
MINI	1994:03–1997:10	−0.04*	1.04***	−0.06	−0.02	2.07	−4.43**	0.92
	1997:11–2003:03	0.02	1.06***	−0.33*	0.16	−0.61	1.64**	
	2003:04–2007:10	0.12***	0.53***	−0.10	0.56**	1.06	−3.14***	
	2007:11–2009:10	0.00	0.90***	−0.21**	−0.03	2.56	1.87	
	2009:11–2013:12	−0.04***	0.67***	0.41	0.03	−1.52	−0.58	
MFBT	1994:03–1996:01	−0.10	1.54***	−2.16***	0.71	−8.10	13.23	0.93
	1996:02–1998:01	0.06*	0.61***	0.95***	−0.43	6.37***	−9.43***	
	1998:02–2011:11	0.03***	0.90***	−0.09	0.05	−0.17	0.63	
	2011:12–2013:12	−0.02	0.73***	−0.42	−0.03	1.49	1.88	
MTWL	1994:03–1996:01	−0.11***	1.40***	−1.11***	0.24	−6.22**	9.16*	0.96
	1996:02–1997:12	0.07***	0.69***	−0.27	−0.07	4.24***	−8.49***	
	1998:01–2013:12	0.00	1.02***	−0.02	0.00	−0.11	0.46	
OTMA	1994:03–1996:01	−0.05*	1.30***	−0.97***	0.66	−4.10	7.78	0.97
	1996:02–1998:01	0.08*	0.69***	−0.24	0.04	3.71*	−5.73**	
	1998:02–2013:12	0.00	0.95***	0.05	−0.19***	−0.55*	0.61**	
EHW	1994:03–1996:01	−0.10***	1.39***	0.70	0.51	−3.78*	9.21**	0.92
	1996:02–1997:12	0.14***	0.66***	−0.70	−0.04	3.24	−3.33	
	1998:01–2006:05	0.03	0.85***	0.14	−0.17	1.31*	−0.54	
	2006:06–2008:11	−0.04**	1.03***	0.52	−0.66***	−2.48	1.95*	
	2008:12–2012:01	0.00	0.76***	−0.03	0.22***	2.01**	−0.64	
	2012:02–2013:12	−0.05***	0.59***	0.25***	−0.48***	1.23*	−0.67	
CGPP	1994:03–1996:01	−0.22***	1.62***	0.41	−1.32	−12.46	22.37	0.84
	1996:02–1997:12	0.15*	0.56***	−1.33**	0.74	−12.98***	20.23***	
	1998:01–2013:12	0.00	1.01***	0.02	−0.09	−0.20	0.07	
CHIN	1994:03–1996:01	−0.09***	1.49***	−1.38*	0.18	−2.79	5.87	0.96
	1996:02–1998:02	0.09*	0.58***	−0.04	0.22	2.75	−3.41	
	1998:03–2007:08	0.00	0.97***	0.09	−0.14	0.02	0.66	
	2007:09–2010:03	0.01	0.93***	0.00	0.38	−1.50	−0.63	
	2010:04–2013:11	0.00	1.04***	0.02	−0.11**	−2.11***	1.12***	
MNM	1994:03–1996:03	−0.01	1.19***	−0.95*	0.97	−3.80	6.94	0.94
	1996:04–1998:02	0.09***	0.64***	−1.24***	0.19	1.20	−3.28	
	1998:03–2013:12	0.00	1.02***	−0.11	−0.02	0.01	−0.28	
MMM	1994:03–1996:01	−0.18**	1.54***	−1.56	−1.30	−20.24	33.07	0.90
	1996:02–1998:02	0.11**	0.58***	−0.68	0.33	−2.82	3.37	
	1998:03–2007:05	0.02**	0.91***	0.05	−0.12	0.57	−0.69	
	2007:06–2013:12	0.00	1.17***	−0.02	0.14	−0.11	−0.50	
MME	1994:03–1996:02	−0.06	1.33***	−0.77**	0.60	−3.56	7.61	0.97
	1996:03–1998:01	0.07*	0.67***	0.36	−0.43	4.48**	−6.66*	
	1998:02–2013:12	0.00	1.00***	−0.05	−0.05	−0.23	−0.10	
CONS	1994:03–1996:01	−0.26***	1.91***	−1.61**	0.66	−11.06	19.43	0.94
	1996:02–1997:12	0.02	0.75***	−0.16	−0.87	1.91	−4.84	
	1998:01–2008:11	0.00	0.97***	0.08	−0.26**	0.30	0.33	
	2008:12–2011:04	0.01	0.66***	−0.13	0.20	2.95***	−0.61	
	2011:05–2013:12	−0.01	0.83***	−0.40***	0.08	0.31	−0.77	
TSPIC	1994:03–1996:02	−0.07*	1.53***	−1.77**	1.98	−4.89	10.84	0.95
	1996:03–1998:02	0.05***	0.62***	0.71	−0.69*	3.47**	−6.23	
	1998:03–2000:02	0.02	1.00***	−0.10	0.07	−0.67	1.21	
	2000:03–2003:07	0.06***	0.77***	−0.23***	−0.13*	−0.25	0.52	
	2003:08–2007:12	0.04**	0.73***	0.24	−0.09	−0.23	−0.23	
	2008:01–2013:12	−0.01	0.87***	0.01	0.12***	0.18	−0.01	

(*continued*)

Table 4. Continued

Industry	Subsamples	Intercept	R_m	OIL^+	OIL^-	I	EX	Adj. R^2
WRTH	1994:03–1996:01	−0.08***	1.45***	−1.32	1.29	1.30	−0.33	0.93
	1996:02–2000:01	0.07***	0.63***	0.14	0.01	1.69	−1.76	
	2000:02–2013:12	0.00	1.00***	0.09	−0.07	−0.90	1.16***	
FIOS	1994:03–1996:01	−0.14***	1.59***	−0.83**	1.36	−2.95	7.70	0.94
	1996:02–2006:12	0.03**	0.85***	0.06	−0.05	0.05	−0.89	
	2007:01–2011:10	0.00	0.69***	0.31*	0.32	3.89**	−1.56	
	2011:11–2013:12	−0.04***	0.63***	−0.05	−0.05	−1.93**	−2.25**	

Notes: The table shows the OLS regression results of the industry stock with breaks in Equation 3. ***, ** and * denote the statistical significance at 1%, 5% and 10% levels, respectively.

explanatory variables because there are other factors that can affect stock markets.[1] Firstly, stock markets are partly affected by market size (Fama and French, 1998; Malkiel and Jun, 2009; Acheampong *et al*., 2014). The respective market capitalization, which is a proxy for industrial market size, is collected from the Resset Financial Database. Secondly, it is interesting to consider the potential effect of the world stock market because Chinese stock returns are exposed to the world market risk with global integration. As He *et al*. (2015) indicate, 'China's stock market has become more interdependent with the global market'. The world stock indices, provided by Morgan Stanley Capital International (MSCI), are derived from the Datastream database. This proxy of the global market has been tested empirically by authors such as Arouri and Nguyen (2010) and Wang *et al*. (2011). We evaluate the augmented version of model in the presence of industrial market size and world market returns. As shown in Table 5, the sign and significance of oil price changes seems to be unaffected after introduction of market size and the global factor. This indicates that our oil–stock correlations are reasonably robust.

In general, we find that the responses to oil price changes are different across the Chinese industries, which supports previous empirical research (e.g. Cong *et al*., 2008; Li *et al*., 2012; Wang and Zhang, 2014). The different industrial sensitivities to oil price changes mean greater risk diversification. This suggests that investment portfolios across industries may be more efficient than only within one industry. As expected, the oil–stock link is not stable over time, which is consistent with some prior studies (Broadstock *et al*., 2012; Moya-Martínez *et al*., 2014). This link might have experienced dramatic changes in recent years due to factors such as stock market and/or oil price bubbles, geopolitical instability or the financial crisis (Moya-Martínez *et al*., 2014). Furthermore, our results are similar to Wang and Zhang (2014), who find that the stock market responds asymmetrically to oil price changes. This finding suggests that investors need to rebalance their portfolios and remain aware of the asymmetric effects of oil price changes.

Driving factors analysis

In this section, we try to find the driving factors behind Chinese industrial sensitivity to oil prices. Using the penalized quantile regression, developed by Koenker (2004), we examine the extent to which the magnitude of industries' correlation with oil price changes depends on cost- and demand-side dependence. One of the main advantages of this approach is that it allows us to investigate whether the effect of each factor on dependent variable is heterogeneous along quantiles of the conditional distribution of dependent variable. In other words, the penalized quantile regression can therefore investigate more subtle effects that would be ignored by the OLS regression. It also provides meaningful estimates of the parameters with less computational complication and more robustness. We use the model as follows:

[1] We would like to thank the anonymous reviewer for pointing out this issue. The housing prices should be also taken into account, since stock market returns may be affected by the estate market (e.g. Liu and Su, 2010; Lin and Fuerst, 2014; Li *et al*., 2015). However, the monthly data are unavailable due to the long time span of this study.

Table 5. Estimation results of robustness check

Industry	Subsamples	Intercept	R_m	OIL^+	OIL^-	I	EX	WORLD	SIZE
AFAF	1994:03–1996:02	−0.19***	1.68***	−0.85	0.44	−6.54	12.74	1.90**	0.10
	1996:03–1998:02	0.10*	0.55***	0.66	−0.21	5.11*	−13.09**	−1.00**	−0.04
	1998:03–2013:12	0.00	0.97***	−0.06	−0.03	−0.77**	0.18	−0.16**	0.16***
MINI	1994:03–1997:10	−0.04	1.02***	−0.13	0.03	1.68	−4.07	0.11	0.05
	1997:11–2003:03	0.01	1.06***	−0.32*	0.15	−0.61	1.56**	−0.00	0.02
	2003:04–2007:10	0.11***	0.41***	−0.18	0.50*	−0.09	−1.31	1.28***	0.27***
	2007:11–2009:10	0.00	0.88***	−0.23	−0.06	2.41	1.88	0.14	−0.02
	2009:11–2013:12	−0.05***	0.61***	0.39	−0.10	−1.65	−0.42	0.25	0.07
MFBT	1994:03–1996:01	−0.14	1.61***	−2.46**	0.60	−7.81	11.96	0.52	−0.24
	1996:02–1998:01	0.05	0.60***	0.93**	−0.39	6.40***	−9.93***	0.14	0.16
	1998:02–2011:11	0.03***	0.86***	−0.08	0.03	−0.28	0.60	−0.07	0.19***
	2011:12–2013:12	−0.02	0.71***	−0.56**	−0.00	0.87	1.53	0.05	0.21
MTWL	1994:03–1996:01	−0.16***	1.46***	−1.08**	−0.05	−6.22*	8.45*	0.31	−0.19
	1996:02–1997:12	0.07***	0.71***	−0.22	−0.24	5.15***	−10.17***	−0.48**	−0.14
	1998:01–2013:12	0.00	0.99***	−0.01	0.01	−0.19	0.29	−0.12**	0.15**
OTMA	1994:03–1996:01	−0.03	1.25***	−0.96**	0.74	−4.28	7.87	0.42	0.12
	1996:02–1998:01	0.09***	0.67***	−0.20	0.01	4.41**	−7.23***	−0.49	0.09
	1998:02–2013:12	0.00	0.93***	0.06	−0.18***	−0.61**	0.55*	−0.10**	0.12***
EHW	1994:03–1996:01	−0.13**	1.41***	0.45	0.56	−3.59	8.24	1.26**	−0.11
	1996:02–1997:12	0.12***	0.50***	−0.51	0.20	3.08	−5.80	−0.03	0.82
	1998:01–2006:05	0.04**	0.77***	0.15*	−0.22**	1.02	−0.46	−0.15	0.22*
	2006:06–2008:11	−0.04***	1.05***	0.56**	−0.58***	−2.27	1.87*	−0.20	0.02
	2008:12–2012:01	0.00	0.70***	−0.05	0.25***	2.36**	−1.10*	0.02	0.23**
	2012:02–2013:12	−0.06***	0.52***	0.22*	−0.38**	1.65**	−0.59	0.15*	0.27**
CGPP	1994:03–1996:01	−0.05	1.21***	0.49	−0.24	−13.76	22.17	2.70	0.84**
	1996:02–1997:12	0.10*	0.41***	0.10	0.33	−2.18	2.90	0.40	1.03**
	1998:01–2013:12	−0.00	0.97***	0.03	−0.12*	−0.48	0.08	0.08	0.19***
CHIN	1994:03–1996:01	−0.08	1.44***	−1.54**	0.32	−3.36	6.31	0.87	0.08
	1996:02–1998:02	0.10**	0.54***	0.04	0.16	3.31**	−4.72**	−0.31	0.09
	1998:03–2007:08	0.02	0.88***	0.08	−0.15*	−0.15	0.64	−0.08	0.21***
	2007:09–2010:03	0.01	0.86***	0.07	0.37***	−1.75	−0.84	−0.08	0.23***
	2010:04–2013:11	−0.01	1.02***	0.01	−0.20*	−2.13***	1.25***	0.15*	0.02
MNM	1994:03–1996:03	−0.03	1.23***	−1.03	0.89	−3.04	5.66	0.43	−0.15
	1996:04–1998:02	0.09***	0.61***	−1.15***	0.19	1.16	−3.44	−0.00	0.16
	1998:03–2013:12	0.01	0.98***	−0.12	−0.03	−0.05	−0.26	−0.04	0.16***
MMM	1994:03–1996:01	−0.07	1.24***	−1.96	−0.84	−21.85*	32.93	2.41	0.51
	1996:02–1998:02	0.11**	0.54***	−0.66	0.32	−1.88	1.72	−0.45	0.25
	1998:03–2007:05	0.03	0.87***	0.04	−0.10	0.52	−0.66	0.03	0.08
	2007:06–2013:12	−0.00	1.12***	−0.02	0.10	−0.13	−0.55	0.07	0.09
MME	1994:03–1996:02	−0.08*	1.37***	−0.97*	0.53	−3.49	7.07	0.66	−0.15
	1996:03–1998:01	0.07***	0.64***	0.32	−0.35	4.72***	−7.76***	−0.25	0.21
	1998:02–2013:12	0.00	0.99***	−0.05	−0.05	−0.26	−0.09	−0.00	0.05**
CONS	1994:03–1996:01	−0.26**	1.87***	−1.93	0.75	−11.48	19.04	1.63	0.00
	1996:02–1997:12	0.02	0.72***	−0.02	−0.83	3.01	−8.25	−0.85	0.23
	1998:01–2008:11	0.00	0.95***	0.09	−0.27***	0.06	0.51	−0.10	0.09
	2008:12–2011:04	0.01	0.66***	−0.14	0.19*	2.79***	−0.49	0.06	0.02
	2011:05–2013:12	−0.02	0.78***	−0.39***	0.07	0.28	−0.88	0.03	0.09
TSPIC	1994:03–1996:02	−0.04	1.44***	−1.67*	2.01	−5.71	11.94	0.34	0.23
	1996:03–1998:02	0.04	0.62***	0.72	−0.67*	3.94*	−7.44*	−0.19	0.08
	1998:03–2000:02	0.02	0.96***	−0.02	−0.07	−0.91	1.70	−0.25*	0.10
	2000:03–2003:07	0.06***	0.76***	−0.24**	−0.12	−0.43	0.66	0.08	0.02
	2003:08–2007:12	0.05**	0.60***	0.18	−0.11	−0.52	0.24	0.01	0.30***
	2008:01–2013:12	−0.01	0.86***	−0.00	0.10	0.15	−0.00	0.05	0.01

(*continued*)

Table 5. Continued

Industry	Subsamples	Intercept	R_m	OIL$^+$	OIL$^-$	I	EX	WORLD	SIZE
WRTH	1994:03–1996:01	−0.11	1.49***	−1.61	1.28	1.76	−1.81	1.09	−0.15
	1996:02–2000:01	0.07**	0.64***	0.14	0.00	1.72	−1.75	−0.01	−0.04
	2000:02–2013:12	0.00	1.00***	0.09	−0.05	−0.82	1.04**	−0.11	0.04
FIOS	1994:03–1996:01	−0.17**	1.63***	−1.10	1.23	−2.69	6.42	1.07	−0.16
	1996:02–2006:12	0.04**	0.82***	0.05	−0.06	0.11	−0.80	−0.00	0.11
	2007:01–2011:10	0.00	0.68***	0.29	0.27	3.70*	−1.48	0.13	−0.01
	2011:11–2013:12	−0.04***	0.63***	−0.03	−0.03	−2.05**	−2.32*	−0.01	−0.05

Notes: The table shows the robustness check of the industry stock with breaks. The world stock market returns and industrial market size are abbreviated as WORLD and SIZE. ***, ** and * denote the statistical significance at 1%, 5% and 10% levels, respectively.

$$\hat{Q}_{\gamma_{it}}(\tau|x_{it}, \alpha_i) = \alpha_i + \eta_1 CSD_{it} + \eta_2 DSD_{it} \qquad (10)$$

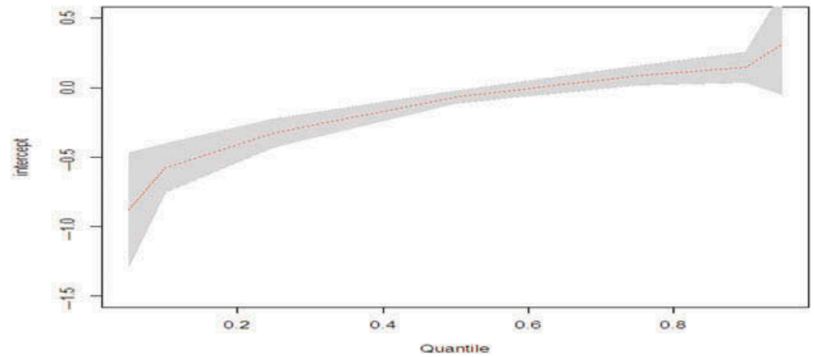
where γ_{it} is the coefficient estimated on the oil changes for industry i in year t ($t = 1995, 1997, 2000, 2002, 2005, 2007, 2010$) by estimating regression (Equation 1). η_1 and η_2 are the coefficients of the cost- and demand-side dependence, respectively. The coefficients denote the extent to which magnitude of industries' correlation with oil price changes depends on the driving factors. The following quantiles are chosen: 0.05, 0.10, 0.25, 0.50, 0.75, 0.90 and 0.95. Table 6 presents the results of the quantile regression with $\lambda = 1.0$ and $\omega = (1/7, 1/7, 1/7, 1/7, 1/7, 1/7, 1/7)$. The vector ω represents the weight of every quantile. Figure 2 illustrates the estimations of intercept, cost-side dependence and demand-side dependence with 95% confidence intervals. In these quantile regression diagrams, the grey areas represent the 95% confidence bands of the estimated value.

The results of quantile regression are reported in Table 6, indicating that the quantile-varying

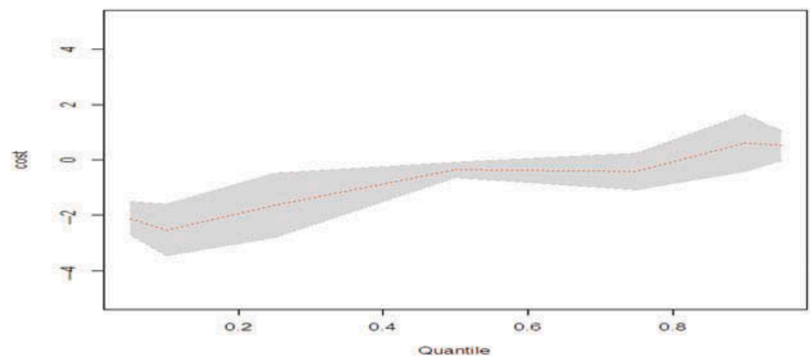
Table 6. The results of quantile regression with fixed ω and different λ

	Quantiles						
	0.05	0.10	0.25	0.50	0.75	0.90	0.95
$\lambda = 0.3$							
Intercept	−0.826***	−0.611***	−0.361***	−0.100***	0.030	0.095*	0.161
CSD	−2.320***	−2.627***	−1.843**	−0.407	−0.576	0.409	0.375
DSD	13.146***	10.495***	7.390**	4.135	6.348	8.966*	7.933
$\lambda = 0.5$							
Intercept	−0.834***	−0.623***	−0.347***	−0.083***	0.068*	0.114**	0.212
CSD	−2.252***	−2.554***	−1.756**	−0.379	−0.406	0.495	0.444
DSD	12.290***	9.691***	6.257**	3.319	2.907	7.463*	5.927
$\lambda = 0.7$							
Intercept	−0.747***	−0.595***	−0.326***	−0.066***	0.075**	0.149***	0.320*
CSD	−2.302***	−2.519***	−1.642***	−0.360*	−0.321	0.606	0.517
DSD	9.931**	8.061**	4.708**	2.653	1.541	5.286	2.602
$\lambda = 0.9$							
Intercept	−0.875***	−0.580***	−0.326***	−0.066***	0.088***	0.149***	0.320**
CSD	−2.118***	−2.534***	−1.642***	−0.360	−0.419	0.606	0.517
DSD	11.511***	7.746***	4.708***	2.653*	2.574	5.286	2.602
$\lambda = 1.0$							
Intercept	−0.875***	−0.580***	−0.326***	−0.066**	0.088***	0.149**	0.320**
CSD	−2.118**	−2.534***	−1.642**	−0.360	−0.419	0.606	0.517
DSD	11.511***	7.746***	4.708**	2.653*	2.574	5.286	2.602

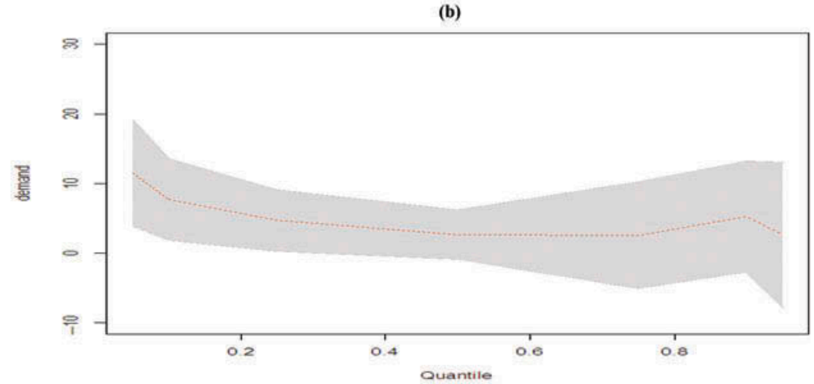
Notes: $\boldsymbol{\omega}$ = (1/7, 1/7, 1/7, 1/7, 1/7, 1/7, 1/7). Cost-side and demand-side dependence are abbreviated as CSD and DSD, respectively. ***, ** and * denote the statistical significance at 1%, 5% and 10% levels, respectively.



(a)



(b)



(c)

Fig. 2. Quantile regression with sensitivity as dependent variable (vertical axes show coefficient estimates of named explanatory variable over the sensitivity distribution; horizontal axes depict the quantiles of the dependent variable). (a) Intercept, (b) cost-side dependence and (c) demand-side dependence. Quantile regression error bars correspond to bootstrapped 95% confidence intervals (200 bootstrap replications).

estimated parameters reveal considerable variation in size, significance and even sign. The sensitivity depends on both cost- and demand-side dependence, from $\tau = 0.05$ to $\tau = 0.25$. In the lower quantiles, the sensitivity is negative, indicating that crude oil price changes and industrial stock market returns are negatively correlated. The sensitivity related to cost-side dependence is rational because oil may be an industry input. However, the finding that demand-side dependence has a greater influence than cost-side dependence is abnormal. A possible explanation is that the customer industries are oil-intensive and play a more important role in explaining the industry's sensitivity to oil prices. Furthermore, because the estimated parameters of cost-side dependence are negative, we can conclude that for industries which are negatively affected by oil price changes, the enhanced cost-side dependence on oil can increase the correlation intensity, and vice versa. Considering the positive parameters of demand-side dependence, these industries lose intensity when demand-side dependence increases. For instance, when $\tau = 0.05$, a growth rate of 1% in cost-side dependence produces about a 0.02% increase in the magnitude of the sensitivity. A growth rate of 1% in demand-side dependence produces about a 0.13% decrease in the magnitude of the sensitivity.

The impact of the cost-side (demand-side) dependence is negative (positive) and significant but only for the lower quantiles ($\tau = 0.05, 0.10, 0.25$). However, we observe no significant effects for the intermediate ($\tau = 0.50$) and upper quantiles ($\tau = 0.75, 0.90, 0.95$). When $\tau = 0.50$, meaning that sensitivity is negligible, both cost- and demand-side dependence have no obvious effect on sensitivity. This phenomenon is likely responsible for the minimal impact of oil price changes on the industry stock market. Additionally, when sensitivity is unusually high (i.e. $\tau = 0.95$), we cannot determine the causes. This may because the factors contributing to high sensitivity are complicated, preventing the ability to attribute just the two driving factors mentioned in our study. Generally speaking, extreme sensitivity is most likely due to some extreme news event.

We can easily observe how a penalized quantile regression method can naturally relate the two driving factors to industrial sensitivity in different quantiles of the sensitivity distribution from Fig. 2. In Fig. 2(a), we plot the bootstrapped intercept for the whole sensitivity distribution. The intercept is close to 0.5 in the upper part of the sensitivity distribution, while it is much lower in the lower parts. From Fig. 2(b) and (c), we find coefficient estimates over the conditional sensitivity distribution for cost- and demand-side dependence. For the lower quantiles, cost-side dependence has a significantly negative association with sensitivity (i.e. if the cost-side dependence increases, a decreasing sensitivity seems to follow). This is then reversed for the upper quantiles, where the coefficient estimate turns positive but not significant. Demand-side dependence is associated with sensitivity more strongly observed in the lower quantiles. The association is still positive for the upper quantiles, although its magnitude is diminished. Additionally, demand-side dependence has a far greater impact on sensitivity. When $\tau = 0.05$, for instance, cost-side dependence has a negative influence and the demand-side dependence has a positive influence with a greater power. Additionally, without involving the sign, both η_1 and η_2 roughly decrease at first, but turn to increase after reaching a minimum at $\tau = 0.50$. In other words, with industries becoming less sensitive to oil prices, the effects of cost- and demand-side dependence are waning.

Considering the values of λ and ω may influence the results, we choose different values to check the robustness (see Tables 6 and 7). From the two tables, estimations and confidence levels are inconsistent.

Table 7. The results of quantile regression with fixed λ and different ω

	Quantiles						
	0.05	0.10	0.25	0.50	0.75	0.90	0.95
$\boldsymbol{\omega}$ = (0.05, 0.10, 0.10, 0.50, 0.10, 0.10, 0.05)							
Intercept	−0.925***	−0.580***	−0.326***	−0.081***	0.089**	0.149**	0.320*
CSD	−2.046***	−2.534***	−1.642**	−0.349	−0.346	0.606	0.517
DSD	12.132***	7.746***	4.708**	2.828	1.500	5.286	2.602
$\boldsymbol{\omega}$ = (0.10, 0.10, 0.10, 0.40, 0.10, 0.10, 0.10)							
Intercept	−0.923***	−0.580***	−0.326***	−0.079***	0.089**	0.149***	0.320**
CSD	−2.049***	−2.534***	−1.642*	−0.351	−0.349	0.606	0.517
DSD	12.105***	7.746**	4.708*	2.803	1.547	5.286	2.602
$\boldsymbol{\omega}$ = (0.05, 0.15, 0.15, 0.30, 0.15, 0.15, 0.05)							
Intercept	−0.923***	−0.580***	−0.326***	−0.079***	0.090***	0.149***	0.320**
CSD	−2.049***	−2.534***	−1.642**	−0.353	−0.336	0.606	0.517
DSD	12.107***	7.746**	4.708**	2.836*	1.360	5.286	2.602
$\boldsymbol{\omega}$ = (0.05, 0.15, 0.20, 0.20, 0.20, 0.15, 0.05)							
Intercept	−0.909***	−0.580***	−0.325***	−0.066***	0.085**	0.149**	0.320*
CSD	−2.069***	−2.534***	−1.642*	−0.360	−0.332	0.606	0.517
DSD	11.930***	7.746**	4.705**	2.653	1.417	5.286	2.602

Notes: $\lambda = 1$. ***, ** and * denote the statistical significance at 1%, 5% and 10% levels, respectively.

For instance, estimations for cost-side dependence vary from −2.320 to −2.046 with 1% confidence level when $\tau = 0.05$. Additionally, a significant influence of cost- or demand-side dependence on the industry stock market appears in the upper quantiles. For example, under the condition of $\lambda = 0.3$ and $\omega = (1/7, 1/7, 1/7, 1/7, 1/7, 1/7, 1/7)$, when $\tau = 0.90$ the estimation of demand-side dependence is significant with 10% confidence level. However, the differences are too small to affect the results.

Overall, our results imply that these factors differently affect industry sensitivities to oil price changes throughout the entire conditional distribution. This finding indicates that the impacts of cost- and demand-side dependence on sensitivities are heterogeneous across industries. These findings support Gogineni's (2010) evaluation of the US. Gogineni (2010) documents that for industries that are negatively (positively) correlated with crude oil price changes, the magnitude of sensitivities depends mostly on cost-side (demand-side) dependence. This argument is theoretically rational, as oil-sensitive industries need to use massive oil. Therefore, rises in oil prices increase costs and reduce returns. Conversely, non-oil-sensitive industries reflect a correlation of oil and stock mostly through the demand-side dependence channel. However, our findings indicate that industries whose stock market returns are negatively correlated with oil price changes (i.e. in the low quantiles) suffer impacts from both aspects. Conversely, industries whose stock market returns are not positively correlated with oil price changes (i.e. in the intermediate and upper quantiles), do not depend on either factor. This result is consistent with Elyasiani *et al.* (2011) who argue that oil-using industries are more likely to be influenced by oil shocks. This is likely due to the development of financial markets and differing institutional innovation in China and the US. Specifically, oil price movements are regulated in China. Although China relies heavily on the imported oil, domestic oil prices are manipulated. Industries can do little thing to improve the cost caused by the input of oil, so the cost-side dependence has a relatively small impact.

A better understanding of how oil impacts sensitivities can augment financial investment decisions. Therefore, it is essential to recognize the effects of these factors in explaining industrial sensitivities to oil price changes. For example, TSPCI sensitivities correspond to the low quantiles because the returns are negatively correlated with oil price changes. Thus, to increase profit, one way is to improve energy efficient by reducing cost-side dependence. Besides, industry decision-makers can also diversify the target customers to include industries that depend on oil through both the cost- and demand-side. Such diversity can help firms hedge risk and shield against potential losses caused by the shocks in oil market.

V. Conclusion

A significant body of empirical literature has been devoted to the relationship between oil and stock. In this article we combine structural breaks and asymmetric effects to investigate the relationship between real crude oil price changes and the Chinese real stock market at the industry level. Our results show that sensitivity changes over time and by industry. Industry sensitivity may be positive, negative, unaffected or even change among these. This finding may be due to breaks having a large impact on industries. Additionally, internal adverse effects of more granular industries combined into one group may contribute to these findings. Furthermore, Chinese stock markets are irrational, leading to fluctuations in stock markets that may not accurately reflect oil price changes. Because effects of oil prices are asymmetric, decision-makers should respond differently.

Furthermore, we further explore reasons for the sensitivity. This article is one of the first to delve into potential driving factors using penalized quantile regression. The results show that both cost- and demand-side dependence affect sensitivity in the lower, but not upper, quantiles. This phenomenon may be caused by China's unique national conditions. Industries positively correlated with oil price changes are always state-owned and monopolistic. Because these industries rely on the nation, people may be blindly optimistic about their profitability. Stocks in these industries are affected by multiple factors, preventing the ability to divide driving factors into cost- and demand-side dependence.

Our findings have several important implications. Firstly, because financial integration between countries and markets has increased, consideration of shocks in the oil market can provide broader perspective for decision-making processes. Investors taking these shocks into account are more likely to hedge against oil price risks and maximize profit when structuring their portfolios and diversification strategies. This can also help policy-makers minimize stock market fluctuations when forming economic policy based on the effect of oil changes. Secondly, the finding that asymmetric effects caused by oil fluctuations can help investors and policy-makers respond to changes in the oil markets. Finally, the results of driving factors part indicate that it is possible to obtain profit by undertaking appropriate investment actions. When oil prices increase, investors should buy the stock of industries that are affected by oil through the demand channel. Decision-makers can mitigate risk caused by oil price changes through developing a much wider variety of customers from several industries with different channels affected by oil.

There are several possible directions for future research. For instance, a much narrower classification of industries may result in a more comprehensive understanding of the impact of real oil price changes on individual industries. Additional factors, such as housing prices, should also be considered. Our methodology could also be revamped in a way that improves estimation accuracy of short panel data.

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