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Stock price synchronicity to oil shocks across quantiles: Evidence from Chinese oil firms

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ABSTRACT

This paper investigates behaviour of stock price synchronicity to oil shocks across quantiles for Chinese oil firms. The spillover effects of the oil market on a firm are segregated into firm-specific and market-wide information. First, our results report a higher level of synchronicity by dynamic conditional correlations than by R-square since the former better captures dynamic linear dependence. Second, we find strong evidence of size effect. In particular, stock price synchronicity is generally higher in large-cap firms than in small-cap ones. Oil shocks affect synchronicity in the upper quantiles differently based on firm size. Third, we also find that synchronicity responds to oil shocks significantly in extreme low quantiles, implying that shocks in the oil market are transmitted to Chinese oil firms via firm-specific information. Finally, we determine that oil shocks have little or no immediate impact on stock price synchronicity; instead, cumulative lagged effect is evident. This evidence highlights the lagging effect of spillover of oil shocks on Chinese oil firms.

1. Introduction

A considerable volume of work has shown that oil prices play an important role in explaining stock price movement (see, for example, Jones and Kaul, 1996; Kilian and Park, 2009; Aloui et al., 2012; Basher et al., 2012; Kang et al., 2015). A common feature of the empirical evidence on the response of stock markets to oil shocks is that they focus on the aggregate market and its industry perspective. For instance, Arouri (2011) investigates the responses of European sector stock markets to oil price changes. Moya-Martínez et al. (2014) examines the sensitivity of the Spanish stock markets at the industry level to movements in oil prices. Martín-Barragán et al. (2013) investigates the impact of oil shocks and stock market crashes on correlations between oil and stock markets of Germany, Japan, UK and US. In other words, these studies take a macro perspective in analysing the role of oil price in determining stock returns. However, there is little analysis of this linkage at the micro-level, especially for Chinese stock market, and our focus is to investigate the spillover from the oil market to individual firms.

Theoretically, the value of a firm is the present value of future cash flow, that is, the stock price of individual firms reflects both firm-specific information (such as, future cash flow) and market-wide information (such as, discount rate) in accordance with Chan and Hameed (2006), Xing and Anderson (2011) and Boubaker et al. (2014). Oil shocks can affect the stock price of a firm by influencing firm-specific information or market-wide information. For example, rising oil prices negatively (positively) affect the future cash flows of an oil-consuming (-producing) firm that reflects the significant reaction of firm-specific information to oil shocks. In addition, rising oil prices also increase interest rates in the economy by inflation and monetary policy. This reflects market-wide information. Unlike the firm-specific information, the change of market-wide information may result in a stock price change in the overall stock market. This raises an interesting and meaningful question for a firm: How do we know which of the two information flows responds significantly to oil shocks? This paper seeks to answer the question by examining the impact of oil shocks on stock price synchronicity across extreme quantiles.

Stock price synchronicity is a measurement of how individual stock prices co-move with the market, and it reflects the proportion of systematic volatility relative to the total volatility or idiosyncratic volatility. In line with prior literature, such as Morck et al. (2000), Chan and Hameed (2006) and Douch et al. (2015), a relatively lower level of stock price synchronicity indicates that the stock price variation is more likely to be caused by firm-specific information, while a relatively higher level indicates that market-wide information plays a leading role, i.e., the stock prices of an individual firm follows changes in the market. Intuitively, the foregoing characteristics of stock price synchronicity provide a practical approach for the identification

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problem, and this motivates us to explore the impact of oil shocks on stock price synchronicity in the quantile-regression framework. In particular, oil shocks are regressed against synchronicities of a firm across tail-quantiles. The significant coefficients in lower quantiles imply that firm-specific factors change with oil shocks, so that spillover effects of oil shocks are firm-specific information. Those of upper quantiles indicate that oil shocks drive the changes of stock prices via market-wide factors, thus the spillover effects of oil shocks are market-wide information.

The primary purpose of this research is to extract information intertwined in oil and stock markets. It will not focus on the relationship between oil and stock returns, but will analyse the impact of oil shocks on stock price synchronicity of a firm to extract useful information and determine features that detect whether spillover effects from the oil market to the stock market are firm-specific or market-wide information for an individual firm.

The study contributes to the literature on this topic in three ways. First, this is the first study to determine whether oil shocks affect stock prices by the influence of firm-specified or market-wide information. Second, we show that the dynamic conditional correlations (DCC) of stock prices between an individual firm and the market are a reasonable substitute for R-square to measure synchronicity. A large (small) absolute value of correlation also means a high (low) level of R-square and synchronicity. In contrast to R-square based synchronicity (Chan and Hameed, 2006; Chan and Chan, 2014; Douch et al., 2015), DCC based measurement is better able to capture the dynamic linear dependence of price variations between an individual firm and the stock market. Third, we analyse impacts of oil price shocks on stock price synchronicity[1] in the short and long run across extreme quantiles where the infinite distributed lag models are expanded into quantile regression. In this way, the impact of oil shocks on stock synchronicity over any time interval can be analysed instead of using averaging data in a series of regression models.

This paper yields some interesting results. Firstly, the stock price synchronicity of the DCC based measurement generally reports a higher level than the R-square based measurement. One possible explanation might be that the latter has poor data fitting to non-normality and heteroscedasticity in financial time series and poor ability to capture dynamic linear dependence. Secondly, stock price synchronicity has significant reaction to oil shocks across the extreme low quantiles that provides strong evidence to support that shocks in the oil market transmitted to Chinese oil firms are firm-specific information. This is consistent with the conclusion that oil shocks have a significant impact on energy-related stock indexes and oil firms (see Cong et al. (2008), Broadstock et al. (2012)). The impacts of oil shock on synchronicity are different based on firm size. The large-cap firms seem to have an insignificant response to oil shocks in the upper quantiles, however, the response of small-cap firms is significant. One possible explanation is that large-cap firms pay lower interest rates and are able to maximize advantages from early payment discounts on trade credit (see Vickery (2008), Narayan and Sharma (2011)). Therefore, shocks in the oil market have limited impact on market-wide factors of large-cap firms. Thirdly, oil shocks have no immediate effect on stock price synchronicity for Chinese oil firms. However, long-run effects are evident. Chen and Lv (2015) noted that Chinese refined oil price reflects only extreme changes in the world crude oil price. Because of the special oil price adjustment mechanism, domestic oil price variations will lag behind changes in international crude oil prices. Another reason may be the proposed under reaction hypothesis (see, for example, Narayan and Sharma, 2011). Short-horizon stock market investors underreact to information while long horizon investors overreact to information, i.e., investors do not respond strongly enough to new information. A strong reaction takes time; hence, the effect of information is felt after some time. Thus, we conclude that the spillover effect of oil shocks is lagging information for Chinese oil firms.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 describes the data and discusses the method for calculating synchronicity. Section 4 introduces the econometric methodology. Section 5 shows the empirical results. Section 6 concludes the paper.

2. Literature review

Given the crucial role of crude oil in the world economy, there is a growing body of research to explore the behaviour of stock price in response to oil shocks. Theoretically, oil shocks can affect stock returns via different channels. For example, Jones and Kaul (1996), based on a standard cash flows/dividends valuation model, found that the oil price shock had a decisive effect on the real stock returns in US, Canada, Japan and England. Huang et al. (1996) noted that oil prices were able to affect specific stock prices by changing future cash flows or discount factors, where the discount factor was composed of the expected inflation rate and the expected interest rate. Narayan and Sharma (2011) adduced the strong evidence of the effects of size on oil price affecting firm returns. In spite of these listed and unlisted paths, we simply classify them as the “firm-specific factors” and “market-wide factors” in accordance with the literature of Morck et al. (2000) and Chan et al. (2013). Our focus is to analyse the quantile behaviour of stock price synchronicity in response to oil shocks. In this way, we will distinguish oil shocks as firm-specific or market-wide information for individual firms.

Studies concerning stock price synchronicity have received increasing attention recently. For instance, Chan and Hameed (2006) examine the relation between the stock price synchronicity and analyst activity in emerging markets. Gul et al. (2010) use Chinese listed firms to analyse the impacts of largest-shareholder ownership concentration, foreign ownership, and audit quality on the amount of firm-specific information incorporated into share prices. Xing and Anderson (2011) research the linkage between stock price synchronicity and public firm-specific information in the United States. Zhang et al. (2016) investigate the ability of R-square and idiosyncratic volatility to capture firm-specific return variation. Feng et al. (2016) investigate the effect of ownership structure and analyst coverage on stock price synchronicity in China. Some other research includes the literature of Chung et al. (2011), Chan et al. (2013), An and Zhang (2013), Devos et al. (2015), Douch et al. (2015), and so on. Differing from their focus on firm characteristics, we investigate the reaction of synchronicity to oil shocks, i.e., cross-market information. More specifically, we propose the following three hypotheses that have not been previously tested:

Hypothesis 1. That oil shocks affect stock price synchronicity differently across the extreme quantiles.[2]

Hypothesis 2. That oil shocks affect stock price synchronicity differently based on firm size.

Hypothesis 3. That there is a lagged effect of oil shocks on stock price synchronicity.

The motivation for testing the above hypotheses comes from discussions concerning the linkages between oil prices and the stock market, such as, the studies about quantile behaviour in Sim and Zhou (2015) and Zhu et al. (2016); the issues related to firm size in Vickery (2008) and Narayan and Sharma (2011); and the question of the lagged effect in Jones and Kaul (1996) and Chang and Yu (2013). Our paper, following this research, tests these hypotheses for Chinese oil firms.

[1] There is a fairly sizable quantity of literature investigating the short- and long-run effects of oil price movements on stock prices. See Apergis and Miller (2009) and Ghosh and Kanjilal (2016) as a simple example.

[2] In fact, the tested procedure for this hypothesis is shown in the following two hypotheses.

Table 1
Details of the sample firms.

Stocks	Abb.	Industry	Listing Date
(a) Shenzhen stock exchange			
Shenzhen Guangju Energy Co.Ltd	GJNY	Wholesale of Energy Products	2000-07-24
Sinopec Shandong Taishan Petroleum Co.Ltd	TSSY	Wholesale of Energy Products	1993-12-15
Maoming Petro-Chemical Shihua Co.Ltd	MHSH	Petroleum Processing and Coking Products	1996-11-14
Yueyang Xingchang Petro-Chemical Co.Ltd	YYXC	Petroleum Processing and Coking Products	1997-06-25
(b) Shanghai stock exchange			
Sinopec Group	ZGSH	Petroleum and Natural Gas Extraction	2001-08-08
Wintime Energy Co.Ltd	YTNY	Comprehensive	1998-05-13
Sinopec Shanghai Petro-Chemical Co.Ltd	SSSH	Petroleum Processing and Coking Products	1993-11-08
PetroChina Co.Ltd	ZGSY	Petroleum and Natural Gas Extraction	2007-11-05

Notes: GJNY, ZGSH and ZGSY represent large-capitalization firms; the market capitalization of ZGSH and ZGSY is much larger than GJNY.

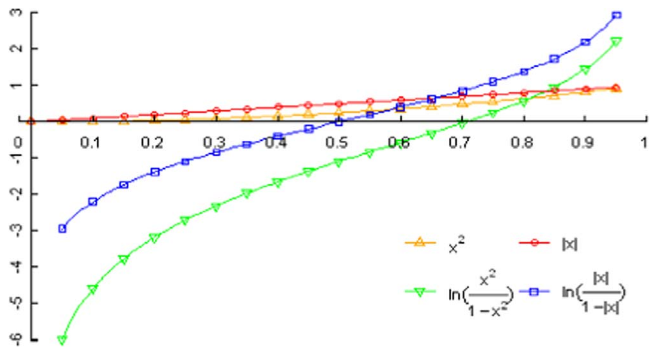

Fig. 1. Comparison of functions used to calculate DCC-based stock price synchronicity. Notes: 1) The part of negative definition domain was not plotted because these functions are even functions. 2) The line of x^2 represents the approach proposed by Bozos et al. (2013). 3) The line of $\ln\left(\frac{|x|}{1-|x|}\right)$ was adopted in this paper, and detailed reasons are listed in the text.

3. Data and stock price synchronicity

3.1. Data

This paper investigates the impact of oil shocks on stock price synchronicity in the extreme lower and upper quantiles. Cong et al. (2008) establish that the real stock return of most Chinese stock market indices is statistically insignificant to oil price movement except for the manufacturing index and some oil firms. Therefore, the time-series data we adopt consists of eight stocks of petroleum firms in China. Table 1 gives the details. The source of stock prices of individual firms is from CSMAR Solution (www.gtarsc.com), and the Shanghai and Shenzhen composite index. The oil prices of West Texas Intermediate (WTI) are obtained from EIA (www.eia.gov).

For each data series, continuously compounded weekly returns used in this paper are calculated $r_{i,t} = 100 \times (\ln(p_{i,t}) - \ln(p_{i,t-1}))$, where $p_{i,t}$ and $p_{i,t-1}$ represent Wednesday closing prices of two adjacent weeks, and the last available closing value is used if the market was closed for trading on Wednesday. In addition, we will drop the first-month data of individual firms after listing on the stock exchange. Key summary statistics of the return data are collected in Table 2. The return series behave similarly to what we usually observe in the literature: they are far from normally distributed and exhibit excess kurtosis and volatility clustering. Evidence from ARCH(10) LM tests suggests the utilization of ARCH- or GARCH-type models to capture the time-variation volatility characteristics.

3.2. Stock price synchronicity

Our measure of stock price synchronicity is based on the literature of Bozos et al. (2013), where the dynamic bi-variant EGARCH model is used to estimate the time-varying synchronicities. This measurement shows us the detailed time-series behaviour of synchronicity in comparison to the R-square based measurement in Morck et al. (2000), Chan and Hameed (2006) and Douch et al. (2015). The basis for measuring synchronicity in Bozos et al. (2013) is, essentially, the time-varying correlations, thus, an obvious alternative approach is to conduct the DCC model.

According to Engle (2002), the bi-variate DCC model is formulated as:

$$r_t = \mu + \phi' r_{t-1} + \varepsilon_t,\ \varepsilon_t = H_t^{1/2} z_t, \tag{1}$$

$$D_t^2 = \mathrm{diag}\{\omega_i, \omega_{market}\} + \mathrm{diag}\{\alpha_i, \alpha_{market}\} \circ \varepsilon_{t-1}\varepsilon_{t-1}' + \mathrm{diag}\{\beta_i, \beta_{market}\} \circ D_{t-1}^2, \tag{2}$$

$$Q_t = (1 - \theta_1 - \theta_2)\overline{Q} + \theta_1 z_{t-1} z_{t-1}' + \theta_2 Q_{t-1}, \tag{3}$$

$$P_t = \mathrm{diag}\{q_{i,t}^{-1/2}, q_{market,t}^{-1/2}\}\ Q_t\ \mathrm{diag}\{q_{i,t}^{-1/2}, q_{market,t}^{-1/2}\}, \tag{4}$$

where r_t is a two-dimensional vector of the weekly returns of an individual stock ($r_{i,t}$) and market ($r_{m,t}$), z_t is the standardized innovation, $D_t = \mathrm{diag}\{hi, t^{1/2}, h_{market,t}^{1/2}\}$ is a diagonal matrix with time-varying standard deviations, and the degree of persistence is measured by β for

Table 2
Summary statistics for weekly returns.

	GJNY	TSSY	MHSH	YYXC	ZGSH	YTNY	SSSH	ZGSY
Mean	0.051	0.015	-0.122	0.014	0.032	-0.202	0.021	-0.333
Std.dev	7.189	8.013	6.968	7.784	5.250	9.376	7.051	4.194
Coef.var	141.731	551.913	-57.113	556.710	162.851	-46.509	330.623	-12.595
Median	0.035	0.000	-0.150	-0.105	-0.145	0.103	-0.278	-0.377
Skew	-0.262	-1.710	-2.122	-1.591	-0.643	-1.600	-0.445	-0.235
Kurtosis	8.227	13.982	17.615	14.765	6.114	13.350	14.605	5.308
Min	-46.674	-73.778	-69.699	-75.451	-36.030	-70.092	-59.215	-22.919
Max	39.392	41.215	23.230	27.576	27.892	49.235	51.083	19.206
JB test	2111.06***	9174.27***	12593.05***	8391.44***	1130.14***	6233.43***	9472026***	475.98***
ARCH(10)	106.030***	19.871**	29.510***	116.920***	19.409**	21.996**	59.265***	48.856***
Nobs	740	1058	916	878	689	789	1057	396

Notes: 1) Nobs is the numbers of observations. Coef.var is the abbreviation of coefficient of variation. JB test is the Jarque-Bera test for normality. 2) The methodology to test for ARCH effects is based on the Lagrange multiplier test with the null of no ARCH effects. 3) Summary statistics for the returns of Shanghai composite index and Shenzhen composite index are not reported because of the different samples used for individual firms, and the authors will provide the data if needed. 4) **, *** represent statistical significant at the 5% and 1% levels, respectively.

Table 3
Model selection of the DCC model by BIC.

		GJNY	TSSY	MHSH	YYYX	ZGSY	YTNY	SSSH	ZGSY
DCC-GARCH									
AR(0)	MVN	11.649	14.080	12.022	12.168	10.806	12.816	11.633	9.908
	MVT	11.165	11.817	11.440	11.654	10.536	11.722	11.267	9.642***
AR(1)	MVN	11.661	12.485	12.040	12.183	10.821	12.808	11.654	9.932
	MVT	11.179	11.836	11.457	11.670	10.547	11.745	11.285	9.662
DCC-EGARCH									
AR(0)	MVN	11.701	12.455	12.031	12.115	10.760	12.614	11.595	9.958
	MVT	11.172	11.744***	11.379***	11.654	10.506***	11.685***	11.254***	9.680
AR(1)	MVN	11.708	12.470	12.080	12.132	10.777	12.862	11.616	9.976
	MVT	11.185	11.765	11.396	11.672	10.519	11.707	11.272	9.696
ADCC-GJR-GARCH									
AR(0)	MVN	11.654	14.047	11.893	12.139	10.790	12.768	11.623	9.959
	MVT	11.156***	11.761	11.409	11.642***	10.532	11.738	11.266	9.687
AR(1)	MVN	11.667	14.130	11.908	12.155	10.806	12.772	11.644	9.982
	MVT	11.172	11.785	11.426	11.662	10.535	11.762	11.285	9.706

Notes: *** represents the suggested model. Actually the same models can be selected by AIC, Shibata, H-Q and log-likelihood.

Table 4
DCC and ADCC model specification and parameter estimation.

Parameters	GJNY	TSSY	MHSH	YYXC	ZGSH	YTNY	SSSH	ZGSY
μ_i	0.006	0.207	-0.124*	0.027	0.051	-0.055	-0.137	-0.222**
	(0.176)	(0.241)	(0.070)	(0.178)	(0.132)	(0.196)	(0.149)	(0.108)
ω_i	1.040	0.075***	0.017***	2.695**	0.042***	0.119***	0.316	0.487
	(0.992)	(0.007)	(0.004)	(1.090)	(0.005)	(0.015)	(0.551)	(0.337)
α_i	0.101**	0.189***	0.148***	0.223***	0.136***	0.179**	0.292	0.243**
	(0.043)	(0.014)	(0.021)	(0.069)	(0.007)	(0.073)	(0.213)	(0.120)
β_i	0.903***	0.979***	0.994***	0.810***	0.986***	0.969***	0.912***	0.756***
	(0.051)	(0.001)	(0.000)	(0.058)	(0.000)	(0.004)	(0.152)	(0.103)
γ_i	-0.040	0.070***	0.043**	-0.141***	0.067***	0.074***	0.060*	
	(0.033)	(0.018)	(0.018)	(0.053)	(0.020)	(0.025)	(0.036)	
μ_{maket}	0.185	0.134	0.249**	0.151	0.047	0.015	0.067	0.043
	(0.141)	(0.119)	(0.124)	(0.124)	(0.124)	(0.116)	(0.115)	(0.167)
ω_{maket}	0.818	0.139***	0.173	1.056***	0.075***	0.129***	0.105***	0.658
	(0.507)	(0.010)	(0.169)	(0.405)	(0.010)	(0.010)	(0.009)	(0.426)
α_{market}	0.142***	0.273***	0.307***	0.109***	0.240***	0.186***	0.279***	0.158***
	(0.045)	(0.031)	(0.081)	(0.035)	(0.021)	(0.023)	(0.014)	(0.056)
β_{market}	0.856***	0.955***	0.943***	0.827***	0.971***	0.951***	0.964***	0.840***
	(0.056)	(0.002)	(0.056)	(0.046)	(0.002)	(0.003)	(0.001)	(0.058)
γ_{market}	0.002	-0.019	-0.010	0.053	0.010	-0.024	0.011	
	(0.048)	(0.021)	(0.028)	(0.045)	(0.019)	(0.022)	(0.019)	
θ_1	0.000	0.106***	0.036***	0.003	0.068*	0.071***	0.075*	0.019
	(0.007)	(0.038)	(0.008)	(0.004)	(0.036)	(0.015)	(0.042)	(0.032)
λ	0.949***	0.877***	0.962***	0.871***	0.813***	0.924***	0.883***	0.651***
	(0.080)	(0.046)	(0.009)	(0.059)	(0.163)	(0.017)	(0.075)	(0.184)
θ_3	0.090			0.136**				
	(0.127)			(0.058)				
λ	4.000***	4.000***	4.000***	4.534***	5.631***	4.000***	4.001***	4.000***
	(0.227)	(0.211)	(0.200)	(0.268)	(0.586)	(0.251)	(0.139)	(0.195)

Notes: 1) The stability condition $\alpha + \beta + \gamma/2 < 1$ is satisfied for standard G.ARCH model and GJR-GARCH model. Standard errors are in parentheses. 2) *, **, *** represent statistical significant at the 10%, 5% and 1% levels, respectively.

the conditional variance process. $\overline{Q}$ is the unconditional correlation matrix of the z_t, P_t is the dynamic conditional correlation matrix, ° is the Hadamard product of two identically sized matrices. Then, the correlation can be calculated by $\rho_{i,maket,\,t} = q_{i,market,\,t}/\sqrt{q_{i,\,t}q_{market,\,t}}$.

To capture the potentially asymmetric effects of positive and negative shocks on conditional variance, the exponential GARCH

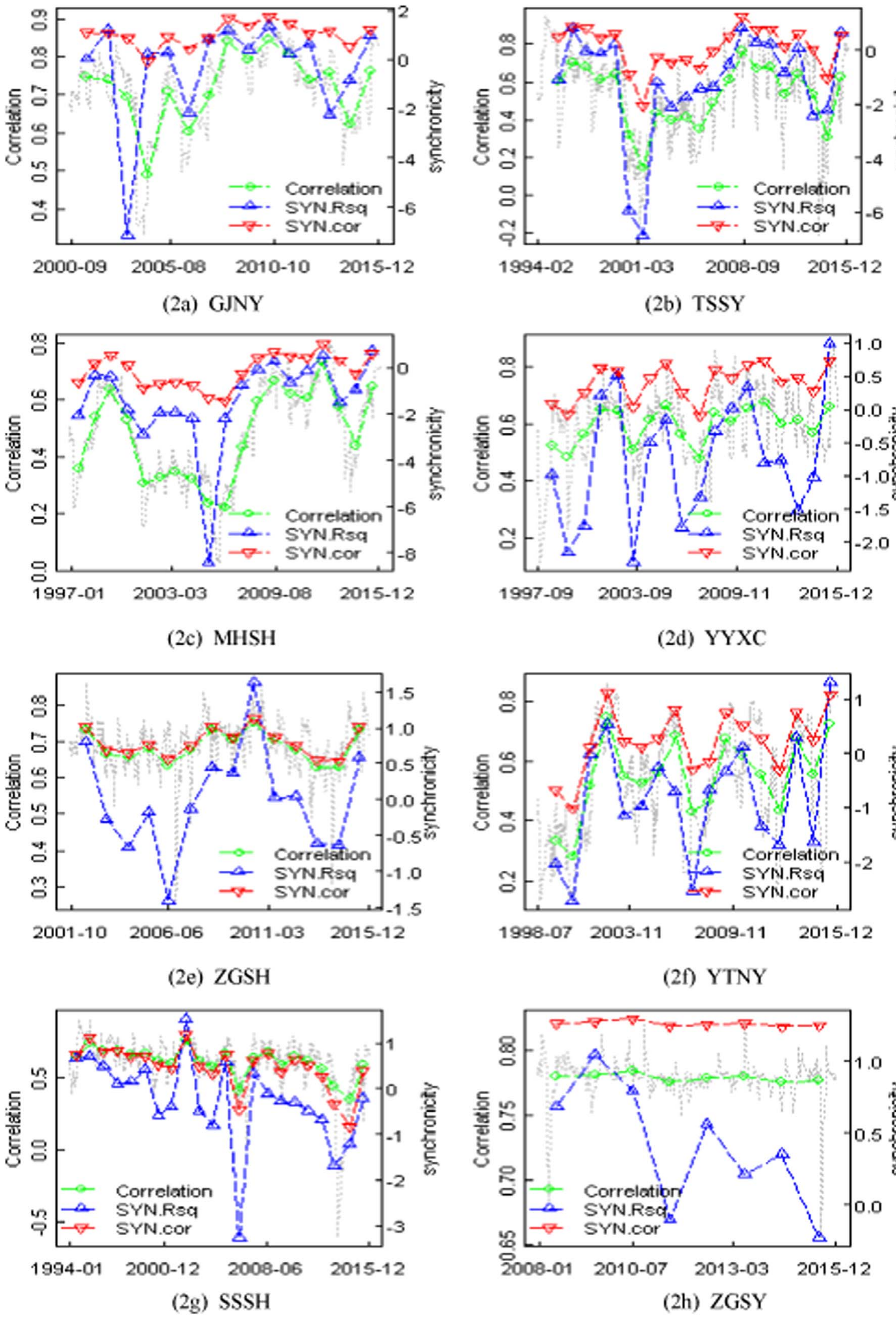

Fig. 2. The time series behaviour of stock price synchronicity (right y-axis) and dynamic conditional correlation (left y-axis). Notes: SYN.Rsq denotes the synchronicity of R-square based measurement, SYN.cor denotes those of DCC-based measurement average every year, Correlation denotes the annual average dynamic condition correlation, and the dynamic condition correlations are also plotted in a grey dotted line.

Table 5
Summary statistic and unit root test for the stock price synchronicity.

	GJNY	TSSY	MHSH	YYXC	ZGSH	YTNY	SSSH	ZGSY
(a) Summary statistic								
Mean	1.016	0.162	-0.097	0.372	0.800	0.182	0.485	1.261
Std.dev	0.550	1.064	0.796	0.549	0.326	0.819	0.685	0.081
Coef.var	0.541	6.566	-8.200	1.479	0.407	4.510	1.413	0.064
Median	1.035	0.275	-0.051	0.441	0.808	0.208	0.558	1.265
Skew	-0.489	-0.855	-0.886	-0.928	-0.871	-0.259	-1.876	-2.256
Kurtosis	0.450	1.425	1.564	2.761	4.425	-0.566	8.637	14.832
Min	-0.712	-4.577	-3.576	-2.046	-1.057	-1.892	-4.795	0.643
Max	2.252	2.862	1.372	1.967	1.832	1.831	2.273	1.543
JB test	35.904***	218.764***	213.418***	405.673***	651.325***	19.049***	3901.839***	3992.487***
Numbers								
Total	735	1052	910	873	685	784	1051	394
$\lvert\rho\rvert \le 0.20$	0	90	38	12	0	32	34	0
$\lvert\rho\rvert \ge 0.80$	179	98	0	19	22	54	43	15
(b) Unit root test								
ADF test								
T+C	-3.099(0)	-4.755(0)***	-2.968(0)	-5.644(0)***	-7.265(0)***	-4.442(0)***	-10.084(0)***	-8.005(0)***
C	-2.9982(0)**	-4.752(0)***	-2.643(0)	-5.308(0)***	-7.270(0)***	-3.970(0)***	-9.714(0)***	-7.957(0)***
N	-1.203(0)	-4.683(0)***	-2.654(0) ***	-4.341(0)***	-2.357(1)**	-3.825(0)***	-6.640(0)***	-0.439(1)
PP test								
T+C	-3.187(4)*	-4.771(1)***	-2.926(9)	-5.644(0)***	-7.156(1)***	-4.492(10)***	-10.338(8)***	-8.159(3)***
C	-3.063(4)**	-4.768(1)***	-2.590(9)*	-5.495(2)***	-7.161(1)***	-3.955(9)***	-9.890(8)***	-8.103(3)***
N	-1.248(0)	-4.697(1)***	-2.602(9)***	-4.437(5)***	-1.903(18)*	-3.798(9)***	-6.764(6)***	-0.274(15)

Notes: 1) "T + C": Unit root regression with an intercept and a time trend, and "C" for a regression with an intercept but no time trend, "N" for a regression with no intercept nor time trend. 2) The summary statistic and unit root test for the returns of WTI is not listed for the same reasons as for stock indexes. However, the returns of WTI used for each variable are stationary. 3) *, **, *** represent statistical significant at the 10%, 5% and 1% levels, respectively.

(EGARCH) model of Nelson (1991) is compared,

$$\ln D_t^2 = \mathrm{diag}\{\omega_i\} + \mathrm{diag}\{\alpha_i(|z_{i,t-1}| - E|z_{i,t-1}|)\} + \mathrm{diag}\{\gamma_i z_{i,t-1}\} + \mathrm{diag}\{\beta_i\} \circ \ln D_{t-1}^2. \tag{5}$$

Cappiello et al. (2006) propose the asymmetric DCC (ADCC) model by combining the DCC model with the GJR-GARCH to reveal asymmetries not only on the conditional variance process but also on the conditional correlation process, the details are as follow.

$$D_t^2 = \mathrm{diag}\{\omega_i\} + (\mathrm{diag}\{\alpha_i\} + \mathrm{diag}\{\gamma_i \cdot I(\varepsilon_{i,t-1} < 0)\}) \circ \varepsilon_{t-1}\varepsilon_{t-1}' + \mathrm{diag}\{\beta_i\} \circ D_{t-1}^2, \tag{6}$$

$$Q_t = (\overline{Q} - A'\overline{Q}A - B'\overline{Q}B - G'\overline{Q}G) + A' z_{t-1}z_{t-1}' A + B' Q_{t-1} B + G' n_{t-1} n_{t-1}' G. \tag{7}$$

where A,B, and G are diagonal parameter matrices and $n_t = I(z_t < 0) \circ z_t$.

Utilizing the estimated dynamic conditional correlations, we define the stock price synchronicity as

$$SYN_{i,t} = \ln(|\rho_{i,t}|/(1 - |\rho_{i,t}|)). \tag{8}$$

It has a similar mathematical formula as the R-square based computation (Morck et al., 2000; Chan and Hameed, 2006; Xing and Anderson, 2011; Nguyen and Truong, 2013). In fact, market participants can rely more on the information observed from the market movement if an individual stock is highly correlated with the market, i.e., a high level of synchronicity. This also reflects the aversion towards investment, since investors generally pay more attention to the extreme cases when the correlation between individual stocks and the market is very higher or low. The curve representing synchronicity is assigned a steeper curve with the larger absolute values at the ends, as shown in Fig. 1. Compared with the prior literature, our measure of stock price synchronicity is appealing for its ability to (i) capture the dynamic linear dependence of price variations between individual firms and the stock market; (ii) model the basic statistical characteristics of stock yields, such as volatility clustering, sharp peaks and fat tail. Thus, the following empirical results will show a higher level of synchronicity than R-square based measurement.

4. Econometric methodology

To discuss the lagged impact of oil shocks on stock price synchronicity across quantiles, we expand the infinite distributed lag (DL) models into the framework of quantile regression. The polynomial inverse lag (PIL) technique of Mitchell and Speaker (1986) is applied to uncover the true lag structure for its flexibility and computational simplicity. Then, we estimate the short- and long-run impacts of this lag structure.

Consider the following distributed lag equation:

$$SYN_t = \mu + \sum_{i=0}^{\infty} w_i \Delta oil_{t-i} + \varepsilon_t, \tag{9}$$

where w_i's are the class of lag structures. Applying the PIL technology, we have $w_i = \sum_{j=2}^{n} \delta_j (i+1)^{-j}$, then the distributed lag model (9) can be written as

$$SYN_t = \mu + \sum_{j=2}^{n} \sum_{i=0}^{t-1} \frac{\delta_j}{(i+1)^j} \Delta oil_{t-i} + \sum_{j=2}^{n} \sum_{i=t}^{\infty} \frac{\delta_j}{(i+1)^j} \Delta oil_{t-i} + \varepsilon_t. \tag{10}$$

In practice, the second summation, called the remainder term, has no available data for computation. Mitchell and Speaker (1986) estimate the regression model by dropping this remainder term as this term is negligible for t greater than about eight, in other words, we wish to estimate

$$SYN_t = \mu + \sum_{j=2}^{n} \delta_j z_{jt} + \varepsilon_t, \tag{11}$$

where $z_{jt} = \sum_{i=0}^{t-1} \Delta oil_{t-i}(i+1)^{-1}$, for $t = 9, \ldots, T$. For a given degree of polynomial n estimates of δ_j's are obtained by the OLS method, then the estimator and confidence interval of lag weights can be derived by the delta method.

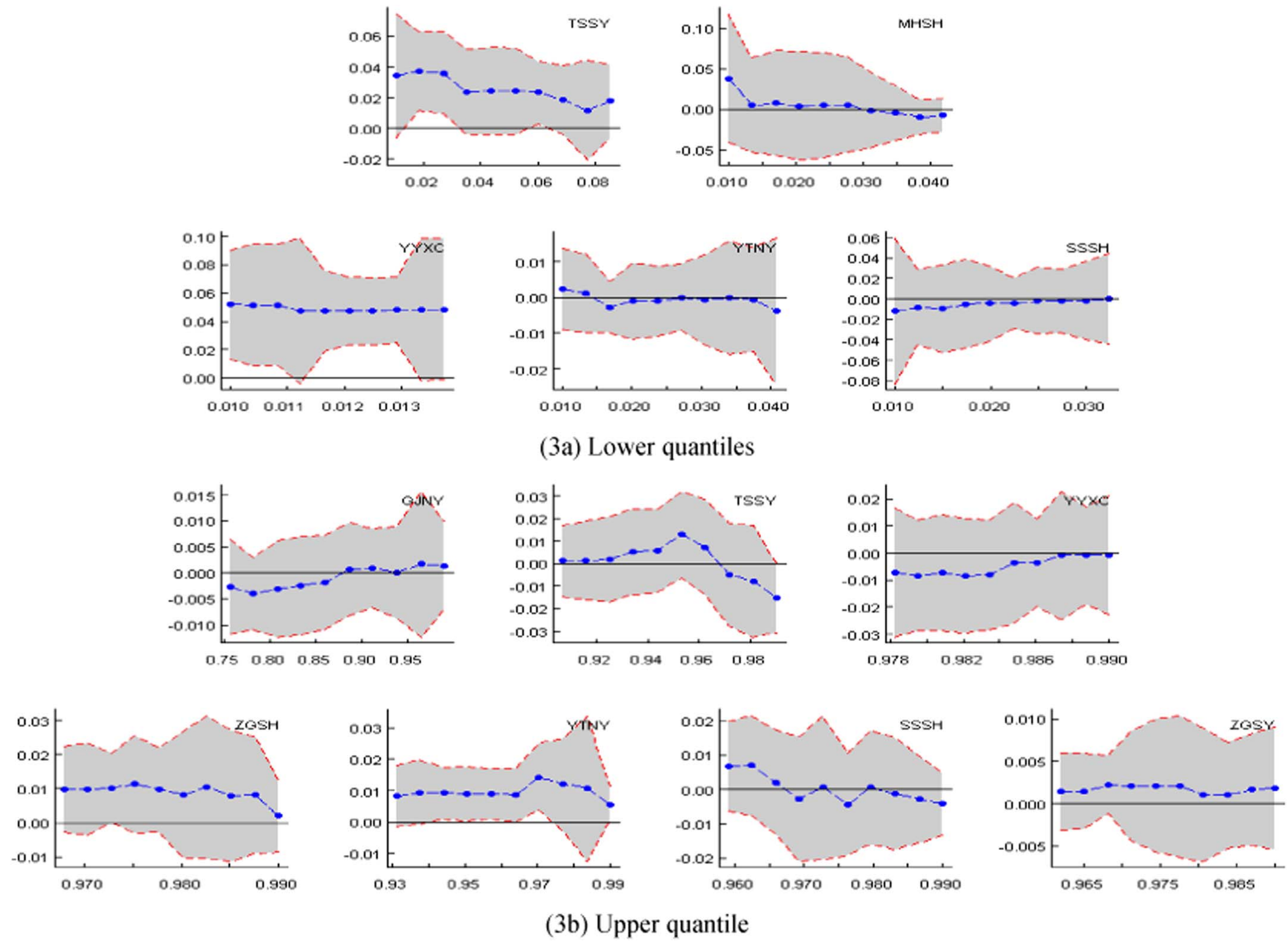

Fig. 3. The short-run impacts of oil price shocks on stock price synchronicity.

We expand the OLS estimation and inference in a more general class of quantile models, where all of the lag weights are allowed to be τ-dependent, and thus they can alter the location, scale and shape of the conditional density. To compare with the foregoing discussion and facilitate later lag structures of quantile frameworks, we make an assumption that the lag structures are invariable across various quantiles, then the lag weight can be written as $w_i(\tau) = \sum_{j=2}^{n} \delta_j(\tau)(i+1)^{-j}$. Solving the following problem

$$\min_{\mu \in R,\, \delta \in R^{n-1}} \sum_{t=9}^{T} \rho_\tau(SYN_t - \mu - z_t'\delta), \tag{12}$$

where $\rho_\tau(u) = u(\tau - I(u<0))$ as in work of Koenker and Bassett (1978), $z_t = (z_{2t}, \ldots, z_{nt})'$ and $\delta = (\delta_2, \ldots, \delta_n)'$ are the $(n-1)$-dimension vectors, we get the estimator $\mu(\tau)$ and $\delta_j(\tau)$'s, then the τ th conditional quantile function of SYN_t, conditional on I_t, can be given by

$$\widehat{Q}_{SYN_t}(\tau \mid I_t) = \mu(\tau) + \sum_{j=2}^{n} \sum_{i=0}^{t-1} \frac{\delta_j(\tau)}{(i+1)^j} \Delta oil_{t-i},$$

where I_t is the σ-field generated by $\{\Delta oil_t, \ldots, \Delta oil_1\}$, and called the PIL-QDL model. Implicit in this perspective is the belief that there is no difference in declining speed of lagged marginal effects for the whole distribution meaning that $\delta_j(\tau)$'s hold all of the inequality over τ. Further, one can obtain the effects of oil price shock on stock price synchronicity over any time interval, such as the short-run impact ($w_0(\tau)$) and the long-run impact ($\sum_i w_i(\tau)$).

5. Empirical results

In our empirical process we conducted an investigation following the steps below. First, we calculate the dynamic conditional correlation (ρ_t) based on the DCC/ADCC models, and then obtain stock price synchronicity (SYN_t). Second, the stationarity of variables is tested with several types of unit-root tests. Third, we get a quick glance of short and long-run effects of oil price shocks on stock price synchronicity by plotting their PIL-QDL estimates and corresponding 95% confidence intervals against the lower and upper quantiles. Of special notice here is the range of lower and upper quantiles, that is, let $N^{lower} = \sum_t I(|\rho_t| \le 0.2)$ and $N^{upper} = \sum_t I(|\rho_t| \ge 0.8)$, the lower and upper quantiles are defined as $T^{\,lower} = [0.01,\ N^{lower}/N^{total}]$ and $T^{\,upper} = [(N^{total} - N^{upper})/N^{total},\ 0.99]$, respectively. Therefore, the implication that low synchronicities reflect firm-specific variations and high synchronicities reflect high return variations caused by market-wide shocks can be guaranteed not only in the relative levels but also in the absolute levels. Fourth, the sup-Wald test is applied in QDL model to examine the existence of short, medium and long-run effects across the lower and upper quantiles. Finally, we show the detailed time-series behaviours of the impacts (over any time interval) of some special quantiles. This paper involve two critical issues: (i) comparison of the DCC-based measurement and R-square-based measurement of stock price synchronicity; (ii) investigation of the short-run and long-run impacts of oil shocks on stock price synchronicity in the extreme lower quantiles and upper quantiles.

Table 3 lists a series of DCC models to calculate the stock price

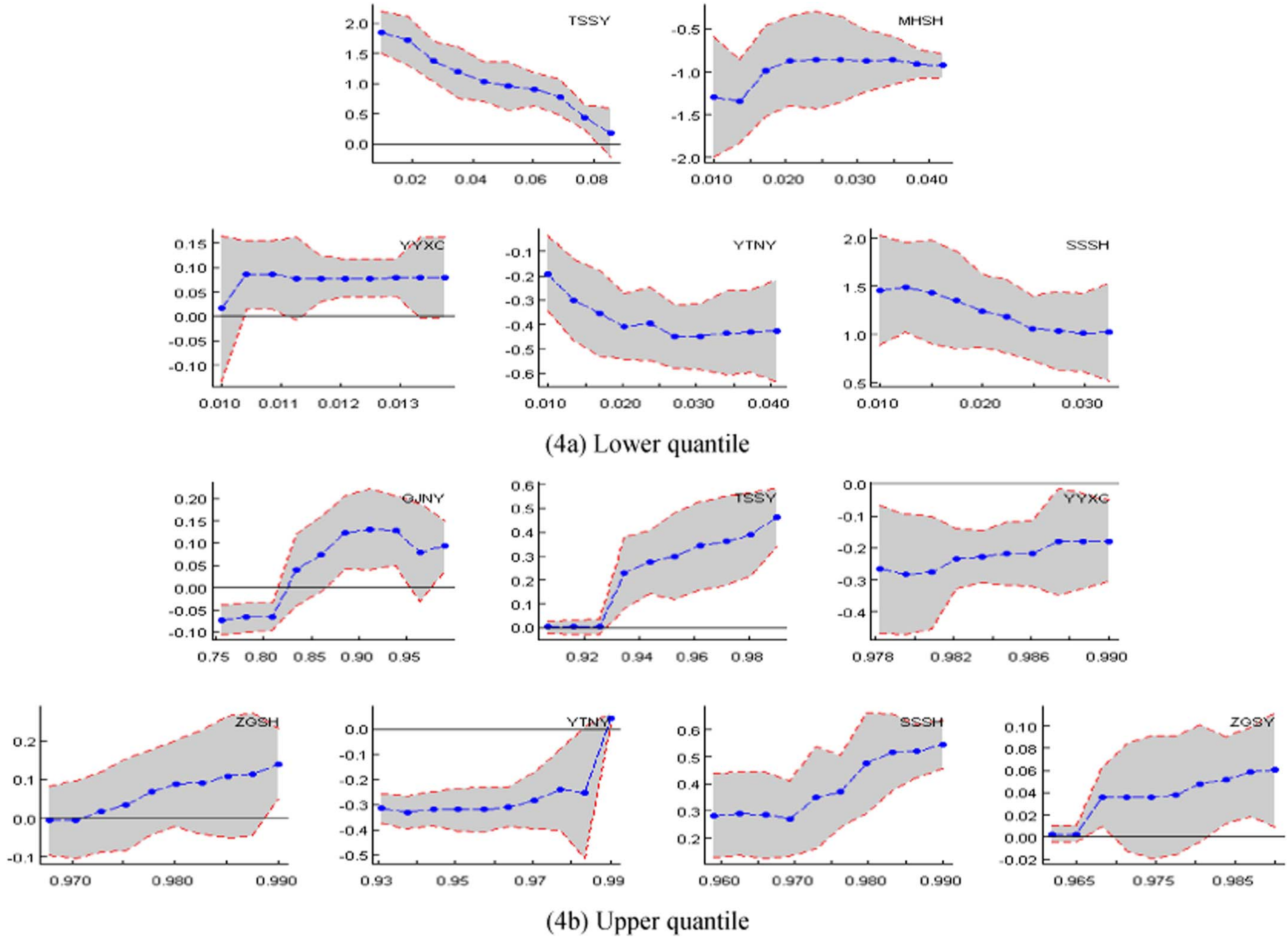

Fig. 4. The long-run impacts of oil price shocks on stock price synchronicity.

synchronicity, and the model selected by BIC. Table 4 presents the DCC and ADCC parameter estimates. Note that the statistical significance of the short- and long-term persistence parameters (α and β) gives support to the conclusion of volatility clustering. One other thing to note is that the significantly positive γ for TSSY, MHSH, ZGSH, YTNY and SSSH implies that good news leads to more volatility than bad news. This counter-intuitive phenomenon contravenes the intention of model specification and reflects the juvenility of the capital market. The short- and long-term persistence parameters of (asymmetric) dynamic conditional correlation (θ_1 and θ_2) behave similarly to those of the variance process. The dynamic conditional correlations are mean reverting because the estimated coefficient, θ_1,θ_2 and $\theta_3/2$, sum to a value less than one.

Fig. 2 shows the time series behaviour of stock price synchronicity as well as the dynamic conditional correlation. A recurring finding that can be seen is that the synchronicity of DCC based measurement (average every single year) generally reports a higher level than those of R-square based measurement. The main reason is that the DCC-GARCH model can capture the dynamic linear dependence between the firm-returns and the market-returns. Greater variability is shown in the synchronicity of R-square based measurements in contrast to the DCC-based measurements, in other words, a very low R-square may be reported at some points where we attribute poor results to non-normality and heteroscedasticity in the return series. The OLS estimation is also sensitive to outliers. Relatively high synchronicity can be observed in GJNY (listed on the Shenzhen stock exchange), ZGSH and ZGSY (listed on the Shanghai stock exchange). This reveals the size effect. Large-cap oil firms are likely to have a higher level of synchronicity than small-cap ones.

Descriptive statistics of stock price synchronicity is provided in Panel (a) of Table 5. As in previous analysis, a relatively high level of means and mediums is shown in the stock price synchronicity for GJNY, ZGSH and ZGSY, while their coefficients of variation are relatively small. Evidence from the JB test confirms the non-normality of synchronicities, revealing the appropriateness and necessity of quantile regression that improves non-normal skewness and kurtosis in estimates. The dynamic conditional correlation that is less than 0.20 or greater than 0.80, is given for each variable. Clearly, it is better to carry out quantile regression across Γ^{lower} and Γ^{upper} rather than use the general definition of lower and upper quantiles because stock price synchronicity is observed at a high level for GJNY, ZGSH and ZGSY even in lower quantiles, while those for MHSH in the upper quantiles are at a low level. Panel (b) of Table 5 shows that the unit root null can be rejected for each variable, providing evidence of a stationary variable.

We then plot the estimates of short and long-run effects and corresponding 95% confidence intervals against the lower and upper quantiles, respectively. From Fig. 3, it can be seen that the short-run impacts, $w_0(\tau)$'s, are statistically insignificant for each variable excluding YYXC in the majority of lower quantiles, TSSY in a few lower quantiles and YTNY in a minority of upper quantiles. In spite of the significance, the short-run impacts exhibit very small magnitudes. Both of them suggest that oil price shocks have little or no short-run effects on stock price synchronicity, meaning that oil shocks may play a

Table 6
Sup-Wald tests for the lower and upper quantiles.

	GJNY	TSSY	MHSH	YYXC	ZGSH	YTNY	SSSH	ZGSY
(a) For T^{lower}								
$w_0(\tau)$		7.883*	0.887	16.375***		0.533	0.190	
$w_1(\tau)$		8.261**	1.411	16.375***		0.573	0.045	
$w_2(\tau)$		14.369***	3.013	16.375***		1.284	0.255	
$w_3(\tau)$		22.157***	2.677	16.375***		2.307	0.254	
$\sum_{i=0}^{3} w_i(\tau)$		34.194***	3.541	16.375***		2.342	0.358	
$\sum_{i=0}^{12} w_i(\tau)$		109.543***	15.614***	16.375***		8.378**	18.138***	
$\sum_{i=0}^{24} w_i(\tau)$		88.139***	82.431***	16.375***		35.476***	36.893***	
$\sum_{i=0}^{49} w_i(\tau)$		94.946***	134.648***	16.375***		45.009***	41.259***	
$\sum_{i=0}^{T} w_i(\tau)$		105.614***	156.627***	16.375***		46.051***	41.335***	
(b) For T^{upper}								
$w_0(\tau)$	1.291	3.787		0.653	4.033	6.885*	1.003	1.733
$w_1(\tau)$	3.244	0.814		1.368	2.329	7.898**	1.240	0.416
$w_2(\tau)$	20.476***	3.426		4.085	2.100	12.711***	7.031	2.579
$w_3(\tau)$	18.356***	0.640		11.134***	0.781	7.386*	2.589	0.783
$\sum_{i=0}^{3} w_i(\tau)$	11.461**	15.214***		7.377**	5.034	12.864***	2.164	3.642
$\sum_{i=0}^{12} w_i(\tau)$	49.967***	15.422***		39.003***	2.839	9.185**	24.297***	1.584
$\sum_{i=0}^{24} w_i(\tau)$	18.943***	3.507		37.984***	2.383	44.623***	101.595***	4.446
$\sum_{i=0}^{49} w_i(\tau)$	18.210***	25.141***		34.170***	3.712	80.497***	137.618***	6.138*
$\sum_{i=0}^{T} w_i(\tau)$	18.320***	55.266***		29.956***	8.816**	109.970***	140.627***	8.007**

Notes: 1) T^{lower} and T^{upper} are the extreme lower and upper quantiles. 2) $w_0(\tau)$ is the short-run impact, $w_1(\tau)$, $w_2(\tau)$ and $w_3(\tau)$ represent the lagged marginal effects, $\sum_{i=0}^{3} w_i(\tau)$, $\sum_{i=0}^{12} w_i(\tau)$, $\sum_{i=0}^{24} w_i(\tau)$ and $\sum_{i=0}^{49} w_i(\tau)$ denote the medium-run effect, representing the monthly, quarterly, semi-annually and annually lagged cumulative effects, respectively. $\sum_{i=0}^{T} w_i(\tau)$: long-run impact. 3) The degree of polynomial n is determined by Bayesian information criterion (BIC). Critical values are obtained by simulations following Chuang et al. (2009). 4) *, **, *** represent statistical significant at the 10%, 5% and 1% levels, respectively.

negligible role in current return variations. Thus, neither firm-specific factors nor market-wide factors of oil firms immediately respond to oil shocks.

Fig. 4 shows the effects of oil price shock on stock price synchronicity in the long run, $\sum_{i=0}^{T} w_i(\tau)$. The QR estimates of long-run effects are statistically significant for both the lower and upper quantiles, and their magnitudes are large enough to be different from zero, indicating that the oil price shocks affect stock price by both firm-specific and market-wide factors. Combining the evidence from short and long-run impacts, we confirm the existence of lagged effect (Hypothesis 3). The spillover effect of oil shocks on stock price is lagged information for Chinese oil firms.

Note that the long-run impact of oil shocks on stock price synchronicity for ZGSH and ZGSY are quite different. The QR estimates are only significant at a few particularly high quantiles with small magnitude. Thus it is reasonable to neglect the impact of oil price shock on ZGSH and ZGSY under normal circumstance. That is, the response of market-wide factors to oil shocks is limited. Combined with the fact that the market capitalization of ZGSH and ZGSY are very much larger than those of other sampled oil firms, we conclude that there is size effect in the long-run impacts (Hypothesis 2).

The sup-Wald tests are applied to check the significance of short and long-run effects. The null hypotheses for each variable are designated by H_{01}: $w_0(\tau) = 0,\ \forall\ \tau \in T^{lower}$ (short-run impacts in the lower quantiles), H_{02}:$w_0(\tau) = 0, \forall\ \tau \in T^{upper}$ (short-run impacts in the upper quantiles), H_{03}: $\sum_{i=0}^{T} w_i(\tau) = 0,\ \forall\ \tau \in T^{lower}$ (long-run impacts in the lower quantiles) and H_{04}: $\sum_{i=0}^{T} w_i(\tau) = 0,\ \forall\ \tau \in T^{upper}$ (long-run impacts in the upper quantiles). Once again the sup-Wald tests prove the conclusions drawn in Fig. 3 and Fig. 4 as shown in Table 6. In addition, we also report the results of the lagged marginal effects ($w_i(\tau)$, $i = 1,\ 2,\ 3$) and medium-run impact ($\sum_{i=0}^{3} w_i(\tau)$, $\sum_{i=0}^{12} w_i(\tau)$, $\sum_{i=0}^{24} w_i(\tau)$ and $\sum_{i=0}^{49} w_i(\tau)$ represent the monthly, quarterly, semi-annually and annually cumulative effects, respectively) to describe the time-series behaviours. Most of the lagged marginal effects in the last month are not significant but the medium-run impacts are significant, corresponding with previous results. We believe that oil price shocks exhibit a gradually deepening influence on stock price synchronicity rather than an immediate impact. Both firm-specific factors and market-wide factor are more susceptible to previous news and information than current news pertaining to the oil market.

From the above results, we not only validate the measurement method for stock price synchronicity but also verify that oil price shock seems to have long-run impacts but little short-run impacts on synchronicity. This paper finally gives more detail on time-series behaviours: how does oil price shock affect the stock price synchronicity over different time intervals?

Fig. 5 shows the short-run impact and lagged marginal impacts (the last two years) at some special quantiles. The magnitude of lagged marginal effects is small around zero in spite of statistical significance, and it approaches zero with the increase of order, conforming to the truth that a shock in the oil market at some point may have a delayed influence on the stock market but this lagged marginal influence will gradually diminish as time goes by. Further, the short-run impact and lagged marginal impacts are very weak even though their cumulative impacts cannot be regarded as a negligible value.

Fig. 6 provides the lagged cumulative effects over different time horizons, i.e., medium-run impacts. One of the most important findings is that the magnitude of lagged cumulative effects is large enough to be different from zero, indicating the important medium-run impacts at these quantiles. However, ZGSH and ZGSY still have small magnitudes at the higher quantiles and this leads to the insignificance of sup-Wald tests, implying strong evidence of size effects once again. Both insignificant and significant lagged cumulative effects for all quantiles converge to finite values, thus the substantial influence of oil price shocks on synchronicity is stable and limited after a certain period. Although able to identify the trace of positive or negative medium-run impacts at any specific quantile, we cannot find the emergence of common trends. In particular, the lagged cumulative effects cannot be roughly summarized as positive or negative, negative

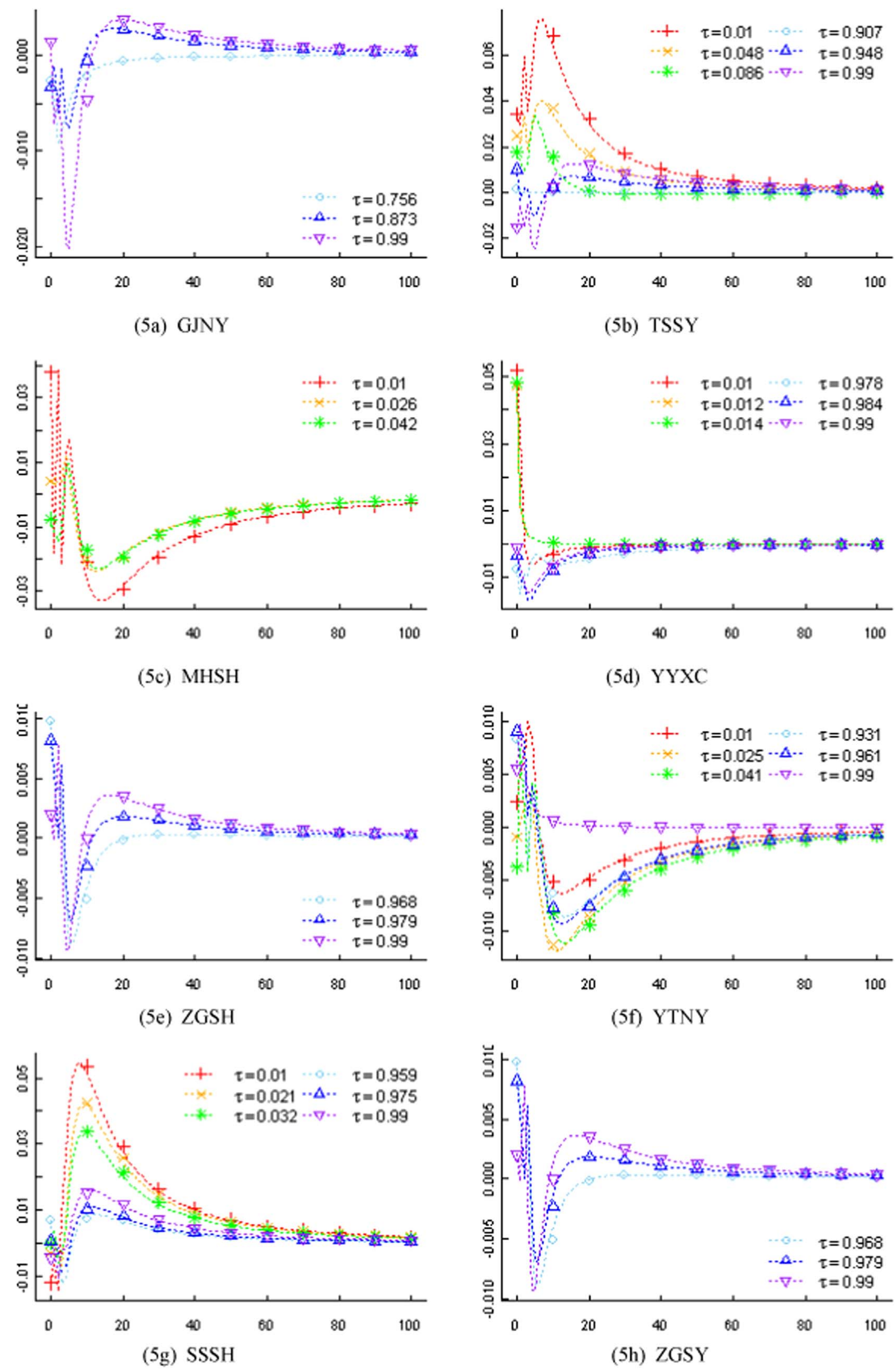

Fig. 5. Instant (short-run) and lagged marginal effects of oil price shock on the stock price synchronicity. Notes: (1) Numbers of x-axis represent the lag order; 2) the plotting quantiles involved 0.01, $0.5N^{lower}/N^{total}$, N^{lower}/N^{total} for lower quantiles and $(N^{total}-N^{upper})/N^{total}$, $(N^{total}-0.5N^{upper})/N^{total}$ and 0.99 for upper quantiles.

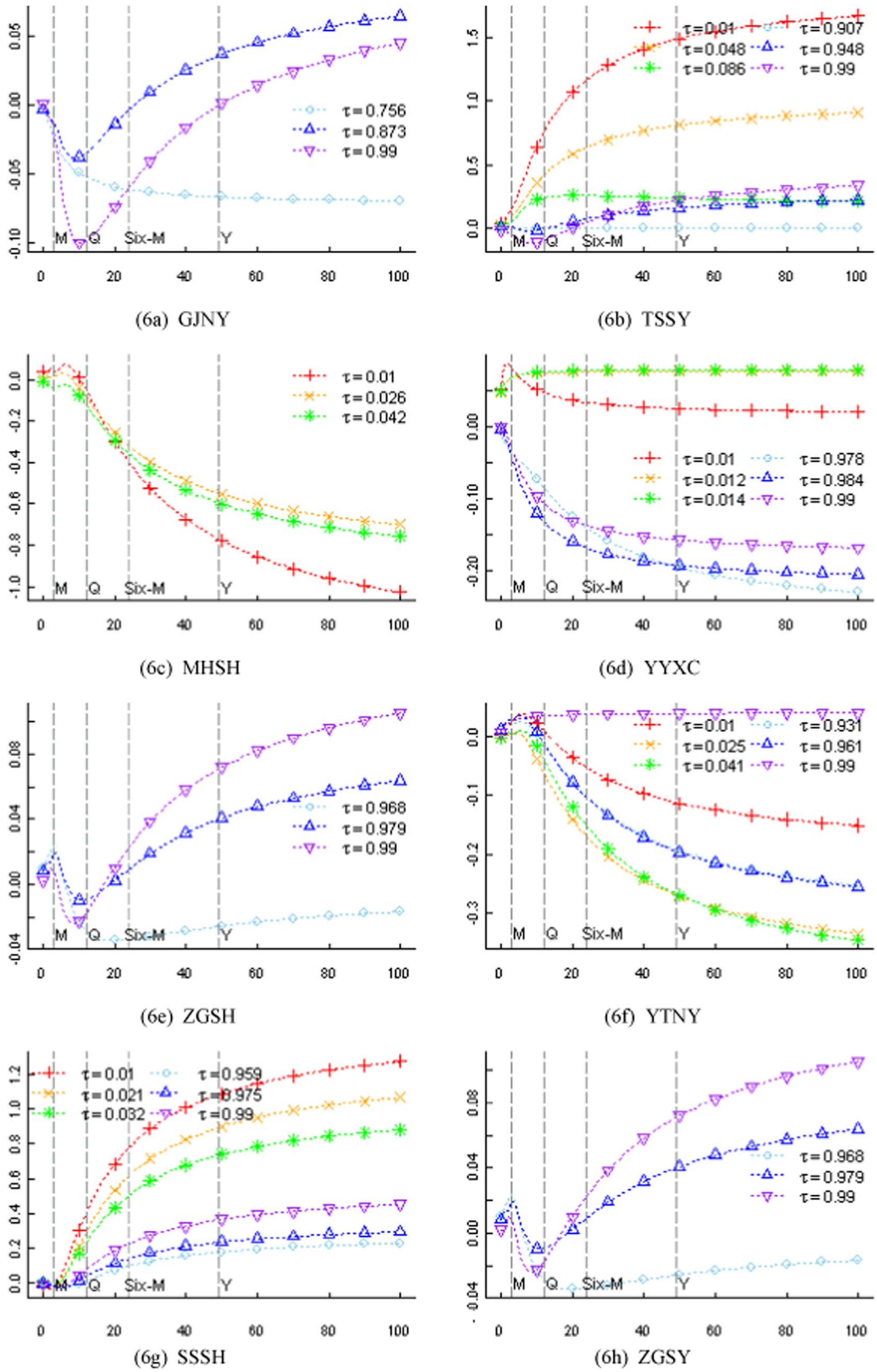

Fig. 6. Cumulative lagged effects of oil price shock on the stock price synchronicity. Notes: 1) "M", "Q", "Six-M" and "Y" denote the medium-run effect, representing the monthly, quarterly, semi-annually and annually cumulative effects, respectively. 2) the lower quantiles: 0.01, $0.5N^{lower}/N^{total}$, N^{lower}/N^{total}; the upper quantiles: $(N^{total}-N^{upper})/N^{total}$, $(N^{total}-0.5N^{upper})/N^{total}$ and 0.99.

influence is detected in MHSH, YYXC and YTNY while TSSY and SSSH are positive; both positive and negative effects are observed in GJNY.

6. Conclusions

This paper investigates the quantile behaviour of stock price synchronicity in response to oil shocks for Chinese oil firms where spillover effects of the oil market on a firm are separated into firm-specific and market-wide information.

Using time series data of listed Chinese oil firms and WTI, the results can be summarized as follows. First, we posit that dynamic conditional correlation is a suitable and advantageous alternative to R-square for calculating stock price synchronicity because of its greater ability to capture dynamic linear dependence and model the statistic characteristics of stock returns. The DCC-based synchronicity does report a higher level in comparison to R-square-based measurements. Second, we find strong evidence of size effect. In particular, firms with relatively small capitalization seem to have a lower level of stock price synchronicity than those with large capitalization. The synchronicity of small-cap oil firms is more susceptible to oil shocks than those with very large capitalization. That is, only market-wide factors of small-cap firms respond significantly to oil shocks. Third, we also find that synchronicity has a significant reaction to oil shocks in extreme low quantiles that is consistent with the earlier conclusion that oil shocks show significant impact on energy-related stock indexes and oil firms. Thus, oil shocks contain firm-specific information for Chinese oil firms. Finally, oil shocks have little or no immediate impact on stock price synchronicity; instead, the cumulative lagged effect is evident. This evidence highlights the lagged spillover effect of oil shocks on Chinese oil firms.

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