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Oil price uncertainty and sectoral stock returns in China: A time-varying approach☆

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ABSTRACT

This paper investigates the time-varying impact of oil price uncertainty on stock prices in China using weekly data on ten sectoral indices over the period January 1997–February 2014. The estimation of a bivariate VAR-GARCH-in-mean model suggests that oil price volatility affects stock returns positively during periods characterised by demand-side shocks in all cases except the Consumer Services, Financials, and Oil and Gas sectors. The latter two sectors are found to exhibit a negative response to oil price uncertainty during periods with supply-side shocks instead. By contrast, the impact of oil price uncertainty appears to be insignificant during periods with precautionary demand shocks.

1. Introduction

The dynamic impact of oil price changes and their volatility on sectoral as well as aggregate stock returns has attracted considerable attention in the recent literature. While the link between oil price uncertainty and aggregate stock returns has important implications for portfolio management strategies in general, specific knowledge of the response of sectoral indices to oil price uncertainty provides crucial information to agents regarding the sectors of the stock market in which they should invest during times of uncertainty with the aim of minimising risk and maximising returns.

The existing empirical evidence on how oil price movements affect equity values mainly concerns the developed economies and is inconclusive, some papers finding a positive effect (e.g., Faff & Brailsford, 1999; Sadorsky, 2001; El-Sharif, Brown, Burton, Nixon, & Russell, 2005; among others), others a negative one (e.g., Jones & Kaul, 1996; Sadorsky, 1999; Cunado & Perez de Gracia, 2014; among others). A well-known study by Kilian and Park (2009) reported that the response of US stock returns to oil price changes depends on whether the latter are driven by supply-side or demand-side shocks. This finding was confirmed by Filis, Degiannakis, and Floros (2011) and Degiannakis, Filis, and Floros (2013), who analysed respectively six net oil-importing and oil-exporting countries, and European industrial sector indices in a time-varying framework. More recently, wavelet analysis for different

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investment horizons has produced time-dependent, and country- or sector-dependent results (e.g., Barunik, Kočenda, & Vácha, 2013; Jammazi, 2012; Madaleno & Pinho, 2014; Reboredo & Rivera-Castro, 2014).[1]

Given the rise of China as a major economic power, a number of empirical studies have also focused on the impact of oil price changes on Chinese stock returns. Most of them examine the response of aggregate returns (e.g., Nguyen & Bhatti, 2012; Wen, Wei, & Huang, 2012; Wang, Wu, & Yang, 2013; Fang & You, 2014; among others). For example, Nguyen and Bhatti (2012) did not find any tail dependence in the relationship between global oil price changes and the Chinese stock market. By using time-varying copulas, Wen et al. (2012) also found limited evidence of contagion between the energy and stock markets in China during the recent financial crisis. More recently, Wang et al. (2013) reported that aggregate demand uncertainty has a stronger influence on stock markets in oil-exporting countries as opposed to oil-importing countries such as China.

However, there are very few papers that investigated the impact of oil price changes on sectoral stock returns in China. The exceptions are the studies by Cong, Wei, Jiao, and Fan (2008) and Li, Zhu, and Yu (2012), both using monthly data. The former estimated a vector autoregression (VAR) model and found that the impact of oil price changes on Chinese sectoral stock returns is negligible, except in the case of manufacturing and oil companies. The latter used a panel method and reported a positive long-run effect of real oil prices on sectoral returns.

Unlike earlier studies on China, the present paper provides evidence on the impact of oil price *uncertainty* on Chinese sectoral returns (as well as on the correlations between oil price changes and individual sectoral returns) in a multivariate dynamic heteroscedastic framework. Specifically, we employ the bivariate VAR-GARCH (generalised autoregressive conditional heteroscedasticity)-in mean model with a DCC (dynamic conditional correlation) specification (Engle, 2002) to analyse weekly data on the stock prices of ten sectors in China: *Healthcare*, *Telecommunications*, *Basic Materials*, *Consumer Services*, *Consumer Goods*, *Financials*, *Industrials*, *Oil and Gas*, *Utilities*, and *Technology*. Moreover, we take a time-varying approach, distinguishing between periods characterised by different types of oil price shocks, namely supply-side, demand-side and precautionary demand shocks as in Kilian and Park (2009). This type of analysis can help investors choose appropriate portfolio management strategies during periods of uncertainty with the aim of minimising risk.

The paper is organised as follows. Section 2 includes a description and a preliminary analysis of the data. Section 3 outlines the econometric methodology. Section 4 discusses the empirical results, and Section 5 offers some concluding remarks.

2. Data description

We employ weekly data (Wednesday to Wednesday) to analyse the time-varying impact of oil price uncertainty on sectoral stock returns in China, because daily or intra-daily data are affected by noise and anomalies such as day-of-the-week effects, while monthly data may be inadequate to capture the response to oil price volatility. Also, the use of midweek data is likely to eliminate to some extent the increased volatility at the beginning and end of the business week, which is due to post-weekend over-reaction and closing positions, respectively. Specifically, we consider ten sectoral indices constructed by Thomson Reuters: *Healthcare*, *Telecommunications*, *Basic Materials*, *Consumer Services*, *Consumer Goods*, *Financials*, *Industrials*, *Oil and Gas*, *Utilities*, and *Technology*. The sample period is January 1, 1997–February 24, 2014, except for *Technology* and *Oil and Gas*, for which the sample starts on May 13, 1998 and June 27, 1997 respectively. Stock prices are in domestic currency (Yuan), and the oil price is the West Texas Intermediate (WTI) Cushing crude oil spot price (US dollars per barrel). The variables in levels are denoted by o_t and s_t, the log oil price and log sectoral stock price respectively, while their first differences ($r_{O,t}$ and $r_{S,t}$) are continuously compounded returns; the data are in percentages and are multiplied by 100.

A wide range of descriptive statistics is displayed in Table 1. Mean weekly changes are positive for the oil price, indicating an upward trend over the sample period. The same applies to sectoral weekly returns, except for Telecommunications and Industrials. The highest mean is that of the Healthcare and Technology sectors (0.135), followed by that of the Consumer Services (0.120) and the Consumer Goods (0.079) ones. Oil price volatility is higher (5.03) than that of all sectoral returns, except for Telecommunications (5.53). As for the third and fourth moments, it appears that both oil price changes and stock sector returns exhibit excess kurtosis and skewness. The latter is negative for oil price changes and positive for sectoral stock returns, except for Healthcare, Consumer Goods and Basic Materials. The Jarque–Bera (JB) test statistics imply a rejection of the null hypothesis that the series are normally distributed.

The Ljung–Box *Q*-statistics for the return series and their squares (calculated up to 10 lags) indicate that there is significant linear and nonlinear dependence, except for the Telecommunications and Financials sectors, which do not exhibit linear dependence. This implies that an ARCH model might be appropriate to capture the volatility clustering in the data, and is also confirmed by Fig. 1, which shows the weekly evolution of the oil price and sectoral stock prices with their corresponding changes. This figure also suggests that the log of the oil price and sectoral stock prices might be non-stationary and exhibit a stochastic trend, while their first differences are covariance-stationary and have a finite variance.[2]

3. The VAR-GARCH-in-mean model

We estimate a bivariate VAR-GARCH (1, 1) with a DCC specification (Engle, 2002) which allows for mean effects. In particular, we distinguish between periods characterised by supply-side, demand-side, and precautionary demand shocks respectively. We

[1] For example, Reboredo and Rivera-Castro (2014) found evidence for the US and Europe of contagion and positive interdependence between oil price changes and stock market returns during the recent financial crisis at both the aggregate and sectoral levels, in contrast to the preceding period when oil prices only affected oil and gas company stocks.

[2] This is confirmed by a battery of unit root tests (the results are not reported here).

Table 1
Summary of descriptive statistics for oil price changes and sectoral stock returns. Data source: Thomson Reuters.

	Sector	Mean	St. Dev	Skewness	Ex. kurtosis	JB	Q(10)	$Q^2(10)$
$r_{O,t}$		0.145	5.037	−0.091	5.885	312.02***	42.20***	201.9***
$r_{S,t}$	*Healthcare*	0.135	3.903	−0.121	5.683	271.05***	23.56***	145.7***
$r_{S,t}$	*Consumer Goods*	0.079	3.736	−0.203	4.837	132.15***	43.60***	194.0***
$r_{S,t}$	*Consumer Services*	0.120	4.180	0.046	5.333	203.61***	58.35***	296.9***
$r_{S,t}$	*Financials*	0.050	4.335	0.954	9.414	1672.3***	10.27	300.2***
$r_{S,t}$	*Industrials*	−0.013	4.327	0.396	6.066	374.5***	43.57***	230.6***
$r_{S,t}$	*Telecommunications*	−0.077	5.538	0.203	5.608	260.08***	8.812	41.40***
$r_{S,t}$	*Basic Materials*	0.003	4.200	−0.102	4.632	101.01***	26.52***	319.3***
$r_{S,t}$	*Utilities*	0.062	3.912	0.309	5.609	268.42***	27.96***	150.6***
$r_{S,t}$	*Oil & Gas*	0.046	4.130	0.579	8.195	972.7***	17.63*	69.92***
$r_{S,t}$	*Technology*	0.135	4.700	0.125	4.948	139.9***	24.20***	127.9***

Notes: $r_{O,t}$ and $r_{S,t}$ indicate oil price changes and stock sector returns, respectively. $Q(p)$ and $Q^2(p)$ are Ljung–Box tests for the *pth* order serial correlation on the returns $r_{i,t}$ and squared returns $r^2_{i,t}$, respectively, where $i = S$ (for stock sector returns), O (for oil price changes). *JB* is the Jarque–Bera test for normality.
*** Indicates statistical significance at the 1% level.
* Indicates statistical significance at the 10% level.

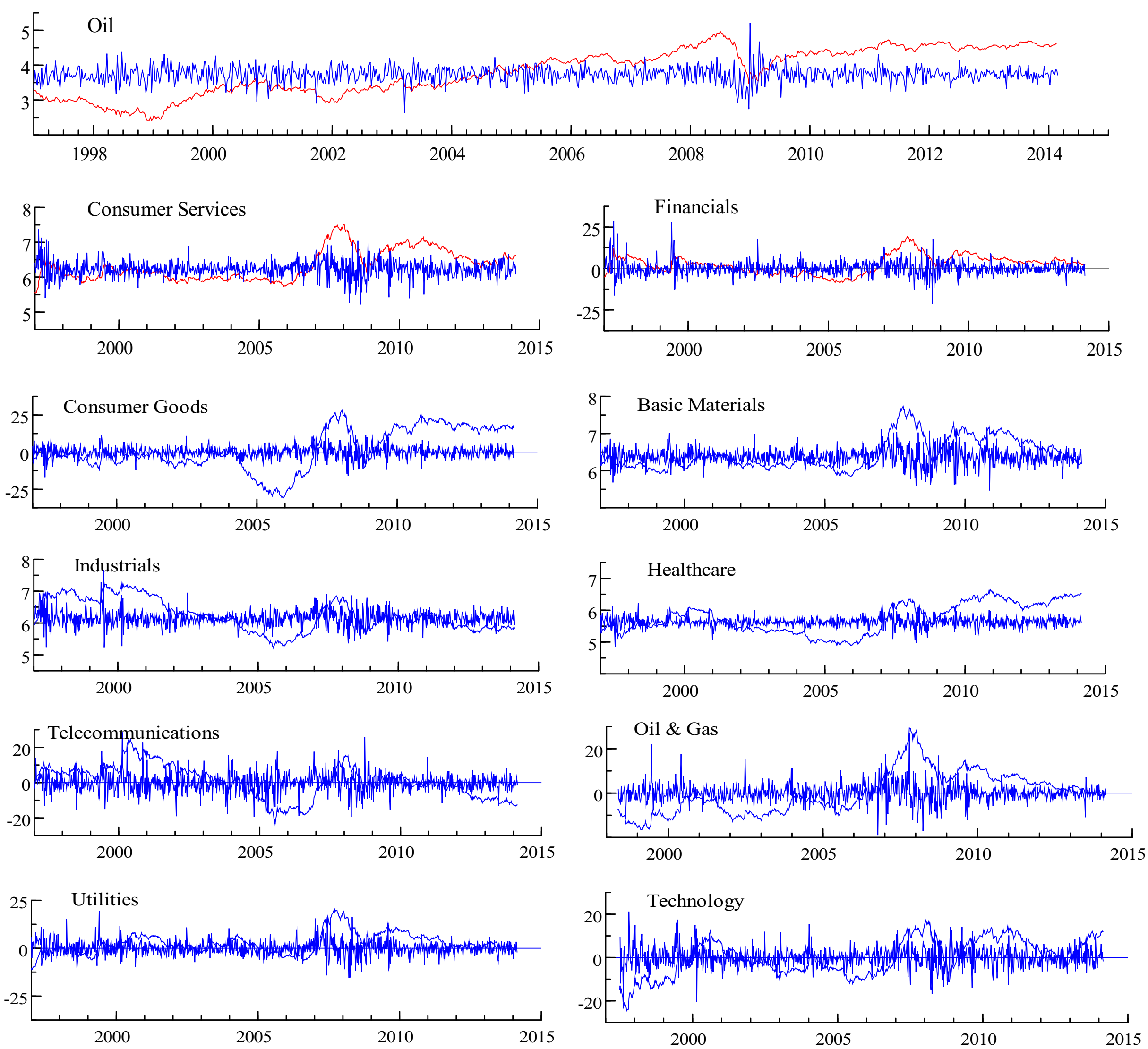

Fig. 1. Weekly oil and sectoral stock prices (in logs) with their corresponding changes.
Source: Thomson Reuters.

Table 2
Results of Gregory and Hansen's (1996) cointegration tests allowing for a shift at an unknown date. Data source: Thomson Reuters.

Regression of s_t on o_t	Model C	Model C/T	Model C/S
Healthcare	−4.171 (8)	−4.649 (9)	−4.145 (8)
	[2003:05:07]	[2009:03:04]	[2003:05:07]
Basic Materials	−3.452 (9)	−4.681 (9)	−4.030 (9)
	[2004:09:22]	[2009:03:04]	[2004:09:22]
Consumer Goods	−3.861 (9)	−4.547 (9)	−3.888 (9)
	[2004:01:28]	[2009:03:04]	[2007:02:21]
Consumer Services	−3.564 (9)	−4.827 (9)	−3.521 (10)
	[2004:09:22]	[2009:03:04]	[2004:09:22]
Financials	−4.010 (8)	−4.736 (9)	−4.245 (8)
	[2006:07:12]	[2009:03:04]	[2006:08:02]
Industrials	−4.099 (8)	−4.624 (9)	−4.099 (9)
	[2006:11:01]	[2009:03:04]	[2006:11:01]
Telecommunications	−3.690 (8)	−4.624 (9)	−3.592 (8)
	[2004:09:22]	[2009:03:04]	[2003:05:07]
Utilities	−3.661 (8)	−4.609 (10)	−4.289 (8)
	[2004:09:22]	[2009:03:04]	[2004:11:10]
Gas and oil	−3.010 (10)	−4.546 (10)	−3.294 (10)
	[2011:07:13]	[2006:08:02]	[2009:02:25]
Technology	−4.015 (9)	−3.943 (9)	−4.347 (9)
	[2003:02:26]	[2007:03:28]	[2002:06:12]

Notes: The test due to Gregory and Hansen (1996) is conducted by regressing the log of stock sector price (s_t) on the log of oil price (o_t). Model C allows for a shift in the intercept, Model C/T allows for a shift in the intercept and the trend, and Model C/S allows for a shift in both the intercept and the slope coefficient of the cointegrating relationship. The corresponding critical values for each model are from Table 1 in Gregory and Hansen (1996). The lag order is chosen on the basis of t-tests in parenthesis (.) subject to a maximum of 10 lags. Breakpoints are in square brackets [.].

Table 3
The estimated bivariate VAR DCC-GARCH-in-mean model for the Financials sector. Data source: Thomson Reuters.

Conditional mean equation					
μ_O	0.159 (0.144)	μ_S	−0.227 (0.219)	η_1	0.005 (0.008)
ϕ_{O1}	−0.049 (0.035)	ψ_{O1}	0.011 (0.023)	η_2	−0.139* (0.074)
ϕ_{O2}	−0.046* (0.026)	ψ_{O2}	0.006 (0.021)	η_3	0.082 (0.056)
ψ_{S1}	0.095*** (0.032)	ϕ_{S1}	0.025 (0.034)	η_4	0.128 (0.318)
ψ_{S2}	−0.007 (0.035)	ϕ_{S2}	0.043 (0.033)		
Conditional variance and correlation equations					
ω_O	0.611** (0.268)	ω_S	1.470** (0.375)	α^{DCC}	0.027 (0.026)
α_O	0.065*** (0.013)	α_S	0.165*** (0.031)	β^{DCC}	0.937*** (0.096)
β_O	0.908*** (0.018)	β_S	0.750*** (0.043)		
Loglik	−5121.74				
Q(5)	15.258 [0.644]	$Q^2(5)$	26.249 [0.051]		
Q(10)	34.588 [0.628]	$Q^2(10)$	40.868 [0.265]		

Notes: Robust standard errors are in parentheses (.). The conditional mean equation is specified as

$$r_{O,t} = \mu_O + \sum_{i=1}^{p} \phi_{Oi} r_{O,t-i} + \sum_{i=1}^{p} \psi_{Si} r_{S,t-i} + \varepsilon_{O,t},$$
$$r_{S,t} = \mu_S + \sum_{i=1}^{p} \psi_{Oi} r_{O,t-i} + \sum_{i=1}^{p} \phi_{Si} r_{S,t-i} + \eta_1 \sqrt{h_t} + \eta_2 D_t^{SS} \sqrt{h_t} + \eta_3 D_t^{DS} \sqrt{h_t} + \eta_4 D_t^{PD} \sqrt{h_t} + \varepsilon_{S,t},$$

where $r_{O,t}$ and $r_{S,t}$ indicate oil price changes and stock sector returns, respectively. D_t^{SS}, D_t^{DS} and D_t^{P} are dummy variables used to capture periods characterised by supply-side, demand-side, and precautionary demand shocks, respectively. The conditional variance equation is specified as $h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}$ for $i = O$ (oil price changes), S (stock sector returns). The dynamic conditional correlation is specified as $Q_t = \left(1-\alpha^{DCC}-\beta^{DCC}\right)\overline{Q} + \alpha^{DCC}\varepsilon_{t-1}\varepsilon'_{t-1} + \beta^{DCC}Q_{t-1}$. $Q(p)$ and $Q^2(p)$ are the multivariate Hosking (1981) tests for the pth order serial correlation on the standardised residuals z_{it} and their squares z_{it}^2, respectively, where $i = O, S$. P-values are reported in square brackets [.].

***Indicates statistical significance at the 1% level.
**Indicates statistical significance at the 5% level.
*Indicates statistical significance at the 10% level.

Table 4
The estimated bivariate VAR DCC-GARCH-in-mean model for the Telecommunications sector.

Conditional mean equation					
μ_O	0.171 (0.153)	μ_S	−0.259 (0.305)	η_1	−0.006 (0.013)
ϕ_{O1}	−0.042 (0.037)	ψ_{O1}	0.031 (0.036)	η_2	0.040 (0.112)
ϕ_{O2}	−0.047 (0.030)	ψ_{O2}	−0.004 (0.032)	η_3	0.148** (0.066)
ψ_{S1}	−0.007 (0.028)	ϕ_{S1}	−0.032 (0.034)	η_4	0.067 (0.376)
ψ_{S2}	0.038 (0.028)	ϕ_{S2}	0.059* (0.032)		
Conditional variance and correlation equations					
ω_O	0.580** (0.256)	ω_S	2.073*** (0.797)	α^{DCC}	0.00002 (0.000001)
α_O	0.065*** (0.013)	α_S	0.109*** (0.031)	β^{DCC}	0.855 (2.303)
β_O	0.910*** (0.018)	β_S	0.826*** (0.049)		
Loglik	−5422.53				
Q (5)	13.840 [0.739]	$Q^2(5)$	17.659 [0.344]		
Q (10)	50.171 [0.089]	$Q^2(10)$	40.150 [0.291]		

Notes: See notes of Table 3.

follow Kilian and Park (2009) for the definition of these shocks (see also Filis et al., 2011). Supply-side and demand-side shocks are defined as changes in the global supply and demand of oil respectively, while precautionary demand shocks are market-specific shocks reflecting changes in precautionary demand resulting from higher uncertainty about possible future oil supply shortfalls.

The conditional mean equation is specified as follows:

$$\begin{aligned} r_{O,t} &= \mu_O + \sum_{i=1}^{p} \phi_{Oi} r_{O,t-i} + \sum_{i=1}^{p} \psi_{Si} r_{S,t-i} + \varepsilon_{O,t}, \\ r_{S,t} &= \mu_S + \sum_{i=1}^{p} \psi_{Oi} r_{O,t-i} + \sum_{i=1}^{p} \phi_{Si} r_{S,t-i} + \eta_1 \sqrt{h_t} + \eta_2 D_t^{SS} \sqrt{h_t} + \eta_3 D_t^{DS} \sqrt{h_t} + \eta_4 D_t^{PD} \sqrt{h_t} + \varepsilon_{S,t}, \end{aligned} \tag{1}$$

where $r_{O,t}$ and $r_{S,t}$ denote respectively oil price changes and sectoral stock returns, the innovation vector $\varepsilon_t|\Omega_{t-1} \sim N(0, H_t)$ is normally distributed with H_t being the conditional covariance matrix, and Ω_{t-1} is the information set available at time $t-1$. The parameters ϕ_{Oi} and ϕ_{Si} measure the response of oil price changes and sectoral stock returns to their own lags, while ψ_{Si} and ψ_{Oi} measure respectively causality from stock returns to oil price changes, and vice versa. The lag length is selected on the basis of the Schwartz Information Criterion (SIC). If necessary, further lags are added to eliminate any serial correlation on the basis of the multivariate Q-statistics of Hosking (1981) on the standardised residuals $z_{it} = \varepsilon_{it}/\sqrt{h_{it}}$ for $i = O, S$.

Table 5
The estimated bivariate VAR DCC-GARCH-in-mean model for the Consumer Goods sector.

Conditional mean equation					
μ_O	0.156 (0.149)	μ_S	−0.176 (0.215)	η_1	0.006 (0.009)
ϕ_{O1}	−0.048 (0.033)	ψ_{O1}	−0.015 (0.023)	η_2	−0.068 (0.067)
ϕ_{O2}	−0.039 (0.028)	ψ_{O2}	−0.015 (0.023)	η_3	0.125** (0.051)
ϕ_{O3}	0.025 (0.028)	ψ_{O3}	0.003 (0.020)	η_4	−0.009 (0.227)
ψ_{S1}	0.097** (0.042)	ϕ_{S1}	0.025 (0.032)		
ψ_{S2}	−0.002 (0.036)	ϕ_{S2}	0.100*** (0.033)		
ψ_{S3}	−0.036 (0.036)	ϕ_{S3}	0.064** (0.032)		
Conditional variance and correlation equations					
ω_O	0.588** (0.267)	ω_S	1.472*** (0.432)	α^{DCC}	0.046 (0.036)
α_O	0.062*** (0.013)	α_S	0.190*** (0.040)	β^{DCC}	0.389 (0.510)
β_O	0.912*** (0.019)	β_S	0.701*** (0.060)		
Loglik	−5024.82				
Q (5)	15.830 [15.830]	$Q^2(5)$	19.431 [0.246]		
Q (10)	47.612 [0.113]	$Q^2(10)$	36.784 [0.432]		

Notes: See notes of Table 3.

Table 6
The estimated bivariate VAR DCC-GARCH-in-mean model for the Oil and Gas sector.

Conditional mean equation					
μ_O	0.221 (0.143)	μ_S	−0.310 (0.246)	η_1	0.013 (0.010)
ϕ_{O1}	−0.049 (0.033)	ψ_{O1}	0.039* (0.022)	η_2	−0.079* (0.047)
ϕ_{O2}	−0.053 (0.035)	ψ_{O2}	−0.036 (0.025)	η_3	−0.039 (0.069)
ψ_{S1}	0.070* (0.039)	ϕ_{S1}	0.009 (0.038)	η_4	0.087 (0.293)
ψ_{S2}	0.036 (0.037)	ϕ_{S2}	0.060* (0.034)		
Conditional variance and correlation equations					
ω_O	0.519** (0.260)	ω_S	0.104* (0.058)	α^{DCC}	0.018** (0.009)
α_O	0.064*** (0.014)	α_S	0.051*** (0.013)	β^{DCC}	0.977*** (0.014)
β_O	0.913*** (0.019)	β_S	0.943*** (0.013)		
Loglik	−4687.81				
Q(5)	11.998 [0.847]	$Q^2(5)$	7.788 [0.954]		
Q(10)	39.915 [0.384]	$Q^2(10)$	18.635 [0.992]		

Notes: See notes of Table 3.

D_t^{SS}, D_t^{DS}, and D_t^{PD} are dummy variables used to examine the time-varying impact of oil price uncertainty on sectoral stock returns, that is, to capture its effects during periods characterised by supply-side, demand-side, and precautionary demand shocks, respectively. More specifically, D_t^{SS} takes the value of 1 for the periods with the supply-side shocks corresponding to the Venezuela general strike of 2002–2003 (in particular December 2002–February 2003), the oil production cuts by OPEC countries over the period March 1998–December 1998 (known as the 1998 oil crisis), and Libya's unrest and the subsequent NATO intervention and Saudi Arabia's increase of its oil production (second week of January, 2011–May, 2011), and 0 otherwise. D_t^{DS} takes the value of 1 for the periods with the demand-side shocks represented by the Asian financial crisis (July 1997–September 1998), the increase of Chinese oil demand (January 2006–June 2007), the recent financial crisis of 2007–2008 (September 2008–December 2009), the downgrade of the US debt status in August, 2011, and the euro zone debt crisis of May and June 2012, 0 otherwise. Finally, D_t^{PD} captures the precautionary demand shocks associated with the terrorist attacks of September 11, 2001, and the Iraq invasion in March 2003; it takes the value of 1 during the last three weeks of September 11, 2001 and the last two weeks of March 2003, and 0 otherwise (see also Filis et al. (2011) and Degiannakis et al. (2013) for choice of these dates).

Note that Eq. (1) does not include a lagged error correction term because bivariate cointegration tests between the (logs of) oil price and each of the sectoral indices in turn indicate that the pairs of series do not share a common stochastic trend even when accounting for an endogenous structural break. This is clearly shown by the results reported in Table 2 for the Gregory and Hansen (1996) test, allowing for structural changes in the parameters of the cointegrating relationship under the following alternative hypotheses: a shift in the intercept (model C), a shift in the intercept and the trend (model C/T), and a shift in the intercept and the slope coefficient of the cointegrating relationship (model C/S). This finding is in contrast to that of Li et al. (2012), who provided evidence of a long-run relationship between oil prices, sectoral stock prices, and the interest rate in China by using panel cointegration techniques with multiple structural breaks.

Table 7
The estimated bivariate VAR DCC-GARCH-in-mean model for the Technology sector.

Conditional mean equation					
μ_O	0.191 (0.151)	μ_S	−0.024 (0.254)	η_1	−0.002 (0.010)
ϕ_{O1}	−0.051 (0.037)	ψ_{O1}	0.008 (0.024)	η_2	−0.097 (0.096)
ϕ_{O2}	−0.055* (0.033)	ψ_{O2}	−0.027 (0.026)	η_3	0.198*** (0.071)
ψ_{S1}	0.049 (0.034)	ϕ_{S1}	0.016 (0.039)	η_4	−0.097 (0.236)
ψ_{S2}	0.084** (0.034)	ϕ_{S2}	0.069* (0.036)		
Conditional variance and correlation equations					
ω_O	0.555** (0.268)	ω_S	1.968*** (0.615)	α^{DCC}	0.0005 (0.00001)
α_O	0.068*** (0.015)	α_S	0.195*** (0.037)	β^{DCC}	0.846*** (0.238)
β_O	0.909*** (0.019)	β_S	0.722*** (0.050)		
Loglik	−5085.51				
Q(5)	20.844 [0.287]	$Q^2(5)$	13.602 [0.628]		
Q(10)	44.311 [0.222]	$Q^2(10)$	43.267 [0.188]		

Notes: See notes of Table 3.

Table 8
The estimated bivariate VAR DCC-GARCH-in-mean model for the Basic Materials sector.

Conditional mean equation					
μ_O	0.161 (0.152)	μ_S	−0.451* (0.260)	η_1	0.012 (0.010)
ϕ_{O1}	−0.052* (0.032)	ψ_{O1}	0.017 (0.021)	η_2	−0.046 (0.076)
ϕ_{O2}	−0.044 (0.032)	ψ_{O2}	0.001 (0.021)	η_3	0.102* (0.060)
ϕ_{O3}	0.023 (0.029)	ψ_{O3}	0.014 (0.022)	η_4	−0.025 (0.241)
ψ_{S1}	0.060* (0.034)	ϕ_{S1}	0.014 (0.036)		
ψ_{S2}	−0.003 (0.036)	ϕ_{S2}	0.066** (0.030)		
ψ_{S3}	−0.018 (0.033)	ϕ_{S3}	0.040 (0.030)		
Conditional variance and correlation equations					
ω_O	0.623** (0.292)	ω_S	0.513*** (0.182)	α^{DCC}	0.011** (0.005)
α_O	0.066*** (0.014)	α_S	0.104*** (0.021)	β^{DCC}	0.988*** (0.006)
β_O	0.908*** (0.020)	β_S	0.865*** (0.027)		
Loglik	−5116.05				
Q(5)	14.568 [0.626]	$Q^2(5)$	11.492 [0.778]		
Q(10)	47.918 [0.107]	$Q^2(10)$	22.442 [0.962]		

Notes: See notes of Table 3.

Table 9
The estimated bivariate VAR DCC-GARCH-in-mean model for the Healthcare sector.

Conditional mean equation					
μ_O	0.157 (0.151)	μ_S	−0.012 (0.209)	η_1	−0.002 (0.008)
ϕ_{O1}	−0.046 (0.035)	ψ_{O1}	0.022 (0.022)	η_2	−0.038 (0.079)
ϕ_{O2}	−0.045 (0.029)	ψ_{O2}	0.006 (0.020)	η_3	0.122** (0.058)
ϕ_{O3}	0.023 (0.028)	ψ_{O3}	0.026 (0.020)	η_4	−0.075 (0.241)
ψ_{S1}	0.058 (0.040)	ϕ_{S1}	−0.006 (0.037)		
ψ_{S2}	0.037 (0.038)	ϕ_{S2}	0.079** (0.034)		
ψ_{S3}	−0.045 (0.038)	ϕ_{S3}	0.068** (0.030)		
Conditional variance and correlation equations					
ω_O	0.578** (0.261)	ω_S	0.665*** (0.199)	α^{DCC}	0.057* (0.032)
α_O	0.065*** (0.013)	α_S	0.160*** (0.029)	β^{DCC}	0.705*** (0.267)
β_O	0.910*** (0.018)	β_S	0.803*** (0.032)		
Loglik	−5061.13				
Q(5)	20.678 [0.240]	$Q^2(5)$	26.126 [0.052]		
Q(10)	49.221 [0.086]	$Q^2(10)$	40.608 [0.274]		

Notes: See notes of Table 3.

Having specified the conditional mean equation, the model is estimated conditional on the DCC-GARCH specification of Engle (2002) to capture the volatility dynamics in the two variables. The estimated model is the following:

$$H_t = D_t R_t D_t, \tag{2}$$

where D_t is a 2×2 matrix with the conditional volatilities on the main diagonal, $D_t = diag\{\sqrt{h_{i,t}}\}$. The common practice in estimating the DCC model is to assume that these are univariate GARCH processes: $h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}$ for $i = O, S$.[3] The correlation in the DCC model is then given by:

$$Q_t = \left(1 - \alpha^{DCC} - \beta^{DCC}\right)\overline{Q} + \alpha^{DCC}\varepsilon_{t-1}\varepsilon_{t-1}' + \beta^{DCC} Q_{t-1}, \tag{3}$$

[3] When fitting the GJR-GARCH model of Glosten, Jagannathan, and Runkle (1993) for the univariate series, the asymmetric parameter was found to be insignificant for oil price changes and all sectoral stock returns.

Table 10
The estimated bivariate VAR DCC-GARCH-in-mean model for the Consumer Services sector.

Conditional mean equation					
μ_O	0.172 (0.154)	μ_S	−0.282 (0.236)	η_1	0.010 (0.009)
ϕ_{O1}	−0.045 (0.036)	ψ_{O1}	0.029 (0.023)	η_2	−0.064 (0.082)
ϕ_{O2}	−0.046 (0.031)	ψ_{O2}	−0.017 (0.024)	η_3	0.063 (0.054)
ϕ_{O3}	0.021 (0.030)	ψ_{O3}	0.017 (0.024)	η_4	−0.042 (0.234)
ϕ_{O4}	−0.048 (0.030)	ψ_{O4}	−0.050** (0.025)		
ψ_{S1}	0.063* (0.036)	ϕ_{S1}	−0.0005 (0.035)		
ψ_{S2}	0.026 (0.035)	ϕ_{S2}	0.083*** (0.029)		
ψ_{S3}	0.0006 (0.036)	ϕ_{S3}	0.094*** (0.030)		
ψ_{S4}	−0.074** (0.036)	ϕ_{S4}	−0.076** (0.034)		
Conditional variance and correlation equations					
ω_O	0.575** (0.258)	ω_S	0.320 (0.215)	α^{DCC}	0.060** (0.030)
α_O	0.067*** (0.012)	α_S	0.079** (0.034)	β^{DCC}	0.527*** (0.200)
β_O	0.908*** (0.018)	β_S	0.899*** (0.045)		
Loglik	−5096.81				
Q(5)	10.332 [0.848]	$Q^2(5)$	8.306 [0.939]		
Q(10)	43.289 [0.188]	$Q^2(10)$	26.01 [0.890]		

Notes: See notes of Table 3.

where $Q_t = (q_{ij,t})$ is the time-varying covariance matrix of ε_t, $\overline{Q}$ is the unconditional covariance matrix of ε_t, and α^{DCC} and β^{DCC} are non-negative scalar coefficients. The stationarity condition is satisfied as long as $\alpha^{DCC} + \beta^{DCC} < 1$. For $\alpha^{DCC} = \beta^{DCC} = 0$, the model reduces to the constant conditional correlation estimator of Bollerslev (1990). Furthermore, since Q_t does not have unit values on the main diagonal, it is rescaled to derive the correlation matrix R_t:

$$R_t = diag\{Q_t\}^{-1/2} Q_t diag\{Q_t\}^{-1/2}, \tag{4}$$

where $diag\{Q_t\}$ is a matrix containing the main diagonal of Q_t and all the off-diagonal elements are zero. A typical element of R_t takes the form $\rho_{ij,t} = q_{ij,t}/\sqrt{q_{ii,t}q_{jj,t}}$ for $i, j = O, S$ and $i \neq j$.

Table 11
The estimated bivariate VAR DCC-GARCH-in-mean model for the Industrials sector.

Conditional mean equation					
μ_O	0.171 (0.152)	μ_S	−0.093 (0.230)	η_1	−0.007 (0.009)
ϕ_{O1}	−0.044 (0.034)	ψ_{O1}	0.022 (0.025)	η_2	−0.050 (0.085)
ϕ_{O2}	−0.044 (0.028)	ψ_{O2}	−0.013 (0.023)	η_3	0.168*** (0.063)
ϕ_{O3}	0.026 (0.030)	ψ_{O3}	−0.006 (0.023)	η_4	−0.085 (0.189)
ϕ_{O4}	−0.047 (0.030)	ψ_{O4}	−0.073*** (0.023)		
ψ_{S1}	0.043 (0.035)	ϕ_{S1}	0.017 (0.037)		
ψ_{S2}	0.007 (0.033)	ϕ_{S2}	0.058* (0.033)		
ψ_{S3}	−0.019 (0.033)	ϕ_{S3}	0.068** (0.028)		
ψ_{S4}	−0.040 (0.033)	ϕ_{S4}	−0.070** (0.032)		
Conditional variance and correlation equations					
ω_O	0.574** (0.265)	ω_S	1.525*** (0.485)	α^{DCC}	0.021 (0.028)
α_O	0.066*** (0.013)	α_S	0.191*** (0.039)	β^{DCC}	0.549* (0.332)
β_O	0.910*** (0.019)	β_S	0.728*** (0.054)		
Loglik	−5139.76				
Q(5)	8.639 [0.927]	$Q^2(5)$	14.344 [0.573]		
Q(10)	40.305 [0.285]	$Q^2(10)$	28.367 [0.813]		

Notes: See notes of Table 3.

Table 12
The estimated bivariate VAR DCC-GARCH-in-mean model for the Utilities sector.

Conditional mean equation					
μ_O	0.179 (0.161)	μ_S	−0.269 (0.216)	η_1	0.005 (0.009)
ϕ_{O1}	−0.043 (0.033)	ψ_{O1}	0.033 (0.023)	η_2	−0.020 (0.076)
ϕ_{O2}	−0.049 (0.030)	ψ_{O2}	−0.026 (0.020)	η_3	0.089* (0.052)
ϕ_{O3}	0.021 (0.027)	ψ_{O3}	−0.011 (0.021)	η_4	−0.153 (0.225)
ϕ_{O4}	−0.050* (0.030)	ψ_{O4}	−0.062*** (0.020)		
ψ_{S1}	0.039 (0.040)	ϕ_{S1}	−0.029 (0.039)		
ψ_{S2}	0.016 (0.040)	ϕ_{S2}	0.020 (0.032)		
ψ_{S3}	0.018 (0.039)	ϕ_{S3}	−0.059** (0.029)		
ψ_{S4}	−0.014 (0.040)	ϕ_{S4}	−0.065** (0.028)		
Conditional variance and correlation equations					
ω_O	0.643** (0.280)	ω_S	0.473 (0.413)	α^{DCC}	0.012 (0.010)
α_O	0.065*** (0.014)	α_S	0.093* (0.050)	β^{DCC}	0.972*** (0.0261)
β_O	0.907*** (0.020)	β_S	0.874*** (0.074)		
Loglik	−5070.18				
$Q(5)$	9.628 [0.885]	$Q^2(5)$	9.361 [0.897]		
$Q(10)$	47.601 [0.093]	$Q^2(10)$	24.077 [0.935]		

Notes: See notes of Table 3.

We use the quasi-maximum likelihood (QML) estimator of Bollerslev and Wooldridge (1992) for all specifications since it computes standard errors that are robust to non-normality in the error process.[4] We also carry out the multivariate Q-statistic (Hosking, 1981) for the squared standardised residuals to determine the adequacy of the estimated model of the conditional variances to capture the ARCH and GARCH dynamics.

4. Empirical results

The QML estimates of the bivariate VAR DCC GARCH (1, 1) parameters as well as the associated multivariate *Q*-statistics (Hosking, 1981) are displayed in Tables 3–12 for the *Financials*, *Telecommunications*, *Consumer Goods*, *Oil and Gas*, *Technology*, *Basic Materials*, *Healthcare*, *Consumer Services*, *Industrials*, and *Utilities* sectors respectively. The Hosking multivariate *Q*-statistics of order (5) and (10) for the standardised residuals indicate the existence of no serial correlation at the 5% level, when the conditional mean equations are specified with $p = 2$ for the Financials, Telecommunications, Oil and Gas, and Technology sectors, $p = 3$ for the Consumer Goods, Basic Materials, and Healthcare sectors, and $p = 4$ for the Consumer Services, Industrials, and Utilities sectors.

As can be seen from the tables, the dynamic interactions between oil price changes and sectoral stock returns, captured by ψ_{Si} and ψ_{Oi}, suggest that there exists causality from stock returns in the Financials, Consumer Goods, Technology, and Basic Materials sectors to oil price changes, causality in the reverse direction in the cases of the Industrials and Utilities sectors, and bidirectional causality in the cases of the Oil and Gas and Consumer Services sectors. By contrast, there appears to be limited dependence in the first moment between Telecommunications and Healthcare stock returns and oil price changes.

The results also suggest that oil price volatility affects stock returns positively during periods characterised by demand-side shocks in all cases except the Consumer Services, Financials, and Oil and Gas sectors. The latter two are found to exhibit a negative response to oil price uncertainty during periods with supply-side shocks instead. By contrast, the impact of oil price uncertainty appears to be insignificant during periods with precautionary demand shocks. Overall, our findings are in line with those of Kilian and Park (2009), Filis et al. (2011), and Degiannakis et al. (2013), who found that the reaction of stock returns to oil price changes and the correlation between them depend on the type of oil price shock. Degiannakis et al. (2013) reported that the type of industry is also a significant determinant of the degree of correlation between European industrial sectors' returns and oil price changes.

The observed positive impact on sectoral stock returns during periods with aggregate demand-side shocks may be due to the fact that China has a major role in determining global oil demand. The fact that it has gone through unprecedented episodes of economic growth over recent years and the resulting higher demand for oil make the estimated positive reaction of sectoral stock returns during periods with demand-side shocks a plausible one for this economy. Also, the finding that Financials and Oil and Gas stock returns respond negatively to oil price uncertainty during periods with supply-side shocks implies an overreaction of these sectoral stock

[4] The procedure was implemented in RATS 8.1 with a convergence criterion of 0.00001, using the quasi-Newton method of Broyden, Fletcher, Goldfarb, and Shanno (see Enders, 2003).

prices to such shocks. The Financials sector is highly sensitive to any negative news such as oil supply cuts, while the Oil and Gas sector-specific index is affected considerably by oil supply shortfalls.

The estimates of the conditional variance equations as well as the dynamic correlations in the DCC-GARCH models indicate that both oil price changes and sectoral stock returns exhibit conditional heteroscedasticity: the ARCH (autoregressive conditional heteroscedasticity) and GARCH parameters are significant at the 10% level in all cases. The persistence of the conditional variance is approximately 0.91 in the case of oil price changes, and it ranges from 0.70 (Consumer Goods) to 0.94 (Oil and Gas) for sectoral returns.

Fig. 2 shows the evolution of the dynamic conditional correlation between the two series. It is apparent that the correlation between sectoral stock returns and oil price changes is time-varying in most cases, with the Oil and Gas and Industrials sectors having the highest correlations. Specifically, the average correlations between the two variables for the various sectors are estimated to be 0.086 (for the Financials), 0.088 (Telecommunications), 0.076 (Consumer Goods), 0.149 (Oil and Gas), 0.083 (Technology), 0.095 (Basic Materials), 0.070 (Healthcare), 0.088 (Consumer Services), 0.110 (Industrials), and 0.061 (Utilities). As far as the impact of the recent financial crisis is concerned, the Basic Materials, Oil and Gas, and Utilities sectors appear to be affected the most: the correlation between oil price changes and these sectoral stock returns exhibits an upward trend ever since the onset of the crisis (see Fig. 2). Instead, the effects of the crisis on the other sectors appear to be only transitory.

Finally, the Hosking multivariate Q-statistics of order (5) and (10) for the squared standardised residuals suggest that the multivariate GARCH (1, 1) structure is sufficient to capture the volatility in the series.

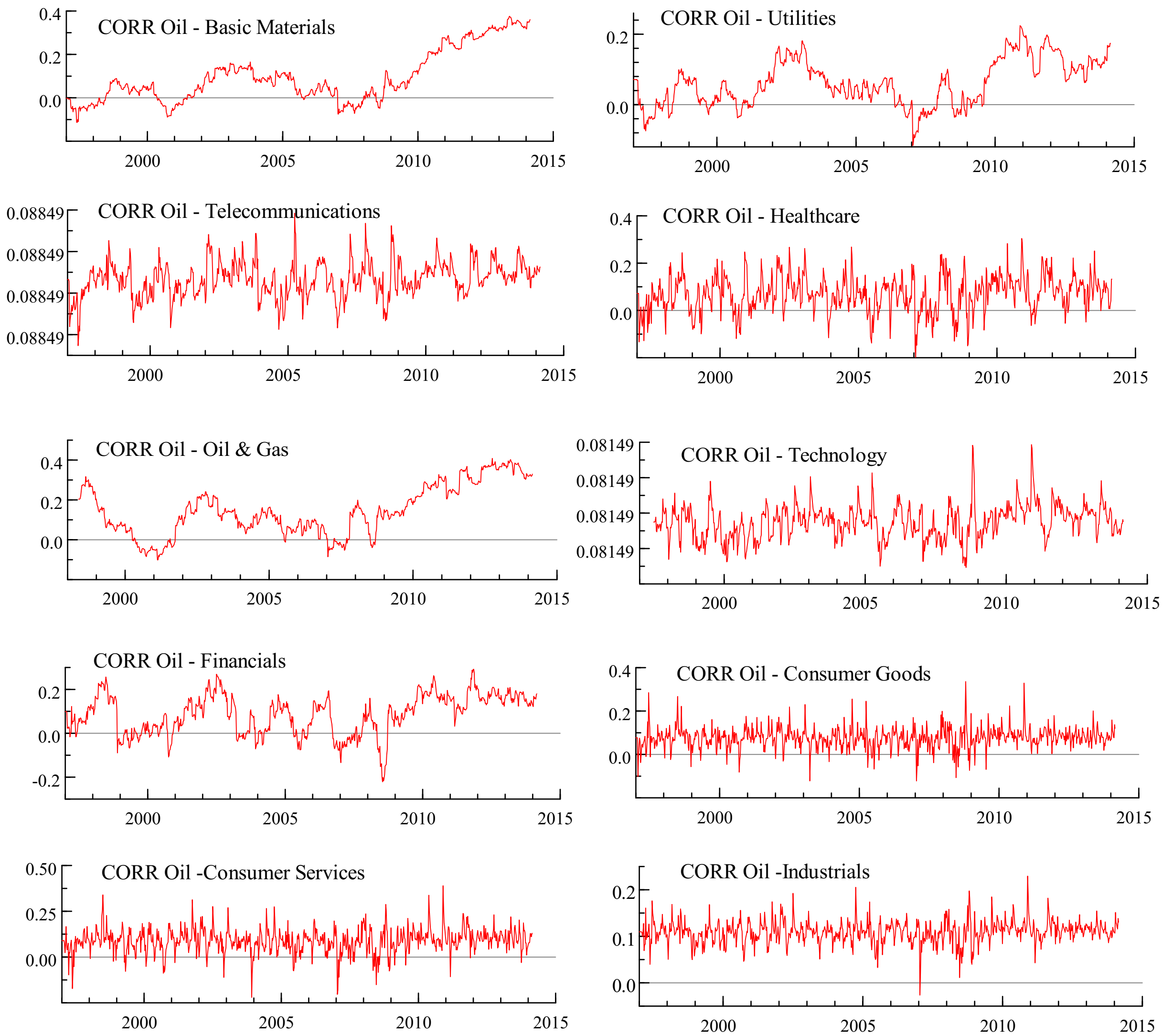

Fig. 2. The evolution of the dynamic conditional correlation between oil price changes and Chinese sectoral stock returns.
Data source: Thomson Reuters.

5. Conclusions

This paper investigates the time-varying impact of oil price uncertainty on stock prices in China using weekly data on ten sectoral indices: *Healthcare*, *Telecommunications*, *Basic Materials*, *Consumer Services*, *Consumer Goods*, *Financials*, *Industrials*, *Oil and Gas*, *Utilities*, and *Technology*. The estimation of bivariate VAR-GARCH-in-mean models suggests that oil price uncertainty affects sectoral stock returns positively during periods with aggregate demand-side shocks in all cases except for the Consumer Services, the Financials and Oil and Gas sectors. The latter two are found to respond negatively during periods with supply-side shocks. Precautionary demand shocks, by contrast, have negligible effects.

Overall, the results indicate the existence of considerable dependence of sectoral stock returns on oil price fluctuations during periods characterised by demand-side shocks in the Chinese case. The implication is that investors cannot use Chinese stocks and oil as effective instruments for portfolio hedging and diversification strategies during such periods. However, an effective investment strategy can exploit the negative response of the Financials and Oil and Gas sectors during periods characterised by supply-side shocks and the insignificant response of the Consumer Services sector to any type of shock.

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