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demand shocks as in Kilian and Park (2009). They concluded that the response of US stock returns to oil price changes depends on whether these are driven by supply-side or demand-side shocks. This finding was confirmed by Filis et al. (2011) and Degiannakis et al. (2013), wp5clis 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). Regarding the third and fourth moments, it is found that both oil price changes and stock

3. The VAR-GARCH-in-mean model

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

$$
\begin{aligned}
r_{O,t} \quad {}_{O} \quad \sum_{i=1}^{p} {}_{Oi} r_{O,t-i} \quad \sum_{i=1}^{p} {}_{Si} r_{S,t-i} \quad {}_{O,t},\\
r_{S,t} \quad {}_{S} \quad \sum_{i=1}^{p} {}_{Oi} r_{O,t-i} \quad \sum_{i=1}^{p} {}_{Si} r_{S,t-i} \quad {}_{1}\sqrt{h_t} \quad {}_{2}D_t^{SS}\sqrt{h_t} \quad {}_{3}D_t^{DS}\sqrt{h_t} \quad {}_{4}D_t^{PD}\sqrt{h_t} \quad {}_{S,t},
\end{aligned}
\tag{1}
$$

where $r_{O,t}$ and $r_{S,t}$ denote respectively oil price changes and sectoral stock returns, the innovation vector ${}_{t} | {}_{t-1} \sim \mathrm{N}(0, \mathrm{H_t})$ is normally distributed with H_t being the conditional covariance matrix, and ${}_{t-1}$ is the information set available at time t-1. The parameters ${}_{Oi}$ and ${}_{Si}$ measure the response of oil price changes and sectoral stock returns to their own lags, while ${}_{Si}$ and ${}_{Oi}$ 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 $z_{it} \quad {}_{it} / \sqrt{h_{it}}$ for $i = O, S$.

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 relationionship between oil prices, sectoral stock prices, and the interest rate in China by using panel cointegration techniques with multiple structural breaks.

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:

$$H_t = D_t R_t D_t, \qquad (2)$$

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: $h_{i,t} = \omega_i + \alpha_i \varepsilon^2_{i,t-1} + \beta_i h_{i,t-1}$ for $\forall t \in S$

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 then rescaled to derive the correlation matrix R_t :

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

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 $\ _{ij,t} \quad q_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}}$ for $i, j \quad O, S$ and $i \quad j$.

We use the quasi-maximum likelihood (QML) estimator of Bollerslev and Woolbridge (1992) for all specifications since it computes standard errors that are robust to non-normality in the error process.[3] 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

[3]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.

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.

[Insert Tables 3-12 about here]

As can be seen from the Tables, the dynamic interactions between oil price changes and sectoral stock returns, captured by $_{Si}$ and $_{Oi}$, 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 case 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 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.

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 prices to such shocks. The Financials sector is highly sensitive to any negative news such as oil supply cuts, whilst 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

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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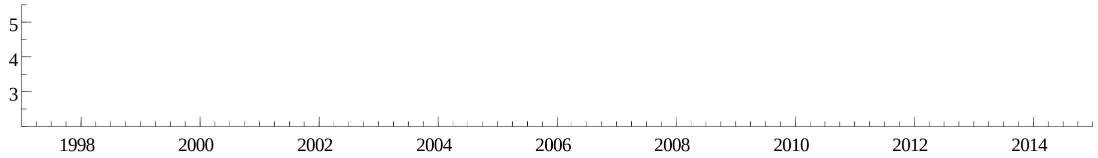
5
4
3
1998
2000
2002
2004
2006
2008
2010
2012
2014

Table 1

Summary of descriptive statistics for oil price changes and sectoral stock returns

	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***
$R_{S,t}$								

Table 3

The estimated bivariate VAR DCC–GARCH–in–mean model for the Financials sector

Conditional Mean Equation

O	0.159 (0.144)	S	-0.227 (0.219)	1	0.005 (0.008)
O1	-0.049 (0.035)	O1			

Table 4

The estimated bivariate VAR DCC–GARCH–in–mean model for the Telecommunications sector

Conditional Mean Equation

$_O$	0.171 (0.153)	$_S$	-0.259 (0.305)	$_1$	-0.006 (0.013)
$_{O1}$	-0.042 (0.037)	$_{O1}$	0.031 (0.036)	$_2$	0.040 (0.112)
$_{O2}$	-0.047 (0.030)	$_{O2}$	-0.004 (0.032)	$_3$	0.148** (0.066)
$_{S1}$	-0.007 (0.028)	$_{S1}$	-0.032 (0.034)	$_4$	0.067 (0.376)
$_{S2}$	0.038 (0.028)	$_{S2}$	0.059* (0.032)		

Conditional Variance and Correlation Equations

$_O$	0.580** (0.256)	$_S$	2.073*** (0.797)	$_{DCC}$	0.00002 (0.000001)
$_O$	0.065*** (0.013)	$_S$	0.109*** (0.031)	$_{DCC}$	0.855 (2.303)
$_O$	0.910*** (0.018)	$_S$	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.

Table 5

The estimated bivariate VAR DCC–GARCH–in–mean model for the Consumer Goods sector

Table 6

The estimated bivariate VAR DCC–GARCH–in–mean model for the Oil and Gas sector

Conditional Mean Equation

O	0.221 (0.143)	S	-0.310 (0.246)	1	0.013 (0.010)
$O1$	-0.049 (0.033)	$O1$	0.039* (0.022)	2	-0.079* (0.047)
$O2$	-0.053 (0.035)	$O2$	-0.036 (0.025)	3	-0.039 (0.069)
$S1$	0.070* (0.039)	$S1$	0.009 (0.038)	4	

Table 8

The estimated bivariate VAR DCC–GARCH–

Table 9

The estimated bivariate VAR DCC–GARCH–in–mean model for the Healthcare sector

Conditional Mean Equation

O	0.157 (0.151)	S	-0.012 (0.209)	1	-0.002 (0.008)
$O1$	-0.046 (0.035)	$O1$	0.022 (0.022)	2	0.030 0 10.98 222251 72(3.2 683.6 (0.079)

Table 11

The estimated bivariate VAR DCC–GARCH–in–mean model for the Industrials sector

Conditional Mean Equation	
o	0.171 (0.152)

Table 12

The estimated bivariate VAR DCC–GARCH–in–mean model for the Utilities sector

Conditional Mean Equation

O	0.179 (0.161)	S	-0.269 (0.216)	1	0.005 (0.009)
$O1$	-0.043 (0.033)	$O1$	0.033 (0.023)	2	-0.020 (0.076)
$O2$	-0.049 (0.030)	$O2$	-0.026 (0.020)	3	0.089* (0.052)
$O3$	0.021 (0.027)	$O3$	-0.011 (0.021)	4	-0.153 (0.225)
$O4$	-0.050* (0.030)	$O4$	-0.062*** (0.020)		
$S1$	0.039 (0.040)	$S1$	-0.029 (0.039)		
$S2$	0.016 (0.040)	$S2$	0.020 (0.032)		
$S3$	0.018 (0.039)	$S3$	0.059** (0.029)		
$S4$	-0.014 (0.040)	$S4$	-0.065** (0.028)		

Conditional Variance and Correlation Equations

O	0.643** (0.280)	S	0.473 (0.413)	DCC	0.012 (0.010)
O	0.065*** (0.014)	S	0.093* (0.050)	DCC	0.972*** (0.0261)
O	0.907*** (0.020)	S	0.874*** (0.074)		
Loglik	-5070.18				
$Q(5)$	9.628 [0.885]				