Disaggregating the impact of oil prices on European industrial equity indices: a spatial econometric analysis

Syed Mujahid Hussain¹ · Amjad Naveed² · Sheraz Ahmed³ · Nisar Ahmad¹

Received: 14 September 2020 / Accepted: 7 August 2021 / Published online: 26 August 2021
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Abstract

This study investigates the relationship between daily returns of oil and ten European industrial equity indices for the period 2008–2017 using the spatial econometric technique. In our settings, the historical co-movements of sectoral returns are incorporated while modelling the contemporaneous relationships between oil and European sectoral returns. After controlling for regional and global equity risk factors, we find that oil returns pose a significantly positive effect on sectoral indices' returns in line with previous studies. However, the magnitude of economic impact found mostly by earlier studies was largely underestimated without considering the co-movements of sectoral indices. The use of spatial econometric technique allowed us to disaggregate the total impact into a direct (due to oil price) and an indirect (due to spillover effect because of intra-industry co-movements) effect of oil price changes. Our results indicate that the direct economic impact of changes in oil prices on industrial returns is almost 31% more than what has been found by earlier studies. The negative spatial dependence among sectoral indices provides a useful tool to identify the source of the indirect impact of oil on overall equity prices in Europe that in turn explains the overestimation of direct impact by 31%.

Keywords Spatial econometrics · European industrial indices · Euro STOXX · Oil prices

JEL codes G20 · G30

✉ Syed Mujahid Hussain
smujahid@squ.edu.om

¹ Department of Economics and Finance, College of Economics and Political Science, Sultan Qaboos University, Muscat, Oman

² Department of Business Development and Technology, Aarhus University, Herning, Denmark

³ School of Business and Management, LUT University, Lappeenranta, Finland

1 Introduction

Oil has been one of the key determinants of global economic growth for the last few decades, and therefore, the research on the effects of changes in oil prices on different asset classes has attracted considerable attention from researchers, academicians and policymakers. Given the tendency of the oil prices to drive the movements of prices in the global stock markets, the relationship between oil prices and the stock market has also been extensively tested across different markets and times (Diaz et al. 2016; Ready 2018; Basher et al. 2018). In the same context, several studies have also analysed the relationship between oil prices and stock returns at the industry level (see e.g. Arouri and Nguyen (2010); Arouri (2011); Degiannakis et al. (2013) and Nandha and Faff (2008)). Usually, these studies have found the asymmetric effect of oil prices on different industrial stock returns. For instance, Nandha and Faff (2008) using 35 global industrial sector indices show that oil price rises are negatively associated with stock returns for all sectors except mining, and oil and gas industries. This negative oil-equity association is mainly due to the slowdowns in overall consumption and investment spending caused by economic downturns and inflationary pressures. Arouri and Nguyen (2010) found that the reaction of stock returns to changes in oil price varies across European industries. Their findings, however, suggested an overall positive impact of oil when averaged across all sectors.

The main issue with earlier studies on the overall oil-equity relationship is that they have generally ignored the contemporaneous co-movements of stock prices among neighbouring industries (see Kocaarslan et al. 2018; Peng et al. 2017; Park and Ratti 2008; Cong et al. 2008). The co-movement is important since the returns from various industries are correlated with each other and that needs to be controlled to measure the precise impact of oil price changes on the industrial stock returns. Therefore, this study aims to analyse the impact of oil price changes on the European industrial stock returns while controlling for cross-correlations of the constituent sectoral returns using spatial econometric techniques.

In the context of spatial econometrics, a situation where observation at location i depends on the observation at location j is known as spatial dependence (Anselin 1988; LeSage and Pace 2009; Kelejian and Prucha 1999). Usually, two reasons are given in the literature for this type of spatial dependence: (i) measurement error when data are collected concerning spatial units such as zip codes, counties, states, census tracts and so on, (ii) interdependence between observations, regions and industries by any economic activities (Anselin 1988; LeSage and Pace 2009). The latter is relevant for this paper as we analyse the effect of oil price changes on industrial stock returns which have been found to be interdependent shown by high to moderate levels (depending on the industrial sectors) of pairwise correlations in time series (see e.g. Degiannakis et al. 2013). Many studies have shown that correlations represent geographical proximity. For example, Barker and Loughran (2007) and Pirinsky and Wang (2006) show that the correlation of stock returns increases with decreasing geographical distance. Building on these studies, we use correlations between industrial sectoral returns as a proximity measure.

In the context of this paper, if there is any change in the oil price, it will subsequently have two effects: (1) direct effect on each industrial index, (2) indirect effect due to co-movement of different industries. The latter effect is also interpreted as a spillover effect from the neighbouring industry, which could be positive or negative. The indirect effect could be attributed to portfolio rebalancing and/or input–output linkages among different industries. Ignoring such inter-dependencies may lead to over- or underestimation of the true effect of oil price changes on the industrial sector returns in an economy.

Consequently, this paper tries to answer three important questions. First, whether there is a significant relationship between oil price changes and industrial stock returns in the Pan-European context? Second, whether the existing relationship is affected by the co-movement of underlying sectoral indices' returns? Third, what is the share of direct (impact of oil prices) and indirect effect (spillover impact from neighbouring industries)?

In this paper, we use correlations among different industrial returns to control for industrial co-movements (weight matrix in the context of spatial econometrics) which is considered as a proxy of proximity since the stock prices of different indices move in tandem, and there is a great degree of synchronicity among stock market valuations (Flavin 2004). We employ data on daily closing prices of ten STOXX600 European sectoral indices and Europe Brent Spot as a proxy for the oil price. Studying the relationship between oil price changes and European industrial sectoral returns is interesting because Europe's economy is generally highly dependent on energy procurement and consumption. Additionally, the formation of the European Union and lifting the intra-country trade barriers has resulted in increased economic linkages among European countries. The constituents of the European industrial sector indices are from different individual countries and thus represent a broader population of European companies than individual country level indices. Our dataset covers the period from January 2008 to October 2017, which allows us to analyse the relationship during and after the recent financial crisis.

The contribution of this paper is twofold: Firstly, to the best of our knowledge, this is the first paper that analyses the effect of oil price changes on industrial returns using spatial econometric techniques. This approach allows us to dissect the total effect of oil price changes on industrial returns into a direct and an indirect effect. It is very important to be able to measure the precise effect, as the size of the impact is an important input in portfolio diversification and hedging decisions. Secondly, we also contribute by examining the impact of oil price changes on sectoral returns during and after the global financial crisis. This enables us to analyse whether the effect varied during and after the financial crisis.

The main findings of our paper reveal that oil prices pose on average a significantly positive impact across European industrial returns. However, this impact is underestimated if we do not consider the intra-industrial co-movements. In general, the direct economic impact of oil prices on industrial stock returns is almost 31% more than what has been found by ignoring intra-industrial co-movements (spatial dependence). Additionally, our findings indicate that these results are robust across two sub-periods, i.e. during and after the financial crises. However, the magnitude of the direct effect is found to be higher after the crisis period. Our results are also

robust to the correlation coefficient of different time lengths indicating no selection bias in determining the historical dependences.

The rest of the paper is organized as follows: A brief overview of the previous literature is provided in Sect. 2. Section 3 describes the data, while our chosen methodology is presented in Sect. 4. Section 5 provides the estimation results of this study, and the paper is concluded in Sect. 6 with a summary of our results and proposed policy recommendations.

2 Literature review

The literature analysing the relationship between oil prices and industrial stock returns can be broadly divided into two branches. The first strand of literature has mainly focussed on the effect of oil price changes (and volatility) on different industrial/sectoral returns and volatility (e.g. Arouri 2011; Arouri and Nguyen 2010; Fang et al. 2018; Phan et al. 2015). The second thread of literature has investigated the effect of oil prices on aggregate stock returns. As our paper is more closely related to the second strand of literature, we provide a brief review of the main studies in that regard.

Diaz et al. (2016) analyse the relationship between oil price volatility and stock returns in the G7 economies using monthly data for the period 1970 to 2014. The authors find that the G7 markets respond negatively to an increase in oil price volatility. Reboredo and Rivera-Castro (2014) examine the relationship between oil and stock markets in Europe and the US at the aggregate and sectoral levels using wavelet multi-resolution analysis. Their findings reveal that oil price changes did not affect stock market returns at either the aggregate or sectoral level during the June 2000 to July 2011 period except for the oil and gas sector. Narayan and Gupta (2015) investigate whether oil prices can predict stock returns using more than 150 years of monthly data for the US stock market and spot crude oil price. They find clear evidence of predictability of the US stock returns by oil prices, which is also supported by the in-sample and out-of-sample evidence of predictability. Park and Ratti (2008) investigate the effect of oil price shocks on the stock markets in the US and 13 European countries. Their findings indicate that oil price shocks have a statistically significant impact on real stock returns in all the markets they study. Cunado and de Gracia (2014) analyse the effect of oil price shocks on stock returns in twelve oil-importing European economies using vector autoregressive (VAR) and vector error correction models (VECM). Their results also suggest that stock market returns are mostly driven by oil supply shocks. However, none of the studies mentioned above has controlled for the co-movements (interaction effect) of constituent industries in the context of modelling industrial returns.

The application of spatial econometrics has been generally limited in finance so far. There are just a few earlier studies that have used spatial econometric techniques to control the neighbourhood effect. For instance, Arnold et al. (2013) modelled different types of spatial dependence in stock returns. In doing so, they incorporated global dependencies, dependencies inside industrial branches and local dependencies in their model. Their findings indicate that spatial modelling in finance

allows for superior risk forecasts in portfolio management. Asgharian et al. (2013) employed spatial econometric techniques to investigate the stock market co-movements with respect to countries' economic and geographical relations. They found that there is strong evidence of shock effect to regional countries mainly coming from the dominant regional economies. In a recent study, Asgharian and Liu (2018) examined the implications of interfirm product market linkages for dependence among the daily stock returns of US publicly traded firms using a spatial econometric regression. They showed the dominance of the competitive effect as compared to the contagion effect in highly concentrated industries, whereas the opposite was found in industries with higher product market variability. Our paper, however, differs from these studies as we employ spatial econometrics to specifically control for the interactions (correlations) of industrial sector returns while exploring the oil-stock return relationship.

3 Data

The paper uses daily closing prices of ten STOXX® European sectoral indices. The sample covers the period from January 2008 to October 2017. To control for the local (European) and global (American) stock markets' effects, the broader STOXX® 600 Europe and S&P500 indices are used, respectively.

Closing prices of ten STOXX® indices are denominated in Euro, while closing prices of S&P500 are converted into Euro using EUR/USD exchange rate to control for the effect of the currency exchange rate. To adjust for dividends, splits and other stock events, the total return index is used instead of the price index. Ten sectoral indices are: (1) oil and gas, (2) basic materials, (3) industrials, (4) consumer goods, (5) health care, (6) consumer services, (7) telecom, (8) utilities, (9) financials and (10) technology. These are Europe-wide indices covering almost 90% of the European listed companies. The proxy for the oil price is Europe Brent Spot issued by Energy Information Administration (EIA) denominated in Euro. For each index and oil, daily logarithmic returns are calculated using the expression:

$$\ln(P_{i,t}/P_{i,t-1})$$

where $\ln$ is a natural logarithm and $P_{i,t}$ represents the price level on the market i at time t .

3.1 Descriptive statistics

Table 1 shows the descriptive statistics of daily returns of each of the indices described above. There are 2564 daily observations of each data series. The common highest mean daily return of about 0.04% is found for the consumer goods sector and the US market, while the lowest average return is reported for the oil sector. The highest standard deviations of 1.88% and 1.84% of daily return are estimated for the financial industry and Brent oil, respectively, whereas the lowest standard deviation is found in the case of the healthcare sector. The minimum

Table 1 Descriptive statistics of daily continuously compounded returns

Sectoral indices	Mean (%)	SD (%)	Min (%)	Max (%)
Oil and gas	0.005	1.586	− 10.034	11.858
Basic material	0.015	1.794	− 12.423	13.292
Industrial	0.027	1.485	− 9.541	9.981
Consumer goods	0.038	1.128	− 6.064	12.597
Health	0.037	1.048	− 6.83	8.612
Consumer services	0.018	1.200	− 8.166	8.345
Telecom	0.011	1.258	− 9.436	9.653
Utilities	− 0.002	1.315	− 8.686	14.861
Financial	− 0.003	1.840	− 13.594	14.674
Technology	0.024	1.485	− 9.981	8.573
<i>Market & Oil indices</i>				
STOXX 600 Europe	0.017	1.281	− 7.924	9.416
S&P composite	0.039	1.335	− 9.098	10.368
Brent oil	− 0.008	1.888	− 10.433	14.622

This table presents descriptive statistics of daily continuously compounded returns of 10 STOXX Europe sectoral indices, European market (STOXX 600) index, US market (S&P 500) and Brent crude oil prices (Euro). The sample period is from January 2, 2008, to October 31, 2017, with 2564 daily observations in each case. The mean, standard deviation (SD), minimum (Min) and maximum (Max) percentages of daily returns are reported in columns

and maximum daily returns are experienced by the financial sector (i.e. − 13.59%) and utilities sector (14.86%), respectively. Overall, the daily returns seem to be randomly distributed around their means.

Table 2 presents the cross-correlations of industrial returns during the sample period. These correlations show that all European sectoral indices are highly correlated. However, the maximum correlation is found between basic material and industrial sector indices i.e. 89%, while the lowest correlation (55%) is between health and basic material sectors. The industrial sector is generally more correlated with all other sectors with consumer services and financial, whereas the health sector is found to have the lowest correlation with other sectors such as oil & gas and financials. Nevertheless, the overall correlations among European sectors are high and thus provide support for our conjecture that the intra-sectoral co-movements of stock prices should be controlled while assessing the impact of an exogenous factor such as oil.

Next, we look at the co-movement of oil prices with the broader European market index (STOXX600) shown in Fig. 1. The line graph represents the oil and market index standardized to 100 at the beginning of the sample period i.e. 1.1.2008. It can be seen that both lines move almost simultaneously in the same direction during the whole period except for a brief divergence in the early period of 2014. Two sharp drops in oil prices during 2008 and 2014–2015 are visible. At the outset of the global financial crisis in 2008, the oil demand almost collapsed,

Table 2 Correlation matrix between EU sectoral indices returns

	Oil & Gas	Basic Material	Industrial	Consumer Goods	Health	Consumer Services	Telecom	Utility	Financial	Technology
Oil and gas	1.00									
Basic material	0.83	1.00								
Industrial	0.79	0.89	1.00							
Consumer goods	0.68	0.71	0.79	1.00						
Health	0.58	0.55	0.62	0.71	1.00					
Consumer services	0.73	0.76	0.88	0.83	0.70	1.00				
Telecom	0.69	0.68	0.75	0.72	0.69	0.81	1.00			
Utility	0.76	0.72	0.76	0.70	0.65	0.77	0.79	1.00		
Financial	0.73	0.80	0.88	0.69	0.56	0.83	0.74	0.73	1.00	
Technology	0.69	0.76	0.84	0.72	0.61	0.81	0.71	0.69	0.76	1.00

This table shows cross-correlations of daily returns of 10 STOXX Europe indices

Fig. 1 The relationship between oil prices and European equity index (STOXX 600)

and the price of oil declined dramatically. The oil price dropped from a peak of 93 Euro per barrel in July 2008 to under 27 Euro at the end of 2008.

The second drop in oil price occurred in 2014 when it stumbled from 85 Euro in June 2014 to 39 Euro in January 2015. It continued to decline further until January 2016 when the oil price dropped to almost the similar level that was seen in 2008. However, this time the reasons for the decline were slow growth prospects and declining economic outlook in emerging markets particularly in China. Overall, Fig. 1 indicates a positive relationship between the oil prices and the European market index, which is also evident by the positive correlation coefficient of 0.373 between the returns of the European market index and oil prices. The next section introduces the spatial econometric methodology to analyse the effect of oil prices changes on the panel of industrial returns.

4 Methodology

The basic methodology of this paper is based on the concept of spatial dependence; a situation where observation at location i depends on the observation at location j (Anselin 1988; LeSage and Pace 2009; Kelejian and Prucha 1999). The researchers from economic geography initially used this concept (of spatial dependence) but now almost all related fields of social sciences are using it (LeSage and Pace 2009). The spatial model state can be explained as follows:

$$y_i = f(y_j), i = 1, \dots, nj \neq i \quad (1)$$

where y_i is an observation at location i and y_j is the same observation at location j . These observations are interdependent because of spatial dependence. As we are analysing the relationship between oil price changes and industrial sectors' equity returns, there might be interdependence among these sectoral returns. This could be due to portfolio rebalancing and/or adjustments by investors regarding equity investments in those industries. Additionally, it could also be due to intra-industry input–output linkages (Leontief 1986). If we assume that there is spatial dependence (interaction between industries) in the underlying industries, then the next step is to measure and capture this spatial dependence in empirical regression models. Various regression structures have been used in the literature to capture spatial dependence. The most common structure is the spatial autoregressive (SAR) model, spatial error model (SEM) and the more general spatial autoregressive combined (SAC) model, which combines both SAR and SEM models.

The SAR model takes the following form:

$$y = \rho Wy + x\beta + \mu \quad (2)$$

where y is a $n \times 1$ vector of the dependent variable, x is $n \times n$ matrix of explanatory (exogenous/explanatory) variables along with vector coefficient β . The scalar ρ represents a regression parameter and μ denotes the stochastic disturbance in the relationship. The parameter ρ reflects the spatial dependence (spatial dependence coefficient) of y (time and cross-sectional subscript ignored for simplicity). In other words, ρ represents the average influence of neighbouring or contiguous observations in vector y . The combined Wy is a spatial lag of the dependent variable, which denotes the endogenous interaction effects among the dependent variable. The W is a nonnegative $n \times n$ matrix describing the spatial configuration or arrangement of the units in the sample. The SEM model can be written as:

$$y = x\beta + \mu, \text{ where } \mu = \lambda W\mu + \epsilon \text{ or } y = x\beta + \lambda W\mu + \epsilon \quad (3)$$

where λ is a spatial autocorrelation coefficient. Many empirical scholars are mainly interested in the SAR and SEM models. SAR is a basic spatial model, which only includes the spatial lag of the dependent variable. In contrast, the SAC model not only includes the spatial lag of the dependent variable, but also adds the spatial lag of disturbance (unobserved) term ($W\mu$) (Elhorst 2014). As stock market returns are expected to follow a random process, it makes more sense to add a spatial lag of unobserved components. Therefore, the SAC model is preferred over the SAR model. The SAC model takes the following form:

$$y = \rho Wy + x\beta + \lambda W\mu + \epsilon \quad (4)$$

The next section addresses the weight matrix, W , and its conditions to obtain consistent estimators for spatial models.

4.1 Neighbourhood and spatial weight matrix W

In this section, we develop the weight matrix that captures the neighbourhood effects. There are various methods and ways to construct the weight matrix in spatial literature (LeSage 1999; Arbia 2006). The spatial weights matrix W is a nonnegative matrix of known constants. The diagonal elements are set to zero by assumption, since no spatial unit can be viewed as its own neighbour. Typically, the weight matrix W is normalized where row sum is equal to unity. If W is an asymmetric matrix before it is normalized, it may have complex characteristic roots (Elhorst 2014). In the context of this study, the weight matrix is constructed by using correlation coefficients among returns on industrial indices.¹

For the empirical estimations, we adopt two types of regressions: (1) linear panel regression as a baseline model for comparison and (2) spatial regression models using the maximum likelihood (MLE) procedure. The final estimate-able forms of equations can be written as follows:

$$R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_2 R_{oil,t} + \beta_3 R_{EU,t} + \beta_4 R_{US,t-1} + \varepsilon_{i,t}. \quad (5)$$

$$R_{i,t} = \alpha + \rho W R_{i,t} + \beta_1 R_{i,t-1} + \beta_2 R_{oil,t} + \beta_3 R_{EU,t} + \beta_4 R_{US,t-1} + \varepsilon_{i,t}. \quad (6)$$

$$R_{i,t} = \alpha + \rho W R_{i,t} + \beta_1 R_{i,t-1} + \beta_2 R_{oil,t} + \beta_3 R_{EU,t} + \beta_4 R_{US,t-1} + \lambda W \varepsilon_{i,t} \quad (7)$$

Equations (5), (6), and (7) represent the panel model for industrial returns and oil price return, spatial autoregressive (SAR) model and spatial autoregressive combined (SAC) model, respectively. In all three Eqs. (5)–(7), $R_{i,t}$ is a dependent variable representing returns of industry i at time t . $R_{oil,t}$, $R_{EU,t}$ and $R_{US,t-1}$ are return on oil prices, return on European stock index and lag return on the US stock index, respectively. The lagged returns of the US market are used to address the time difference in the trading hours of European and US markets. In Eq. (7), W is the weight matrix and $\varepsilon_{i,t}$ is the usual random error term.

5 Empirical findings

The results obtained from the simple panel regression (with fixed effects) model, SAR model and SAC model (i.e. Eqs. 5–7) are presented in Table 3. To test the linear relationship between oil price and European industrial returns, we first ran the panel regression where the dependent variable is industrial returns ($R_{i,t}$), and independent variables are returns of oil ($R_{oil,t}$), STOXX 600 Europe ($R_{EU,t}$), lagged S&P500 ($R_{US,t-1}$) and lagged sectoral return ($R_{i,t-1}$). The first column in the Table 3 shows panel regression estimates, where oil price returns are found to be positively and significantly related to overall industrial returns with an estimated

¹ Barker and Loughran (2007) and Pirinsky and Wang (2006) suggest that correlation of stock returns can be used a proxy for geographical proximity.

Table 3 Panel and spatial regression analysis—Full sample

	Panel regression with fixed effects	SAR: spatial autoregressive model	SAC: spatial autoregressive combined
$R_{oil,t}$	0.0085*** (3.25)	0.0137*** (5.38)	0.0111*** (5.55)
$R_{EU,t}$	0.961*** (241.86)	1.561*** (74.18)	1.261*** (35.02)
$R_{US,t-1}$	−0.0089** (−2.24)	−0.00884** (−2.30)	−0.00565* (−1.85)
$R_{i,t-1}$	0.0138*** (3.85)	0.0110*** (3.17)	0.00591** (2.01)
Spatial Rho		−0.620*** (−28.98)	−0.309*** (−8.31)
Lambda			−0.294*** (−7.94)
Variance (σ_e^2)		0.0000504*** (110.51)	0.0000510*** (112.58)
Observations	25,640	25,640	25,640
R-squared	0.739	0.739	0.738

The table presents coefficients of fixed effects panel data, spatial autoregressive (SAR) and spatial autoregressive combined (SAC) regressions. The dependent variable is industrial sector returns ($R_{i,t}$) and independent variables are oil returns ($R_{oil,t}$), European index returns ($R_{EU,t}$), S&P500 returns ($R_{US,t}$) and 1-day lag industrial sector returns ($R_{i,t-1}$). Corresponding t -stats are in parenthesis. The level of significance is denoted by *, ** and *** for 10%, 5% and 1%, respectively

coefficient of 0.0085. The market sensitivity indicator (β_3) is 0.961 representing the aggregate market *beta* of European sectoral indices. Interestingly, the lagged US returns ($R_{US,t-1}$) negatively affect European sectoral returns implying that European sectoral indices decline after S&P500 closes positively a day before. The autoregressive term, i.e. the effect of own lagged industrial returns ($R_{i,t-1}$), is positive and significant, showing a positive autocorrelation in European industrial returns.

The panel regression results could be biased since they do not consider the co-movement of industrial returns and thus may represent an under or overestimation of the direct impact of oil price changes on European sectoral returns. To address the issue of misrepresentation of panel regression estimates, we employ spatial econometric techniques to capture the effects caused by the co-movement of constituent industries' returns (usually referred to as 'neighbourhood effect'). Additionally, this technique will help us to decompose the total effect of oil returns into a direct and indirect impact on sectoral returns. The results of spatial models based on the SAR and SAC specifications are reported in columns 2 and 3 of Table 3, respectively.

First, we focus on the SAR model results where the spatial lag of the dependent variable ($WR_{i,t}$) is used as an explanatory variable. The coefficient estimate of oil

returns is positive and statistically significant with the value of 0.0137, which is also consistent in terms of direction with the results from panel regression results. However, the magnitude of the effect is higher than its counterpart coefficient reported in Column 1. It is also interesting to note that the beta of the industrial returns with that of the aggregate market increases (1.561 versus 0.961) when we control for the cross-correlations of industrial returns. Moreover, while the lagged effect of the US market on the European industrial returns virtually remains the same, the impact of its own lagged returns slightly decreases from 0.0138 to 0.011 with the SAR model. The spatial lag of the dependent variable ($WR_{i,t}$) turns out to be significant with the coefficient estimate (ρ) of -0.620 showing negative spatial dependence among European sectoral indices. This indicates that positive returns in each sector reduce the returns of other sectors, which could be interpreted as a competition effect in line with Blonigen et al. (2007). Many other studies have found evidence of negative spatial dependence. For instance, Garretsen and Peeters (2009) and Blanc-Brude et al. (2014) have reported negative spatial dependence for foreign direct investment; Filiztekin (2009) and Pavlyuk (2011) for regional employment; Garrett and Marsh (2002) for the cross-border lottery shopping; and Saavedra (2000) and Boarnet and Glazer (2002) for studies of welfare competition or federal grants competition among local governments.

The theoretical explanations of negative spatial dependence have also been provided in the literature. For example, Maurseth and Frank (2009) argue that Myrdal (1957) backwash effect is consistent with negative spatial dependence. The backwash effect indicates that growth in one region is harmful to growth in neighbouring regions since it may attract resources and skilled labour from neighbouring regions and reduce their growth potential. A similar explanation can be found in Blonigen et al. (2007) about foreign direct investment and export growth. Because the production set-up from home country to host country is directly at the cost of other host countries. It seems that negative spatial dependence may occur when competition between regions (or industries, countries, agents) offsets mutual factors.

This study contributes to the same literature by showing that negative spatial dependence also occurs in stock market returns of different sectoral indices as competition to attract investors between different sectors may lead to a negative impact on other sectors. This may imply that equity investors quickly rebalance their portfolios towards more profitable sectors when they face negative shocks in one sector.

Next, we look at the results from the SAC model that are reported in column 3. The SAC model uses both the spatial lag of the dependent variable ($WR_{i,t}$) and the spatial lag of the unobservable component ($W\epsilon_{i,t}$) as independent variables. The findings show that estimated coefficients of both oil returns and beta of the industrial returns for the overall European market are positive and significant with the value of 0.0111 and 1.261, respectively. These values are higher compared to those reported for simple panel regression results (column 1), indicating that these coefficients will be underestimated unless we control for the correlations of sectoral returns (neighbourhood effect) using the spatial regressions. However, the coefficients measuring the impact of its own lagged returns and that of the US market index are considerably lower than the similar regression estimates reported in column 1—implying that these parameters are overestimated in the traditional panel regressions ignoring the

Table 4 Spatial partitioning of direct, indirect and total impact (SAC)

	Direct	Indirect	Total
$R_{oil,t}$	0.0111*** (5.60)	-0.00269*** (-4.73)	0.00842*** (5.63)
% of total impact	131%	-31%	100%
$R_{EU,t}$	1.271*** (33.27)	-0.308*** (-8.10)	0.963*** (413.08)
% of total impact	132%	-32%	100%

t statistics are presented in parentheses. The level of significance is denoted by *, ** and *** for 10%, 5% and 1%, respectively

intra-industry correlations. Additionally, the parameter estimates from both spatial lag variables (ρ and λ) are significant with the value of -0.309 and -0.294 , respectively, confirming negative spatial dependence in line with the SAR results reported in column 2. Importantly, while the magnitude of the coefficients changes with the spatial regressions (in both SAR and SAC models) in comparison with the simple panel regression, the overall model fitness (R-Squared) remains the same across all three models.² This implies that panel regression may provide spurious estimates, and therefore, it is important to employ the spatial econometric techniques which consider the neighbourhood effect while measuring the impact of oil price changes on the industrial returns. This is in line with earlier studies suggesting that incorporating spatial dependence into traditional models can improve the efficiency of statistical estimations (see e.g. Miller et al. 2007).

5.1 Direct, indirect and total impacts

In this section, we dissect the total effect into a direct and indirect effect of oil price changes on industrial returns using the SAC model. The direct effect measures the change in industry i 's dependent variable caused by a change in one of its explanatory variables and additional feedback effects. The indirect (spillover) effect measures the change in industry i 's dependent variable caused by a change in another industry j 's explanatory variable. However, both direct (includes feedback) and indirect (spillover) effects occur over time.³

The results are reported in Table 4. The first row shows the direct, indirect and total effect of oil price changes (oil return) on the panel of industrial returns. The coefficient for the total effect is 0.00842 (in column 3), which includes both direct and indirect (spillover) effects. Interestingly, the total effect is almost similar to what we have found in the case of panel regression (column 1 of Table 3). However, by

² This is in line with the results reported in earlier literature suggesting that the SAC model generally does not improve the explanatory power (in the form of R^2) of the models in comparison with SAR, especially if the same observed variables are used in both models. See Elhorst (2014), Guliyev (2020), Efthymiou & Antoniou (2013) for more details on this.

³ For detailed discussions about the direct and indirect effects, see LeSage and Pace (2009) and Naveed and Ahmad (2016).

Table 5 Direct, indirect and total effect from spatial (SAC) model (during and after the financial crisis)

Period	Variable	Direct	Indirect	Total
During the financial crisis (2008–2012)	$R_{oil,t}$	0.00701* (2.13)	− 0.00164* (− 2.03)	0.00537* (2.13)
	% of total impact	130%	− 30%	100%
After the financial crisis (2003–2017)	$R_{oil,t}$	0.0127*** (5.98)	− 0.00329*** (− 4.12)	0.00944*** (6.12)
	% of total impact	135%	− 35%	100%

t statistics are in presented parentheses. The level of significance is denoted by *, ** and *** for 10%, 5% and 1%, respectively

looking at panel regression results (in Table 3), we cannot differentiate between direct and indirect (spillover) effects. Table 4 clearly shows these effects where an indirect effect is significant and negative and accounts for 31% of the total effect. It implies that the direct effect remains underestimated by 31% while using the traditional linear models due to the omitted effects coming from co-movements (spillovers) of neighbourhood industries' returns.

The second row presents the estimated beta of the industrial returns about the broader European market index (STOXX 600). The results show that the indirect impact of the overall market on sectoral returns is about −32%, which is ignored in the panel regressions. This indirect effect is caused by the inter-relationship of underlying industries' returns. These findings again confirm the superiority of spatial models in precisely measuring the direct effect of oil prices changes on sectoral returns.

5.2 Recession and post-recession analysis

The oil prices are considered directly related to economic cycles so that during times of economic growth (downturn), the demand for oil increases (decreases). Accordingly, previous studies have found that the relationship between oil and stock prices is time-dependent (Filis et al. 2011). Therefore, we also examined whether oil had any systematic impact on European stocks during and after the global financial crisis period. To test the asymmetries in the relationship between oil prices changes and European industrial returns during boom and bust periods, we split our sample into two sub-periods: (1) during the financial crisis (2008–2012) and (2) after financial crises (2013–2017).

Table 5 reports the direct, indirect and total effects of oil price changes on the sectoral returns using the SAC model on two sub-periods. The detailed results of the panel, SAR and SAC models estimated on both sub-periods are reported in Appendix (Tables 6 and 7, respectively). According to the estimated coefficients reported in Table 5, the direct effect of oil price changes is positive and the indirect effect is negative as before; however, the size of the estimated coefficient and significance level is different across two sub-periods. In general, the distribution of direct and indirect effects in terms of %age is almost the same in both periods. Nevertheless,

Table 6 Results for sub-sample 2008–2012

	Fixed effect panel	Spatial autoregressive (SAR) model	Spatial autoregressive combined (SAC) model
$R_{oil,t}$	0.00517 (1.19)	0.00858** (2.03)	0.00705** (2.13)
$R_{EU,t}$	0.955*** (168.34)	1.520*** (51.92)	1.243*** (27.05)
$R_{US,t-1}$	-0.00901 (-1.64)	-0.00881* (-1.66)	-0.00559 (-1.32)
$R_{i,t-1}$	0.0139*** (2.77)	0.0105** (2.17)	0.00515 (1.24)
Constant	0.0000138 (0.18)		
Spatial		-0.585*** (-19.62)	-0.297*** (-6.23)
Rho			-0.284*** (-5.99)
Lambda			
Variance (σ_e^2)		0.0000731*** (79.00)	0.0000738*** (80.37)
Observations	13,050	13,050	13,050
R-squared	0.731	0.731	0.731

The table presents coefficients of fixed effects panel data, spatial autoregressive (SAR) and spatial autoregressive combined (SAC) regressions for the sub-sample 2008–2012. The dependent variables are industrial sector returns ($R_{i,t}$) and independent variables are oil returns ($R_{oil,t}$), European index returns ($R_{EU,t}$), S&P500 returns ($R_{US,t-1}$) and 1-day lagged industrial sector returns ($R_{i,t-1}$). Corresponding t-stats are given in parenthesis. The level of significance is denoted by *, ** and *** for 10%, 5% and 1%, respectively

the magnitude of coefficient measuring the impact of oil price changes on industrial returns is higher after the financial crisis compared to the crisis period. Overall, the division of the total period into two sub-periods based on the US subprime crisis revealed that the equity market returns remained less sensitive to oil price changes during the crisis period and the sensitivity doubled after the financial crisis. This result is consistent with earlier findings (i.e. Filis et al. 2011; Degiannakis et al. 2013) on the changing role of oil during different stages of economic development.

Overall, all three specifications (Eqs. 5–7) yield a positive association between the oil price changes and European sectoral returns. To check, whether our results are comparable with those reported in previous studies, we specifically looked at the studies like ours that have focussed on the European industrial indices. For example, Arouri and Nguyen (2010) analyse the short-term oil-stock movement relationship at the aggregate and sectoral level in Europe using the weekly data from January 01, 1998, to November 13, 2008. Their results suggest that reactions of stock returns to oil price changes vary across industries. However, when we calculate the average of the returns response coefficients across different sectors, the mean response is found

Table 7 Results for sub-sample 2013–2017

	Fixed effect panel	Spatial autoregressive (SAR) model	Spatial autoregressive combined (SAC) model
$R_{oil,t}$	0.0109*** (3.86)	0.0162*** (5.96)	0.0127*** (5.93)
$R_{EU,t}$	0.977*** (179.43)	1.666*** (53.37)	1.307*** (21.55)
$R_{US,t-1}$	-0.00344 (-0.57)	0.000224 (0.04)	0.00167 (0.37)
$R_{i,t-1}$	0.0105** (2.02)	0.00771 (1.55)	0.00366 (0.88)
Constant	0.00000134 (0.03)		
Spatial		-0.703***	-0.336***
Rho		(-22.37)	(-5.44)
Lambda			-0.326*** (-5.29)
Variance (σ_e^2)		0.0000268*** (77.01)	0.0000273*** (78.88)
Observations	12,600	12,600	12,600
R-squared	0.757	0.757	0.757

The table presents coefficients of fixed effects panel data, spatial autoregressive (SAR) and spatial autoregressive combined (SAC) regressions for the sub-sample 2013–2017. The dependent variables are industrial sector returns ($R_{i,t}$) and independent variables are oil returns ($R_{oil,t}$), European index returns ($R_{EU,t}$), S&P500 returns ($R_{US,t-1}$) and 1-day lagged industrial sector returns ($R_{i,t-1}$). Corresponding t-stats are given in parenthesis. The level of significance is denoted by *, ** and *** for 10%, 5% and 1%, respectively

to be positive with a value of 0.0045,⁴ which is close to the total effect (0.0041) found during the sub-period 2008–2012 and almost half of the total effect (0.0094) found in the second sub-period 2013–2017 in this study. Interestingly, the direct effect of oil price changes on European sectoral returns was found to be significantly higher than found by Arouri and Ngyuen (2010) in both sub-periods. This might be due to the better estimation technique that addresses the issue of neighbourhood (spillover) effect of European sectoral indices while estimating the relationship between oil price and sectoral returns. The positive impact of oil on overall sectoral indices is mainly driven by the dominant positive effect of the oil price changes on the oil and gas sector. Krokida et al. (2020) show that a positive aggregate demand shock in oil prices implicitly causes an increase in European equity returns of oil-related industries, albeit having a negative impact on the aggregate stock return of the European equity market.

⁴ This number is based on the average of coefficient values reported in column 4 of Table 4 in Arouri and Nguyen (2010).

Similarly, Degiannakis et al. (2013) investigate the time-varying correlations between oil prices changes and ten European sectoral indices' returns using the monthly data for the period from January 1992 to December 2010. Their findings indicate largely positive correlations between the oil and the majority of the sectoral returns during their whole sample period. However, they find that these correlations vary across time depending on the nature of the oil price shock. This is in line with Arouri and Nguyen (2010) suggesting that oil price increases are likely to be seen as an indicator of higher expected economic growth and earnings.

5.3 Robustness measures

In this section, we check whether our results are robust with different specifications of our dependent variable, i.e. the panel of industrial sectors' returns. In doing so, we run two-panel regressions with an alternative measure of our dependent variable. Firstly, we regress the overall EU stock index (STOXX® 600) returns on oil price changes while controlling for the global impact and its own lagged returns. The coefficient for the oil return effect is positive and significant with a value of 0.231 confirming a positive relationship between the oil price changes and broader European index returns. Secondly, we create an equally weighted index of the 10 sectoral returns that are part of our original sample and regress it on the oil returns while controlling for the effect of European stock index returns (STOXX® 600 index), global impact (US) and its own lagged returns. The results again indicate a positive relationship (with a coefficient value of 0.088) between the equally weighted index returns and oil price changes confirming our results reported in the previous section.

We also checked whether our results are sensitive to different specifications of the weight matrix. To that end, we constructed correlations between underlying industries for various periods and used them in our estimations. Our findings show that our results are robust, and this is due to the fact the cross-correlations between industries estimated from different historical lengths (i.e. 6 months to 2 years) remained mostly the same over time.⁵

6 Conclusion and policy implications

This paper aimed to analyse the effect of oil prices on industrial returns by considering the co-movements of neighbouring industries. The previous literature has shown that returns from various industries are correlated with each other, thus linear regression models that try to estimate the relationships between industrial equity returns and any exogenous variables may have reported over/underestimated coefficients. The cross-correlations among industrial sector returns need to be controlled for while performing econometric estimations (Kocaarslan et al. 2018; Peng et al. 2017; Park and Ratti 2008; Cong et al. 2008).

⁵ The detailed results of robustness analysis are not shown here to conserve the space. However, they can be obtained from authors upon request.

Therefore, this paper particularly addresses the issue of co-movements of equity sector returns while estimating the impact of oil price changes on European sectoral indices using spatial econometrics approach in quantifying the neighbourhood (co-movements of industries' returns) effect. For the empirical analysis, we use daily closing prices of ten STOXX[®] European sectoral indices and Europe Brent Crude Spot as oil prices for the period 2008–2017. To control for the local (European) and global (American) stock markets' effects, the broader STOXX 600 Europe and S&P500 indices are used, respectively.

Our findings show that there is a positive and significant effect of oil price returns on European industrial returns. This relationship is significant regardless if we use panel or spatial econometric techniques. However, in spatial regression models, we were able to identify the direct and indirect effects of oil price changes. Moreover, the relationship between oil price returns and industrial returns is found to be underestimated using the standard models where intra-industrial co-movements are not taken into consideration. In general, the direct economic impact on industrial stock returns is almost 31% more than what has been found by ignoring intra-industrial co-movements. Our analyses also indicate that there is a negative spatial dependence among different industries. Additionally, our findings indicate that there is a positive relationship between oil and industrial stock prices across different periods, i.e. during and after financial crises. However, the magnitude of the effect is stronger after the crisis.

Our results have clear policy implications for the policymakers, investment managers and hedgers. Firstly, the policymakers need to measure the precise impact of any exogenous change (e.g. oil prices) on equity prices, which could be done using the spatial econometric approach applied in this paper. Secondly, negative spatial dependence found in this paper may have important implications for the portfolio managers in terms of diversifications opportunities across different industrial returns. Moreover, accurate estimation of the direct and indirect impact of oil prices can be useful to devise the appropriate hedging strategies across different classes of assets such as equity and commodities.

For future research, it would be interesting to apply spatial econometric techniques at the industry level while controlling for the interactions among constituent firms. The same competitive effect could also be present among companies within the same industries which may lead to biased estimation of market betas and other factors of systematic risk. Similarly, the cross-country analysis of the regional stock indices can also be carried out considering the neighbourhood effect. Another interesting avenue for future research is to analyse the effect of new coronavirus on the relationship among the equity indices and crude oil prices. During an initial phase of the new coronavirus, both the equity markets and crude oil prices were negatively affected owing to the supply and demand shocks of the crude oil, and uncertainty surrounding the equity and financial markets. We look forward to exploring these avenues in our future work.

Appendix

Tables 6 and 7

Funding None of the authors received any funding for this research.

Declarations

Conflict of interest The authors declare there are no conflicts of interest.

Informed consent Informed consent is not applicable for this study.

Ethical approval This article does not contain any studies with human participants or animals.

References

- Anselin L (1988) Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. *Geogr Anal* 20:1–17
- Arbia G (2006) *Spatial econometrics: statistical foundations and applications to regional convergence*. Springer Science & Business Media, New York
- Arnold M, Stahlberg S, Wied D (2013) Modeling different kinds of spatial dependence in stock returns. *Empir Econ* 44:761–774
- Arouri MEH (2011) Does crude oil move stock markets in Europe? A sector investigation. *Econ Model* 28:1716–1725
- Arouri MEH, Nguyen DK (2010) Oil prices, stock markets and portfolio investment: evidence from sector analysis in Europe over the last decade. *Energy Policy* 38:4528–4539
- Asgharian H, Hess W, Liu L (2013) A spatial analysis of international stock market linkages. *J Bank Financ* 37:4738–4754
- Asgharian H, Liu L (2018) Stock return dependence and product market linkages. Available at SSRN 3031200.
- Blonigen BA, et al (2007) FDI in space: Spatial autoregressive relationships in foreign direct investment. *Eur Econ Review* 51(5):1303–1325
- Barker D, Loughran T (2007) The geography of S&P 500 stock returns. *J Behav Financ* 8:177–190
- Basher SA, Haug AA, Sadorsky P (2018) The impact of oil-market shocks on stock returns in major oil-exporting countries. *J Int Money Financ* 86:264–280
- Blanc-Brude F, Cookson G, Piesse J et al (2014) The FDI location decision: distance and the effects of spatial dependence. *Int Bus Rev* 23:797–810
- Boarnet MG, Glazer A (2002) Federal grants and yardstick competition. *J Urban Econ* 52:53–64
- Cong R-G, Wei Y-M, Jiao J-L et al (2008) Relationships between oil price shocks and stock market: an empirical analysis from China. *Energy Policy* 36:3544–3553
- Cunado J, de Gracia FP (2014) Oil price shocks and stock market returns: evidence for some European countries. *Energy Econ* 42:365–377
- Degiannakis S, Filis G, Floros C (2013) Oil and stock returns: evidence from European industrial sector indices in a time-varying environment. *J Int Finan Mark Inst Money* 26:175–191
- Diaz EM, Molero JC, de Gracia FP (2016) Oil price volatility and stock returns in the G7 economies. *Energy Econ* 54:417–430
- Efthymiou D, Antoniou C (2013) How do transport infrastructure and policies affect house prices and rents? Evidence from Athens, Greece. *Transp Res Part A Policy Pract* 52:1–22
- Elhorst JP (2014) *Spatial panel data models*. Spatial econometrics. Springer, New York, pp 37–93
- Fang S, Egan P (2018) Measuring contagion effects between crude oil and Chinese stock market sectors. *Q Rev Econ Financ* 68:31–38

- Filis G, Degiannakis S, Floros C (2011) Dynamic correlation between stock market and oil prices: the case of oil-importing and oil-exporting countries. *Int Rev Financ Anal* 20:152–164
- Filiztekin A (2009) Regional unemployment in Turkey. *Pap Reg Sci* 88:863–878
- Flavin TJ (2004) The effect of the Euro on country versus industry portfolio diversification. *J Int Money Financ* 23(7–8):1137–1158
- Miller J, Franklin J, Aspinall R (2007) Incorporating spatial dependence in predictive vegetation models. *Ecol Model* 202(3–4):225–242
- Maurseth PB, Frank B (2009) The german information and communication technology (ICT) industry: spatial growth and innovation patterns. *Reg Stud* 43.4:605–624
- Garretsen H, Peeters J (2009) FDI and the relevance of spatial linkages: do third-country effects matter for Dutch FDI? *Rev World Econ* 145:319–338
- Garrett TA, Marsh TL (2002) The revenue impacts of cross-border lottery shopping in the presence of spatial autocorrelation. *Reg Sci Urban Econ* 32:501–519
- Guliyev H (2020) Determining the spatial effects of COVID-19 using the spatial panel data model. *Spat Stat* 38:100443
- Kelejian HH, Prucha IR (1999) A generalized moments estimator for the autoregressive parameter in a spatial model. *Int Econ Rev* 40:509–533
- Kocaarslan B, Soytaş U, Sari R, Ugurlu E (2019) The changing role of financial stress, oil price, and gold price in financial contagion among US and BRIC markets. *Int Review Financ* 19:541–574
- Krokida SI, et al (2020) The effects of oil price shocks on the prices of EU emission trading system and European stock returns. *The Eur J Financ* 26(1):1–13
- Leontief W (1986) *Input-output economics*. Oxford University Press, Oxford
- LeSage JP (1999) *Spatial econometrics: regional research institute*. West Virginia University Morgantown, West Virginia
- LeSage J, Pace RK (2009) *Introduction to spatial econometrics*. Chapman and Hall/CRC, London
- Myrdal, G (1957) *Economic Theory and underdeveloped regions*. Duckworth, London.
- Nandha M, Faff R (2008) Does oil move equity prices? A global view. *Energy Econ* 30:986–997
- Narayan PK, Gupta R (2015) Has oil price predicted stock returns for over a century? *Energy Econ* 48:18–23
- Naveed A, Ahmad N (2016) Technology spillovers and international borders: a spatial econometric analysis. *J Borderl Stud* 31:441–461
- Park J, Ratti RA (2008) Oil price shocks and stock markets in the US and 13 European countries. *Energy Econ* 30:2587–2608
- Pavlyuk D (2011) Spatial analysis of regional employment rates in Latvia. *Sustain Spat Dev* 2:56–62
- Peng C, Zhu H, Jia X et al (2017) Stock price synchronicity to oil shocks across quantiles: evidence from Chinese oil firms. *Econ Model* 61:248–259
- Phan DHB, Sharma SS, Narayan PK (2015) Oil price and stock returns of consumers and producers of crude oil. *J Int Financ Mark Inst Money* 34:245–262
- Pirinsky C, Wang Q (2006) Does corporate headquarters location matter for stock returns? *J Financ* 61:1991–2015
- Ready RC (2018) Oil prices and the stock market. *Rev Financ* 22:155–176
- Reboredo JC, Rivera-Castro MA (2014) Wavelet-based evidence of the impact of oil prices on stock returns. *Int Rev Econ Financ* 29:145–176
- Saavedra LA (2000) A model of welfare competition with evidence from AFDC. *J Urban Econ* 47:248–279

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