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Oil and the U.S. stock market: Implications for low carbon policies

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ABSTRACT

We extend the existing understanding of the relation between oil prices and stock markets in two ways: (1) by evaluating the effects of the oil market on the U.S. stock market, at an aggregate level and for all forty-nine U.S. industry specific portfolios, and (2) by scrutinizing the dynamic nature of this relation within a Structural Vector Autoregression (SVAR) specification for a large set of rolling samples with fixed size. Results indicate that the effect of oil prices on the U.S. stock market depends on the type and timing of the shock. An oil supply shock generally does not have a statistically measurable effect on stock market performance. Conversely, an aggregate demand shock has a positive effect on nearly all sectors while an oil-specific demand shock has a negative effect on stock returns for most industries. These results suggest that investors can shift the portfolios consistent with smaller effects of oil-related shocks and the costs of carbon taxes and/or tradeable permits may be smaller than commonly thought if stock prices represent the net present value of profits.

1. Introduction

In the early 1970s, oil price spikes highlighted two economic issues: the role of fossil fuels in economic growth and environmental externalities associated with the combustion of fossil fuels, including climate change. Interactions between these issues prompted policy towards a "Low Carbon Economy," in which interventions seek to enhance economic growth and reduce greenhouse gas emissions. Although these efforts gradually reduce economic dependence on oil, oil price swings are economically important because oil supplies nearly one-third of world's total energy.[1] Under these conditions, policy interventions, such as a carbon tax, raise concerns about higher production costs (especially for the oil dependent sectors of the economy), higher unemployment, lower corporate and government revenues (Martin et al., 2014), and more generally lower economic growth (Metcalf and Stock, 2020).

If stock prices represent the net present value of future profits, the stock market reflects the economy's overall activity (see among others Hamilton, 1983; Gisser and Goodwin, 1986; Mork, 1989; Hooker, 2002; Nandha and Faff, 2008). In this context, we estimate alternative models that can help in answering the following questions: How do oil shocks affect the U.S. stock market at an aggregate and disaggregated level and does the magnitude and persistence of these shocks change over time? We interpret these findings relative to two additional questions; (1) what do changes in the magnitude and persistence of oil shocks imply about the need to hedge stock portfolios against the effects of oil shocks and (2) can the magnitude and persistence of oil shocks be used to analyze policy that aims to reduce carbon emissions in nations where such policy is not yet been implemented?

To answer the first set of questions, we use Kilian's (2009) methodological framework and estimate a Structural Vector Autoregression (SVAR) model from rolling windows of a fixed size for both the aggregate U.S. stock market and all sectoral stock indexes. These results extend the literature in two ways; first we disaggregate previous efforts, which examine the effects of the oil market on aggregate measures of the U.S. stock market, by generating results for all forty-nine U.S. industry-specific portfolios (sectors) that are defined by the 4-digit SIC code classification. Only some of these sectors are analyzed by previous efforts. For example, Elyasiani et al. (2011) analyze thirteen sectors while Reboredo and Rivera-Castro (2014) investigate eight sectors. Second, we quantify the dynamics of the relation between oil prices and stock returns by repeatedly estimating our SVAR specification from rolling samples of fixed size (in total, 17,400 samples are analyzed). Hence, the

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[1] See the Statistical Review of World Energy (2020) by BP.

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rolling sample analysis allows the dynamic assessment of the oil-related shocks' impact (in terms of magnitude and significance) on the stock market.

We interpret these results relative to the literature[2] on the economic and financial impact of oil prices. Many studies find that on average, higher oil prices have a negative effect on the macroeconomy or financial markets (e.g. Ciner, 2001; Papapetrou, 2001; Basher and Sadorsky, 2006; Park and Ratti, 2008; Rahman and Serletis, 2011; Lippi and Nobili, 2012; Jo, 2014; Mumtaz et al., 2018), although results from more recent samples suggest that the negative effects are less severe (e.g. Blanchard and Gali, 2007; Cologni and Manera, 2009; Baumeister and Peersman, 2013; Choi et al., 2018). Differences among studies could stem from their assumptions about the exogeneity/endogeneity of oil prices.

Studies that assume oil prices are exogenous use a variety of methodologies, which range from frequency-dependent regressions to different versions of the market model. Nandha and Faff (2008) estimate a two factor 'market and oil' pricing model for thirty-five indices of global industry and find that higher oil prices have a negative effect on most industries, except the Mining and Oil and Gas sectors. Elyasiani et al. (2011) reach similar conclusions for nine of the thirteen U.S. industries examined. Hammoudeh et al. (2010) implement typical GARCH type specifications and find that the oil market enhances the volatility of stock returns for oil-intensive sectors but reduces volatility in the other sectors. Using a more traditional cointegration framework, Bondia et al. (2016) show that oil prices have a short-run effect on stock prices for firms that produce alternative forms of energy (proxied by the Arca Tech 100 Index), while Nazlioglu and Soytas (2012) use panel cointegration techniques to show that oil prices affect prices for several agricultural commodities. Beyond the time domain, Ciner (2013) use frequency dependent regressions, in which coefficients are permitted to vary over time, and find that the persistence of an oil shock influences its effect on the stock market; shocks that persist for less than 12-months and more that 36-months have a negative effect, while shocks that persist for 12 to 36-months have a positive effect. Similarly, Reboredo and Rivera-Castro (2014) use a wavelet multi-resolution analysis and find that oil prices have a measurable effect on the European and U.S. stock markets (both the aggregate and eight sectors) after the 2008 financial crisis, but not before.

Conversely, analyses that assume oil prices are endogenous rely on the VAR modelling framework. Using a VARMA-BEKK-AGARCH framework, Salisu and Oloko (2015) validate a bidirectional shock spillover effect between oil and stock markets. Using an unrestricted VAR specification, Cong et al. (2008) find that oil price shocks do not affect most Chinese industries, except manufacturing and some oil companies. The same methodology generates similar conclusions for thirty-eight European industries (Scholtens and Yurtsever, 2012) and for most industries in G7 countries (Lee et al., 2012).

Kilian (2009) argues that oil-related shocks cannot be identified from an unrestricted VAR because it assumes that model errors are correlated, which undermines the identification of innovations. Instead, Kilian (2009) argues that economic theory and stylized facts should be used to impose the restrictions that identify structural shocks. Specifically, Kilian (2009) suggests imposing exclusion restrictions, which show that demand and supply shocks have different effects on oil prices and hence on the stock market.[3] Using this approach, Kang et al. (2017) find that oil supply shocks do not affect the stock price for major oil and gas companies, while oil demand shocks have a positive effect. Using the same strategy for identification, Li et al. (2017) show that the impact of oil supply shocks and oil-specific demand shocks have equal but opposite effects on the oil and gas sector.

This identification scheme is criticized as too restrictive. Peersman and van Robays (2009) suggest identification schemes based on the signs for one or more variables; Kilian and Murphy (2012) expand this scheme to include restrictions on supply and demand elasticities. For example, Koh (2017) imposes sign restrictions and finds that only oil-specific demand shocks have a negative impact in most Asian stock markets, while oil supply or aggregate demand shocks have smaller effects. Basher et al. (2018) combine a SVAR specification, which is identified with sign restrictions, and a Markov-Switching model for major oil-exporting countries and find that stock market effects depend on the nature of oil price shocks.

Instead of restrictions based in theory, some propose identification schemes based on heteroskedasticity. This is possible by classifying model innovations based on their volatility. Initial efforts assume that changes in volatility are determined exogenously (Rigobon, 2003; Rigobon and Sack, 2003; Lanne and Lütkepohl, 2008), while more recent approaches identify changes in volatility endogenously, using GARCH (Lütkepohl and Milunovich, 2016) or Markov Switching (MS) specifications (Herwartz and Lütkepohl, 2014). Lütkepohl and Netsunajev (2014) find that shocks identified using this data driven approach, shocks recovered using the Kilian (2009) identification method, and shocks identified using sign restrictions, deliver similar results in explaining oil price movements. Furthermore, Lütkepohl and Netsunajev (2014) find that oil supply shocks always play a minor role in the formulation of oil prices, while aggregate demand shocks have a larger effect, but the magnitude of that effect declines since the mid-1980s.

Beyond the methods used to analyze the relation between oil and stock markets, we also extend the interpretation of this relation. Specifically, we use our results to analyze the economic impact of policies that aim to abate carbon emissions, especially in nations yet to implement such policy, such as the U.S. As of 2019, twenty-five countries have a carbon tax or are scheduled to have a carbon tax soon. In these twenty-five nations, observations can be analyzed using several techniques. A standard VAR model suggests that a carbon tax on gasoline and diesel does not have a statistically significant impact on GDP for the province of British Columbia, Canada (Bernard et al., 2018). A similar result for British Columbia is generated by a Difference-in-Difference approach (Metcalf, 2019). Analyzing a panel of European countries, Metcalf (2019) finds a small, positive impact on GDP. Metcalf and Stock (2020) use a local projection method to conclude that carbon taxes do not affect economic growth and employment in thirty-one European countries. Finally, Metcalf and Stock (2020b) use a more extensive dataset to reach the same conclusions as Metcalf and Stock (2020).

In nations yet to implement a carbon tax, empirical techniques cannot be used to assess impacts. Instead, Computable General Equilibrium (CGE) models are used to evaluate the economic costs for a set of counterfactual scenarios (e.g., difference in the GDP path when no tax and a tax of a certain level are considered). Using this framework, McKibbin et al. (2015) find that a $15 per ton carbon tax (increasing 4% annually) can increase GDP, employment, and wages in the long run if the tax is made revenue neutral by reducing taxes on capital. Similarly, Goulder and Hafstead (2017) and Goulder et al. (2019) find that a carbon tax in the U.S. can generate revenues that offset costs and adverse distributional effects across industries. Finally, a multi-sector Computable General Equilibrium model finds that a $43.40 carbon tax in 2019 could achieve environmental goals by 2025, with only a modest negative impact on GDP (Chen and Hafstead, 2019).

But these CGE models are not subjected to rigorous statistical testing and their performance is uncertain (Dixon and Rimmer, 2013). To expand the ability to evaluate climate policy *ex ante*, we analyze the relation between oil prices and stock markets. We postulate that the economic cost of policy instruments that seek to reduce emissions by raising energy prices may be smaller than commonly thought because: (i) there is a very weak relation between the stock market and oil related

[2] This literature includes several influential papers; Bernanke et al. (1997), Hooker (2002), Barsky and Kilian (2004), Segal (2011), Baumeister and Peersman (2013), Mohaddes and Pesaran (2017).

[3] The following studies use the same identification; Kilian and Park (2009), Fukunaga et al. (2010), Kang and Ratti (2013), and Broadstock and Filis (2014).

shocks, both on the aggregate and disaggregate level, and (ii) on average, most sectors respond similarly to the aggregate stock market index, although some sectors generate idiosyncratic responses to oil shocks, as their exposure to the oil market is different (for instance, Precious Metals, Automobiles and Trucks and Petroleum and Natural Gas).

The results and methods used in this paper are described in the following sections. Section 2 presents the data and Section 3 describes the methodology. The results are analyzed in Section 4, while Section 5 discusses our results.

2. Data

We analyze monthly observations for global oil production, the price of crude oil, global economic activity, aggregate returns to U.S. equities, and returns to equities in forty-nine sectors of the U.S. economy. The sample includes observations from January 1973 to December 2016. To proxy global oil supply, we use global production of crude oil including lease condensate (Fig. 1).[4] Observations are obtained from the U.S. Energy Information Administration and are measured in millions of barrels pumped per day (averaged by month). The real price of crude oil is proxied by the U.S. refiners' acquisition cost of imported crude oil (Fig. 2), which we obtain from the U.S. Department of Energy.[5] Oil prices are converted to real (1982–1984 = 100) dollars per barrel by dividing the nominal price by the U.S. CPI, which is obtained from the FRED database of the Federal Reserve Bank of St. Louis.

Real global economic activity (*REA*) is proxied by using the Kilian (2009, 2019) index (*KI,* hereafter).[6] The advantages of the *KI* relative to industrial production or real GDP are discussed in the literature (Kilian, 2009, 2019; Basher et al., 2012). The *KI* is linearly detrended to remove the effects of technological advances in ship-building and other long-term trends in the demand for sea-transport. *KI* measures cyclical variations in ocean freight rates; thus, it can be interpreted as an index that represents the business cycle. Nonetheless, the *KI* embodies the cost of fuel (largely oil) including fuel surcharges, used to power the ships and so the *KI* is directly related to the price of crude oil (Kolodzeij and Kaufmann, 2014). Finally, we obtain observations for the prices of U.S. equities from the MSCI database. We chose the MSCI index for stock prices because it is value-weighted and therefore reflects a substantial percentage of total market capitalization. Specifically, the 620 constituents of the MSCI index represent 85% of the free float-adjusted market capitalization. To obtain real stock prices, we divide the MSCI index by the U.S. CPI and use the standard logarithmic difference to calculate real annualized stock returns (Fig. 4).

Industry-specific observations for the forty-nine U.S. industry specific portfolios are defined by the 4-digit SIC code for all equities that are traded on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX) and the National Association of Securities Dealers Automated Quotations (NASDAQ). The industry specific portfolios returns are presented in the Appendix (see Figs. A.1 to A.49).[7]

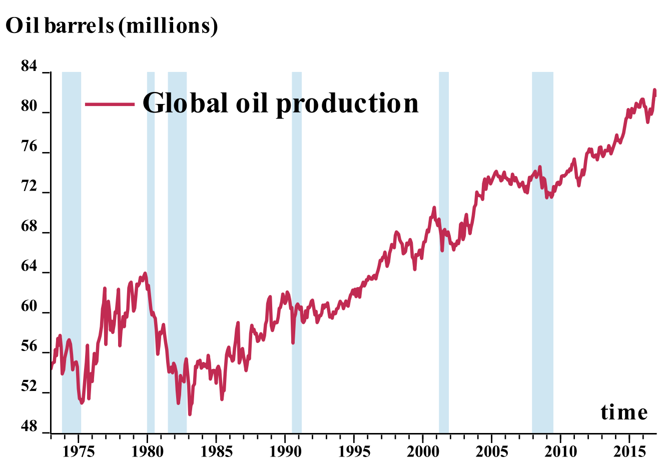


Fig. 1. Global oil production.

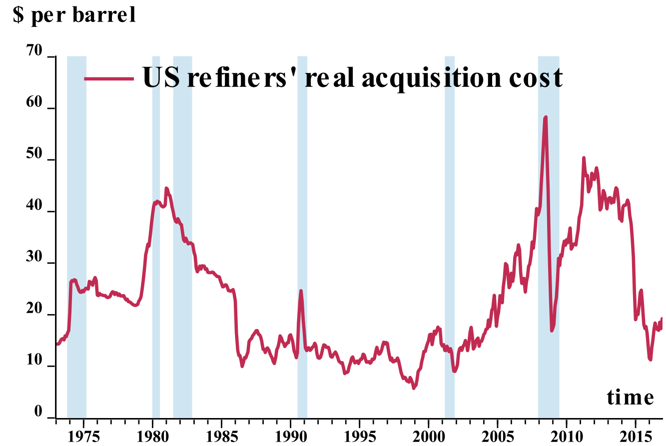


Fig. 2. Real oil prices.

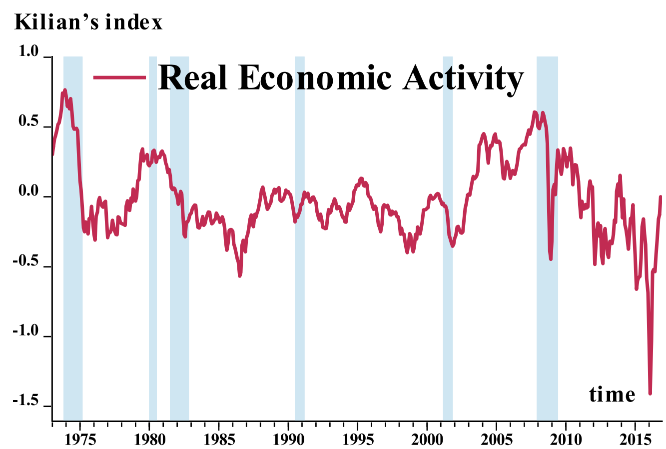


Fig. 3. Real economic activity.

[4] The shaded areas in Figures 1 to 4 denote recessions defined by the NBER.

[5] Note that observations start in 1974:1 but we extend it backward using the method described by Barsky and Kilian (2001). Because this price includes transportation costs, which is used to measure global economic activity, this creates a relation by definition between prices and economic activity (Kolodzeij and Kaufmann, 2014). To evaluate the degree to which the results are robust, we re-estimate the model with the real spot price of WTI. The results are qualitatively similar to those presented in Section 4 and are available upon request. Although Brent now is viewed as a more accurate benchmark than WTI (Scheitrum et al., 2018), we use WTI because observations are available for the entire sample; observations for the spot price for Brent start in 1983.

[6] Data are available on Kilian's website: http://www-personal.umich.edu/~lkilian/. For an update, see Kilian (2019). The latter does not affect our results.

[7] The data come from Kenneth R. French library, available at:https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

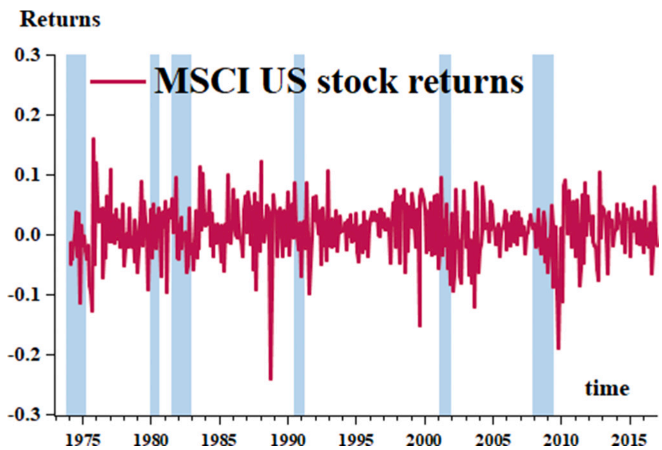


Fig. 4. U.S. stock market index.

3. Methodology

3.1. The SVAR specification

To examine the relation among supply, demand, oil-specific demand shocks and the U.S. stock market, we augment the general VAR specification of Kilian (2009) with stock market returns as given in *Eq.* (1):

$$A_0 y_t = a_0 + \sum_{i=1}^{24} A_i y_{t-i} + \varepsilon_t \quad (1)$$

where, $y_t = (O^p, R^{ea}, O^{pr}, S^r)$ is a 4 × 1 vector of endogenous variables. Specifically, O^p is the growth (logarithmic difference) of global oil production, R^{ea} and O^{pr} denote logarithms of real economic activity and real crude oil prices, respectively. S^r represents real stock returns, A_0 and A_i denote 4 × 4 matrices of the contemporaneous coefficients and the coefficients of the lagged endogenous variables, respectively. Finally, a_0 is a 4 × 1 vector of constant terms and ε_t are the serially and mutually independent structural innovations.

The variance-covariance matrix of the structural shocks is normalized as $\sigma_i^2 I_4$. To retrieve the reduced structural VAR model, we multiply *Eq.* (1) by A_0^{-1} as follows:

$$y_t = B_0 + \sum_{i=1}^{24} B_i y_{t-i} + u_t \quad (2)$$

where, $B_0 = A_0^{-1} a_0, B_i = A_0^{-1} A_i$, $u_t = A_0^{-1} \varepsilon_t$ and u_t are the reduced-form VAR innovations. We obtain the structural innovations by imposing exclusion restrictions on A_0^{-1} that are based on economic theory. Following Kilian and Park (2009), we decompose the structural innovations with the following identification:

$$u_t = \begin{pmatrix} u_t^{O^p} \\ u_t^{R^{ea}} \\ u_t^{O^{pr}} \\ u_t^{S^r} \end{pmatrix} = \begin{pmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{pmatrix} \begin{pmatrix} \varepsilon_{1t}^{\text{Supply Shock (Oil)}} \\ \varepsilon_{2t}^{\text{Demand Shock (Aggregate)}} \\ \varepsilon_{3t}^{\text{Demand Shock (Oil-specific)}} \\ \varepsilon_{4t}^{\text{Other Shocks (stock retutns)}} \end{pmatrix} \quad (3)$$

This procedure identifies: (i) oil supply shocks (ε_{1t}), (ii) aggregate demand shocks (ε_{2t}), (iii) oil-specific demand shocks (ε_{3t}), and finally, (iv) other shocks which embody innovations attributed to the stock market (ε_{4t}).[8] We interpret oil-specific demand shocks as precautionary demand shocks that arise from uncertainty related to the difference between expected oil supply and expected demand (Kilian, 2009; Kilian and Park, 2009). This difference may be associated with unexpected demand growth, unexpected reductions in crude oil supply, or both. This interpretation is questioned by Hamilton (2011), who suggests that oil-market specific shocks are speculative demand shocks caused by speculative motives and forward-looking behavior. With no consensus on the interpretation, we use the more general term "Oil-specific demand shocks."

The restrictions used in *Eq.* (3) impose a block-recursive structure. Four assumptions assure their validity. First, innovations attributed to (i) economic activity or (ii) oil-specific demand do not affect global oil production in the very short run. Second, global oil supply shocks can affect real economic activity in the short run (but not vice-versa). That is, global oil supply shocks affect economic activity within a month. Moreover, the small (in absolute terms) short run price elasticity of crude oil demand implies that oil-specific demand shocks do not affect economic activity (Kilian, 2009). Third, real oil prices respond to both oil supply and aggregate demand shocks in the short run. Finally, the global oil market is contemporaneously predetermined with respect to the domestic stock market. This assumption is common in the literature because it is highly unlikely that the U.S. stock market could affect the three global oil market variables within a month (Lee and Ni, 2002; Kilian and Vega, 2011).

3.2. The rolling SVAR

To examine the dynamics of the relation between oil prices and stock returns, we estimate the SVAR model from rolling windows of fixed size. To the best of our knowledge, this approach has not been used to analyze the relation between the oil and stock markets. Rehman et al. (2018) use a similar framework to assess the impact of the oil related structural shocks on the price returns of five precious metals, but not on the sectoral stock returns. Rehman et al. (2018) use rolling windows of 122 observations to estimate a dynamic connectedness measure (among the oil market shocks and each one of the investigated precious metals) by combining the Kilian and Park (2009) SVAR identification scheme along with the Diebold and Yilmaz (2014) connectedness approach. Rehman et al. (2018) find that aggregate demand shocks have the largest effect on markets for precious metals, except gold.

Here we estimate the model described in *Eq.* (1) using 348 rolling windows, each with 180 monthly observations. The first rolling window includes observations from January 1973 to December 1987, the second rolling window includes observations from February 1973 to January 1988, and so on. We use rolling windows of a fixed length (as opposed to expanding windows) to facilitate the comparison of standard errors across windows. For each window, we derive the impulse responses that proxy the effect of each oil-related shock on stock returns over a 15-month forecast horizon.

4. Empirical results

4.1. U.S. aggregate stock market

Figs. 5 to 7 present the effects of the three oil-related shocks on the aggregate U.S. stock market index for: i) the full sample (i.e.,

[8] This last shock does not have a direct structural interpretation. Once structural innovations are identified, the analysis of the impulse responses assumes that the magnitude of all shocks is one-standard deviation (this is a common practice in the literature). Moreover, we normalize the oil supply shocks such that a shock increases the price of oil. Thus, our analysis assumes a negative oil supply shock, a positive aggregate demand shock, and a positive oil-specific demand shock.

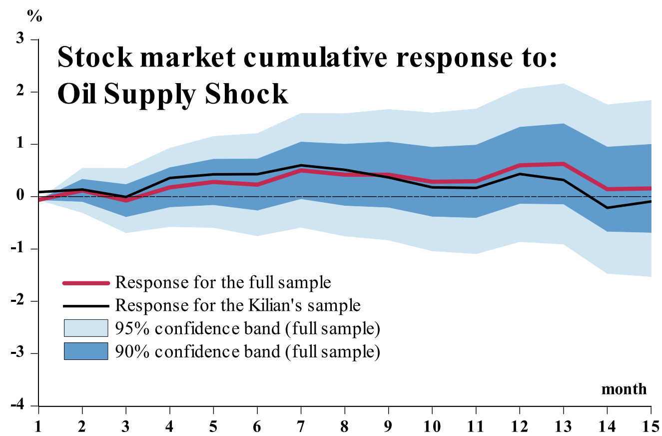


Fig. 5. Oil supply shock.
Notes: (i) The magnitude of the shock is equal to one standard deviation. (ii)The shock is normalized such that to imply an increase in the price of oil (negative shock).

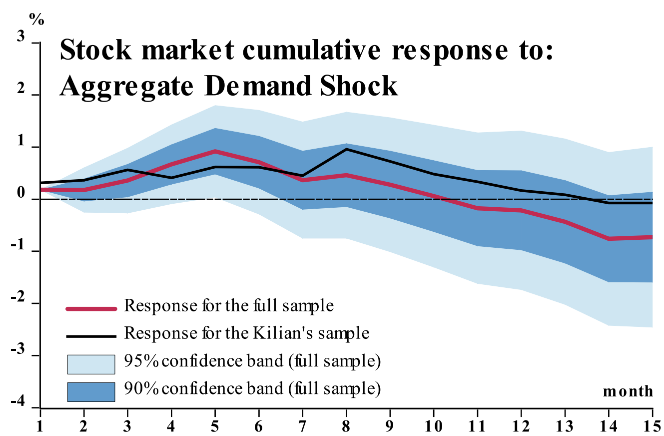


Fig. 6. Aggregate demand shock.

1973:01–2016:12) and ii) the Kilian and Park (2009) sample (i.e., 1973:01–2006:12) (K&P, hereafter).[9] Oil supply shocks have almost no effect on aggregate stock market returns (Fig. 5). In other words, an unexpected decline of oil supply does not have a statistically measurable effect on stock returns at any horizon. This result is consistent with K&P as well as those generated by Wang et al. (2013), Güntner (2014) and Foroni et al. (2017).

During the first six months, an aggregate demand shock increases returns (Fig. 6, p-value<0.1). Consistent with economic theory, an increase in aggregate demand stimulates the economy, which lifts stock prices. Nonetheless, increased economic activity boosts oil demand,

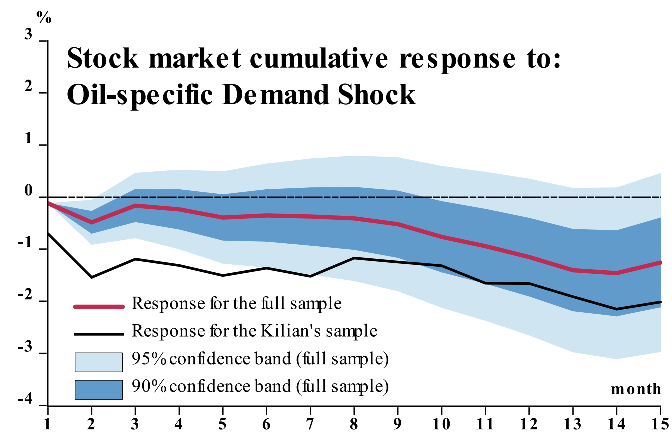


Fig. 7. Oil-specific demand shock.
Note: The magnitude of both shocks is equal to one standard deviation.

which raises oil prices. Higher oil prices depress economic activity, which is consistent with the net effect returning to zero. Indeed, the effect of an aggregate demand shock is not statistically different from zero at the end of the fifteen-month impulse horizon.

Both samples indicate that an oil-specific demand shock has a negative effect on stock market returns in the long-run (Fig. 7). This negative effect is larger in the K&P sample such that a statistically measurable negative effect (p-value <0.05) does not appear in the full sample until month eight. Other studies generate similar conclusions (e.g., Gupta and Modise, 2013; Güntner, 2014; Li et al., 2017), whereas conflicting results are described by Apergis and Miller (2009). Together, these results indicate that the effect of oil prices on stock market returns depends on the cause(s) of oil price changes.

Next, results of estimates from rolling windows allow us to examine the dynamics of these three oil price shocks on stock market returns (Figs. 8-10). Each figure shows the impulse responses of U.S. stock market returns in a three-dimensional coordinate system. The vertical left-axis (titled: impulse response) displays the magnitude of the impulse responses (in percentage); the bottom horizontal axis (titled: end of fixed size rolling sample) displays the end date for the rolling window (e.g. the first impulse response is estimated from a window that includes observations from 1973:1 to 1987:12); the bottom vertical axis (titled: horizon) displays the impulse horizon, and surface colors display the magnitude of the impulse response.[10] Negative responses are yellow and red, while blue and purple display positive responses. Finally, the two-dimensional contour plot into the bottom of the figure highlights the significant responses (p-value<0.05); red color implies a negative response value (p-value <0.05), while the purple color implies a positive response value (p-value <0.05).

The impact of a shock in oil supply becomes increasingly negative over time (Fig. 8). Across all forecast horizons, statistically insignificant positive effects rapidly shift to statistically insignificant negative effects for windows that end in 2003 and beyond. Towards the end of the sample period, negative effects become statistically significant for short forecast horizons. Of the total responses estimated, only 3.4% are significant. Together, these results indicate that reductions in the global oil supply do not have a significant impact on the aggregate U.S. stock market. The lack of a relation suggests that OPEC decisions do not have a statistically measurable effect on returns in financial and commodity markets.

Aggregate demand shocks change returns in the stock market from zero or negative to positive through the total sample period (Fig. 9). At the start of the rolling samples, the effects are mainly negative (but statistically insignificant), while this relation becomes positive and

[9] We present the Kilian and Park (2009) sample results for comparison reasons only. Consistent with Kilian (2009), we estimate *Eq.* (1) using twenty-four lags. This lag length is conservative; specifications with shorter lag-orders can bias the results in ways that exaggerate the explanatory power of oil supply and oil-specific demand shocks (Ciner, 2013). Finally, Sims et al. (1990) argue that if the order of integration is uncertain a priori, the VAR should be specified in levels. Specifying the VAR in levels generates precise estimates of the impulses responses if the time series are stationary. If this assumption is incorrect, and the variables are non-stationary, the loss of the asymptotic efficiency widens the error bands. Conversely, incorrectly assuming that a stationary time series has a unit root makes the estimates inconsistent. Given this trade-off, we follow Kilian and Park (2009) and assume that REA and oil prices are stationary. Under these conditions, the maximum penalty is the loss of asymptotic efficiency.

[10] See the color bar above Figures 8, 9 and 10.

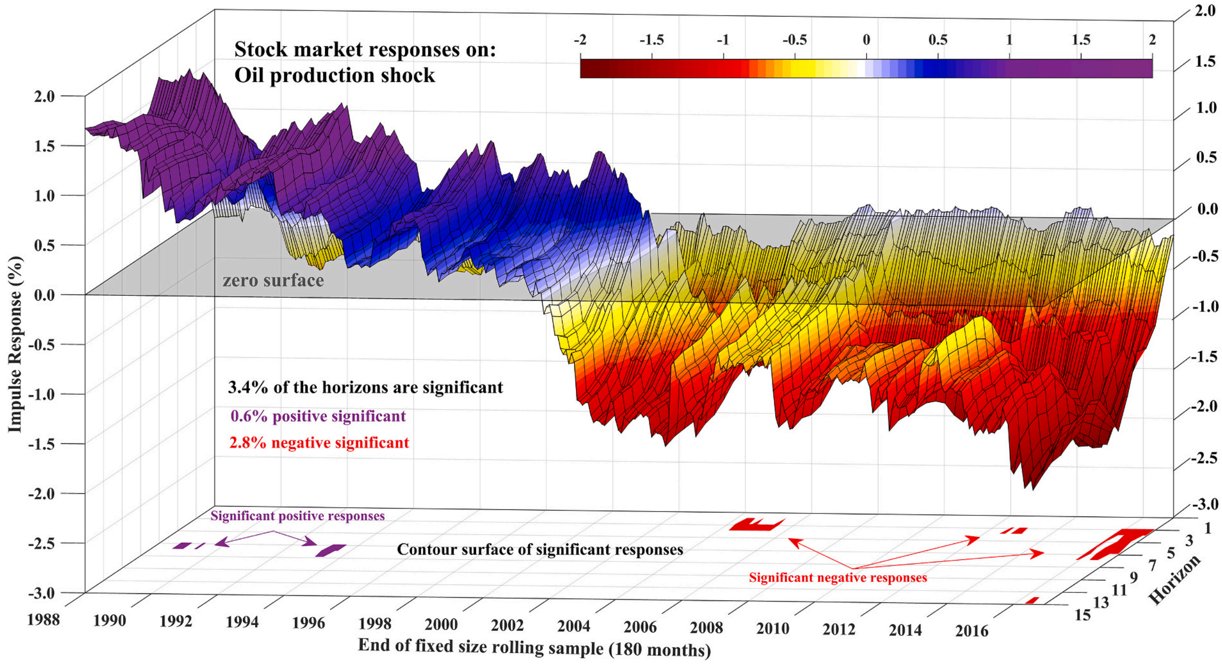


Fig. 8. Stock market rolling responses on oil supply shock.
Notes: (i) In all rolling samples the magnitude of the shock is equal to one standard deviation. (ii) The shock is normalized such that to imply an increase in the price of oil (negative shock).

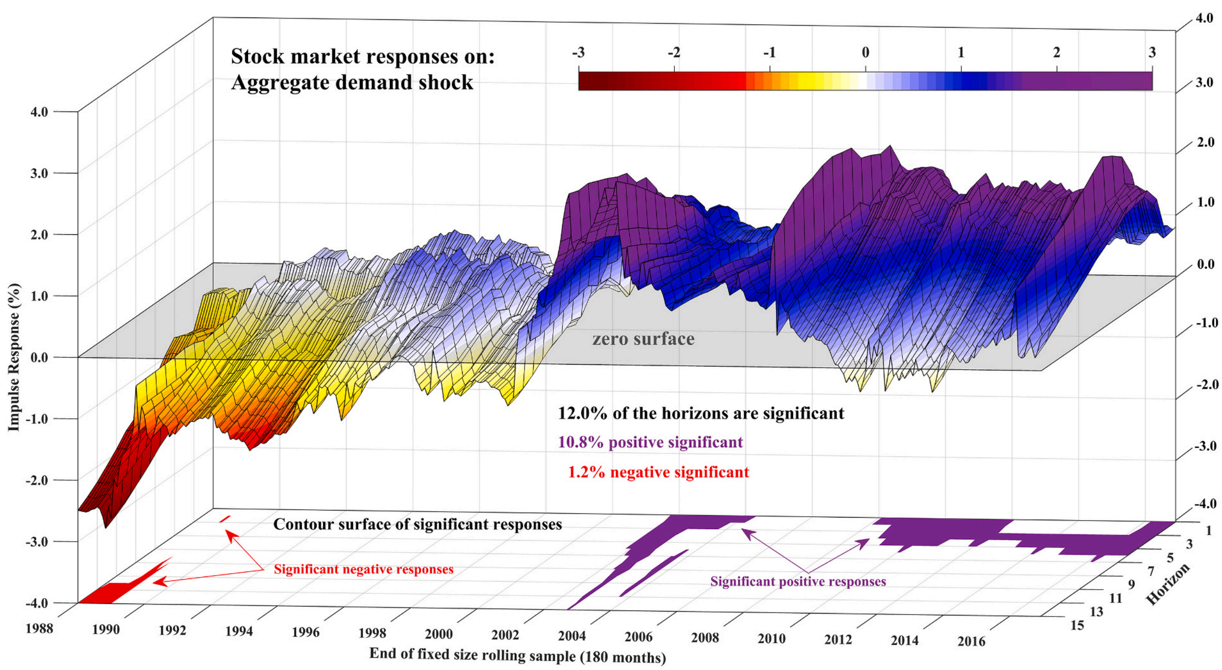


Fig. 9. Stock market rolling responses on aggregate demand shock.
Note: In all rolling samples the magnitude of the shock is equal to one standard deviation.

significant after 2000. After 2008, a significant positive impact appears systematically only in short horizons. This time-dependent impact is consistent with Foroni et al. (2017) and Lütkepohl and Netsunajev (2014) who find that aggregate demand shocks become less important after the mid-1980s. This change may be related to the net import position (with regard to crude oil) by the U.S. economy. In 2006, production of crude oil from tight formations starts to increase rapidly such that the U.S. imports ever-decreasing quantities of crude oil. Under these conditions, higher crude oil prices have a less negative and perhaps positive effect on U.S. economic activity. Overall, 12% of the total estimated responses are significant at the 0.05% significance level.

Oil-specific demand shocks have a negative and significant effect on stock market returns at all impulse horizons for the samples that end after 2001 and before 2010. This pattern is consistent with results reported by Kolodzeij and Kaufmann (2014), who find no correlation between crude oil prices and the S&P500 stock index from 1997 to 2003, a negative correlation from 2003 to 2008, and a positive (but insignificant) relation thereafter. These patterns can be explained in two ways.

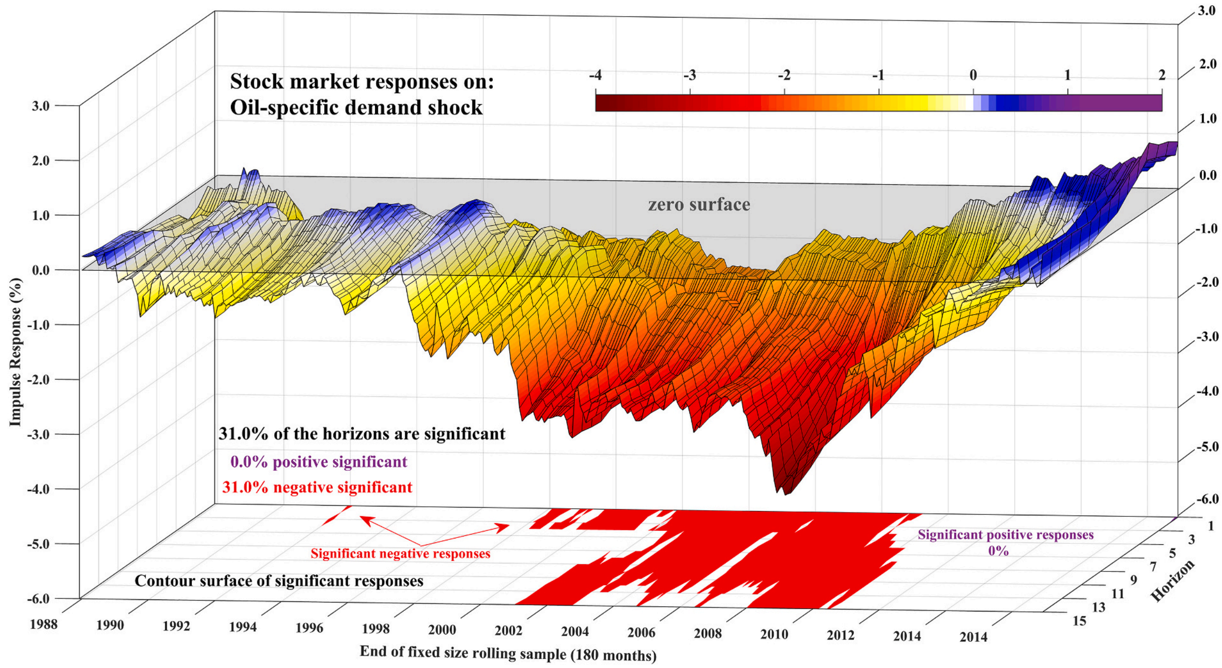


Fig. 10. Stock market rolling responses on oil-specific demand shock.
Note: In all rolling samples the magnitude of the shock is equal to one standard deviation.

Some postulate that increased speculation in the oil market (Kaufmann and Connelly, 2020) increases the correlation between oil and stock prices (Alquist and Kilian, 2010; Hamilton and Wu, 2014). Conversely, other argue that the reduction in interest rates during the financial crisis reduces convenience yields, which lower the returns to holding crude oil as a commodity (Kolodzeij et al., 2014).

Overall, results generated by estimating the SVAR model from rolling windows indicate that the effect of an oil price shock on the U.S. stock market depends on the type and timing of the price shock. Furthermore, no systematic pattern is obvious. Indeed, the relation between oil prices and the aggregate U.S. stock market index is rather weak. This result may be generated by the aggregate nature of the analysis. Specifically, the relation between oil price shocks and the U.S. stock market may vary by sector, and these relations may offset one another when aggregated across sectors. This explanation is explored below by disaggregating the relation between oil shocks and the U.S. stock market among the forty-nine SIC sectors.[11]

4.2. U.S. Stock industry portfolios

To investigate the relation among oil production, aggregate demand, and oil-specific demand shocks in each of the forty-nine U.S. sectors, we estimate SVAR models for the K&P sample and the full sample. Parallel to Figs. 5, 6 and 7, results for each sector appear in Appendices B, C and D. For most of the forty-nine sectors, an oil supply shock generally does not have a statistically measurable effect on performance (see Figs. B.1 to B.49 in the Appendix B). Furthermore, this result does not vary between the K&P and the full sample. Although the Healthcare, Medical Equipment, and Computer Software sectors (Figs. B.11, B.12 and B.36, respectively) respond positively to a supply shock, this positive response cannot be characterized as systematic and persistent because it is not supported by results from the rolling windows (Figs. 11.11.1, 11.12.1 and 11.36.1); only 8.45%, 13.91% and 8.81% of the responses, respectively, are positive and significant. Broadstock and Filis (2014) and Kang et al. (2017) find similar results, while Kang and Ratti (2013) and Li et al. (2017) assign a more important role to oil supply shocks.

Conversely, an aggregate demand shock has a positive effect on nearly all sectors, especially over short impulse horizons (see Figs. C.1-C.49 in the Appendix C). This positive effect is more apparent for Agriculture, Non-Metallic and Industrial Metal Mining, Petroleum and Natural Gas, and Real Estate (Figs. C.1, C.28, C.30 and C.47, respectively).[12] These sectors produce primary inputs and therefore a demand shock increases the use of and price for their outputs.[13] This price effect probably sustains the positive effect of the demand shock over the entire impulse horizon. Conversely, the price effect in the primary sectors probably suppresses economic activity in secondary industries, which may be responsible for the negative effect of a demand shock at longer impulse horizons. In general, the positive effect of an aggregate demand shock on most industries is consistent with previous results (see Kang and Ratti, 2013; Ready, 2018; and Nazlioglu and Soytas, 2012).

Finally, an oil-specific demand shock has a negative effect on stock returns for most industries (Figs. D.1 to D.49; Appendix D). This negative effect is especially strong in the Candy and Soda (Fig. D.3), Consumer Goods (Fig. D.9), Autos (Fig. D.23), Shipping Containers (Fig. D.40), and

[11] To evaluate the degree to which the results (for the full sample and the rolling samples) generated by the SVAR specification discussed in section 3.1 are robust, we repeat the analysis with a different identification scheme. In particular, estimating a Bayesian SVAR specification with sign restrictions from the full and the rolling sample analyses (for a small but representative number of sub-samples) indicates that the trajectories of the estimated stock market responses are qualitatively similar for all three structural innovations (results are available upon request). These results are consistent with Kilian and Murphy (2012) and Lütkepohl and Netsunajev (2014). We are grateful to an anonymous reviewer who suggested this comparison.

[12] These results, however, should be viewed again with caution as the rolling sample results (Figures 11.1.2, 11.28.2, 11.30.2 and 11.47.2) reveal that the significant positive responses are 11.36%, 25.40%, 29.25% and 33.89%, respectively among the total responses.

[13] This interpretation is formally tested by Fukunaga et al. (2010) who show that global demand shocks act mainly as positive demand shocks because they raise the output and price in most industries.

Retail (Fig. D.43) sectors.[14] Sectors that display the opposite effect include Healthcare (Fig. D.11), Coal (Fig. D.29), and Petroleum and Natural Gas (Fig. D.30).[15] The positive effect on Petroleum and Natural Gas is consistent with higher prices for their output. The positive effect in the coal sector may be associated with the price for coal at electricity generating plants (Kaufmann and Hines, 2018).

Similar to the surfaces in Figs. 8, 9 and 10, the effects of shocks shown in Appendices B, C and D may change over time. Hence, we repeat the analysis using rolling windows (Figs. 11.*i.j*; $i = 1, \ldots, 49$ and $j = 1,2,3$). Space limitations preclude 3D representations; instead, Figs. 11.*i.j* show the significance of the estimated responses on a rolling basis for every sector and all shocks. In particular, red areas in each figure identify negative significant responses, while purple areas identify positive significant responses. Similarly, percentages in red signify the percentage of the responses that are negative and significant, while percentages in purple signify the percentage of total responses that are positive and significant. Finally, figures with a light blue background indicate responses to an oil supply shock, light pink indicate responses to a demand shock and light green indicate responses to an oil-specific demand shock.

A negative oil supply shock has a modest effect on most sectors, with the total average percentage of significant responses (positive and negative) in all sectors being 8.93%. The majority of the significant responses are negative (6.66% are negative and 2.27% are positive; Figs. 11.*i*.1 with $i = 1, \ldots, 49$). Across all sectors, the largest percentage of significant responses (32.07%) is associated with the Medical Equipment sector, followed by Metals (28.68%), Insurance (23.95%), and Pharmaceutical (22.61%). The remaining sectors have values below 20%. Together, the results for all sectors fail to establish that a shock to oil supply has a statistically measurable negative effect on the stock returns (Figs. 11.*i*.1, with $i = 1, \ldots, 49$). This negligible effect is consistent with several studies (e.g., Kilian, 2009; Wang et al., 2013; Foroni et al., 2017). Nonetheless, other studies support the hypothesis that the effects of oil supply shocks are equal or greater than the effects of other types of shocks (e.g., Kang and Ratti, 2013; Li et al., 2017; Ready, 2018).

Much like results for an oil supply shock, an aggregate oil demand shock does not have a statistically measure effect on most of the forty-nine individual sectors (Figs. 11.*i*.2 with $i = 1, \ldots, 49$). The percentage of all responses that are significant (positive and negative) is 10.97%. Of these, most (10.06%) are positive (only 0.91% are negative). Fabricated Products (42.03%) have the largest response, followed by Real Estate (33.89%), Oil and Gas (29.25%), Healthcare (25.46%), Mines (25.40%), and Wholesale (20.98%). The remaining sectors have percentages below 20%. Again, the totality of results in Figs. 11.*i*.2, with $i = 1, \ldots, 49$, do not support the hypothesis that an aggregate demand shock has a positive effect on the stock returns. Any positive response tends to be sporadic and time dependent.

Finally, an oil-specific demand shock has a negative effect on most (47) of the forty-nine sectors, but these negative effects are mainly insignificant (see Figs. 11.*i*.3 with $i = 1, \ldots, 49$). The total average percentage of significant responses (positive and negative) is 16.71% (0.49% are positive and 16.22% are negative). Retail has the highest percentage (45.40%) of negative responses, followed by Restaurants (45.15%), Automobiles and Trucks (40.75%), and Printing and Publishing (33.01%). The remaining sectors have values less than 30%. Negative responses are more pronounced in the rolling windows towards the middle of the sample period, especially at shorter forecast horizons. Although the percentage of significant responses is larger than the responses generated by oil supply and demand shocks, the effects of an oil-specific demand shock are infrequent and time dependent, which is consistent with previous results (Kilian and Park, 2009; Güntner, 2014; and Li et al., 2017).

In total, our results show a very weak relation between the stock market and changes in oil prices, both at the aggregate and disaggregate level. At the same time, our findings emphasize the need to disaggregate the relation between oil and stock markets and to examine how each sector's exposure to the oil market affects how the relation changes over time. As expected, most sectors respond similarly to the aggregate index. Nonetheless, many sectors show idiosyncratic responses (for instance, Precious Metals, Automobiles and Trucks, and Petroleum and Natural Gas), which cannot be detected by simply analyzing an aggregate index.

5. Discussion and conclusions

Our findings have two important implications for investors and policy makers. First, the shrinking effect of oil price shocks suggests that investors can reduce their efforts to hedge their portfolios against oil price shocks. Second, the smaller effects of oil price shocks suggest that the economic effects of policies to abate carbon emissions are smaller than suggested by macroeconomic models.

Oil price shocks prompt investors to hedge their portfolios against oil price related shocks (e.g., supply shocks or oil-specific demand shocks) by incorporating stocks from sectors that are positively and significantly synchronized to the direction of each shock (Nandha and Faff, 2008). The results, presented in Figs. 11.*i.j* ($i = 1, \ldots, 49$ and $j = 1,2,3$) suggest that investors can hedge against supply shocks and oil-specific demand shocks by loading their portfolios with stocks from the Precious Metals sector (see Fig. 11.27.1) and the Petroleum and Natural Gas sector (see Fig. 11.30.3), respectively.

Nonetheless, the importance of such efforts may be declining over time. Consistent with previous results, we find that the effects of oil price shocks on the stock market decline over time. This reduction may be related to the declining fraction of U.S. energy consumption supplied by petroleum. Petroleum supplies 47.6% of U.S. energy consumption in 1977; by 2019 oil supplies 36.8% of consumption. This decline begs the question; will oil price shocks be replaced by shocks associated with other forms of energy and/or other commodities? This is possible because oil prices are correlated with prices for other commodities (e.g., Pindyck and Rotemberg, 1990; Kilian, 2009).

We postulate that the macroeconomic importance of oil price shocks probably will not be replaced by price shocks associated with other forms of energy or non-energy commodities because; (1) oil is more volatile than most commodities, (2) this volatility spreads from crude oil to other forms of energy, and (3) the influence of the non-economic forces that amplify oil price volatility may be waning. Historical analyses indicate that prices for crude oil, refined petroleum, and natural gas are more volatile than prices for about 95% of products sold by U.S. producers (Regnier, 2007). Furthermore, this volatility originates with the price of crude oil and spreads to other forms of energy. Several studies find that changes in the price of crude oil are transmitted to the price of natural gas (Panagiotidis and Rutledge, 2007; Kaufmann et al., 2009; Ramberg and Parsons, 2012; Kaufmann and Hines, 2018). Furthermore, the coupling between the price of crude oil and natural gas weakens over time (Serletis and Rangel-Ruiz, 2004; Ramberg and Parsons, 2012). Conversely, Bachmeier and Griffin (2006) find that changes in natural gas prices are transmitted to crude oil prices, albeit very slowly.

The relatively high rate of price volatility for crude oil is created partially by non-economic forces (Prindle, 1981; Yergin, 1991; Noguera-Santaella, 2016). Consistent with these historical narratives, statistical analyses indicate that the oil market displays prolonged periods when real oil prices stray from the price that is implied by market fundamentals (Kaufmann and Connelly, 2020). Causes for these diversions include speculation, behavior by a dominant producer group (e.g., OPEC

[14] Even in sectors with a strong negative effect, less than half of the rolling samples show statistically significant negative effects. In particular, the negative significant responses are 11.36%, 25.02%, 40.75%, 29.71% and 45.40%, respectively.

[15] In these three sectors, the positive significant responses are 0.80%, 3.54% and 5.31%, respectively.

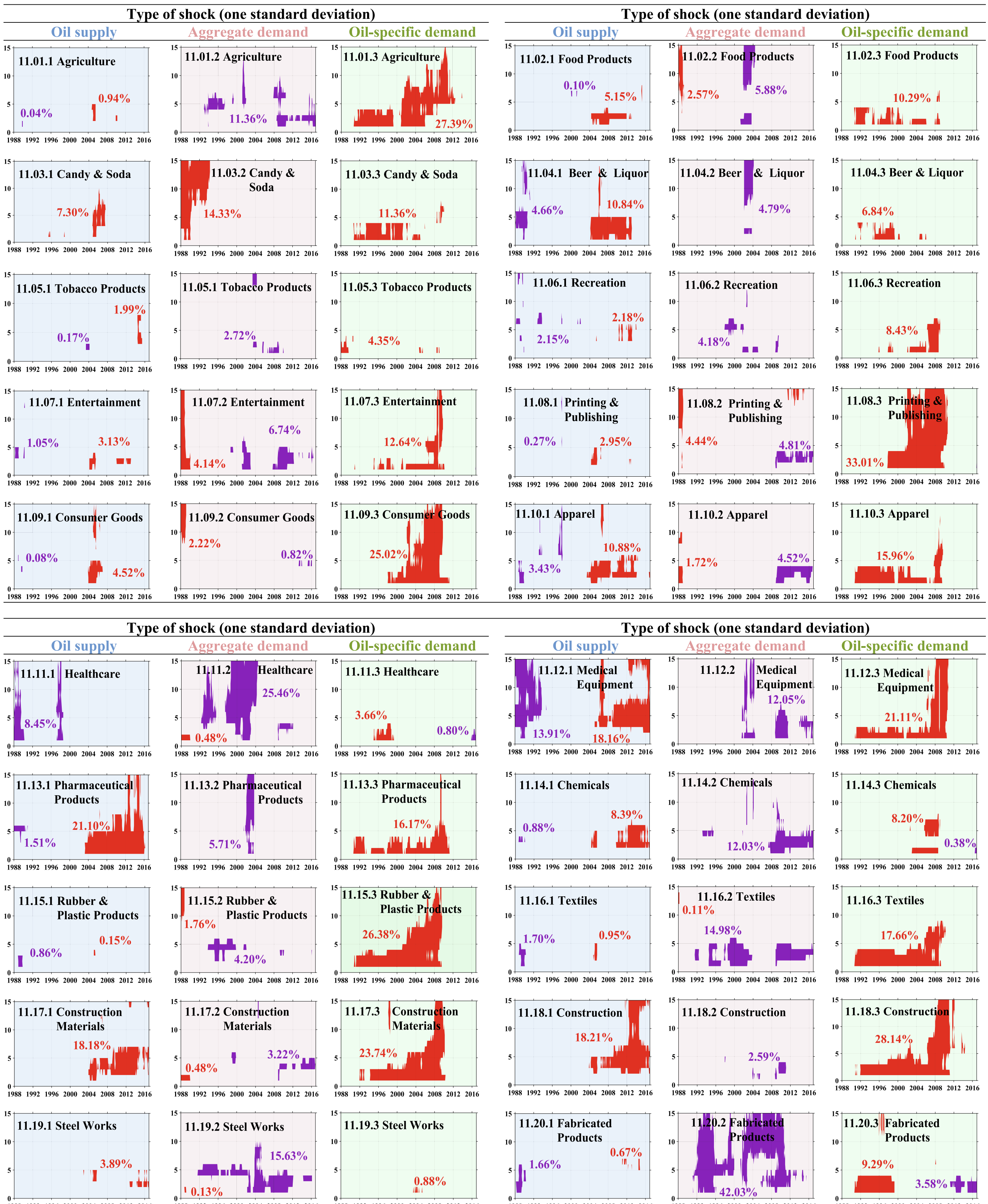


Fig. 11. *i. j.* Impulse responses significance per industry ($i = 1, \dots, 49$) and type of shock ($j = 1,2,3$) for rolling samples of fixed length (180 obs.).
Note: The oil supply shock is normalized such that to imply an increase in the price of oil (negative shock).

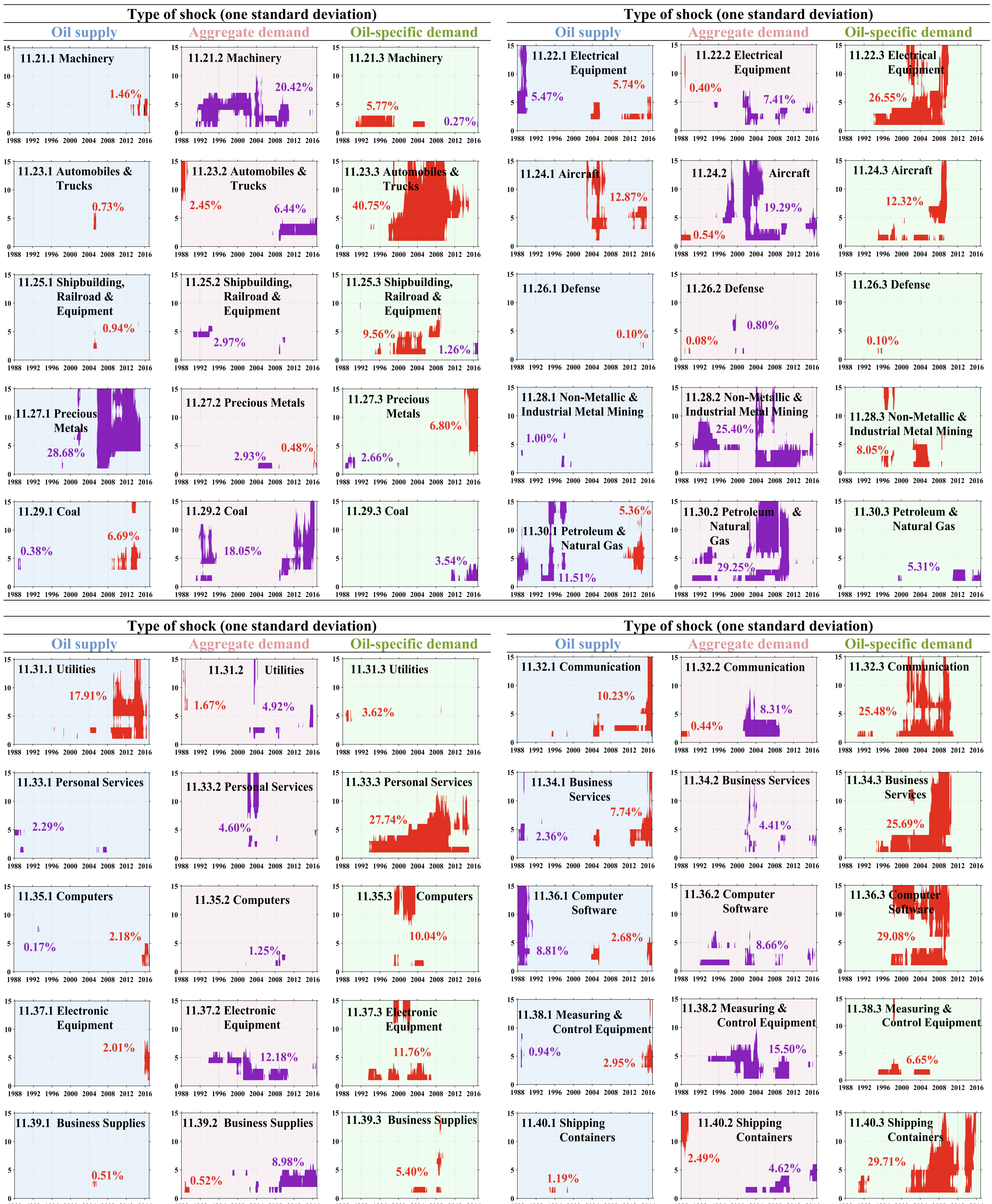
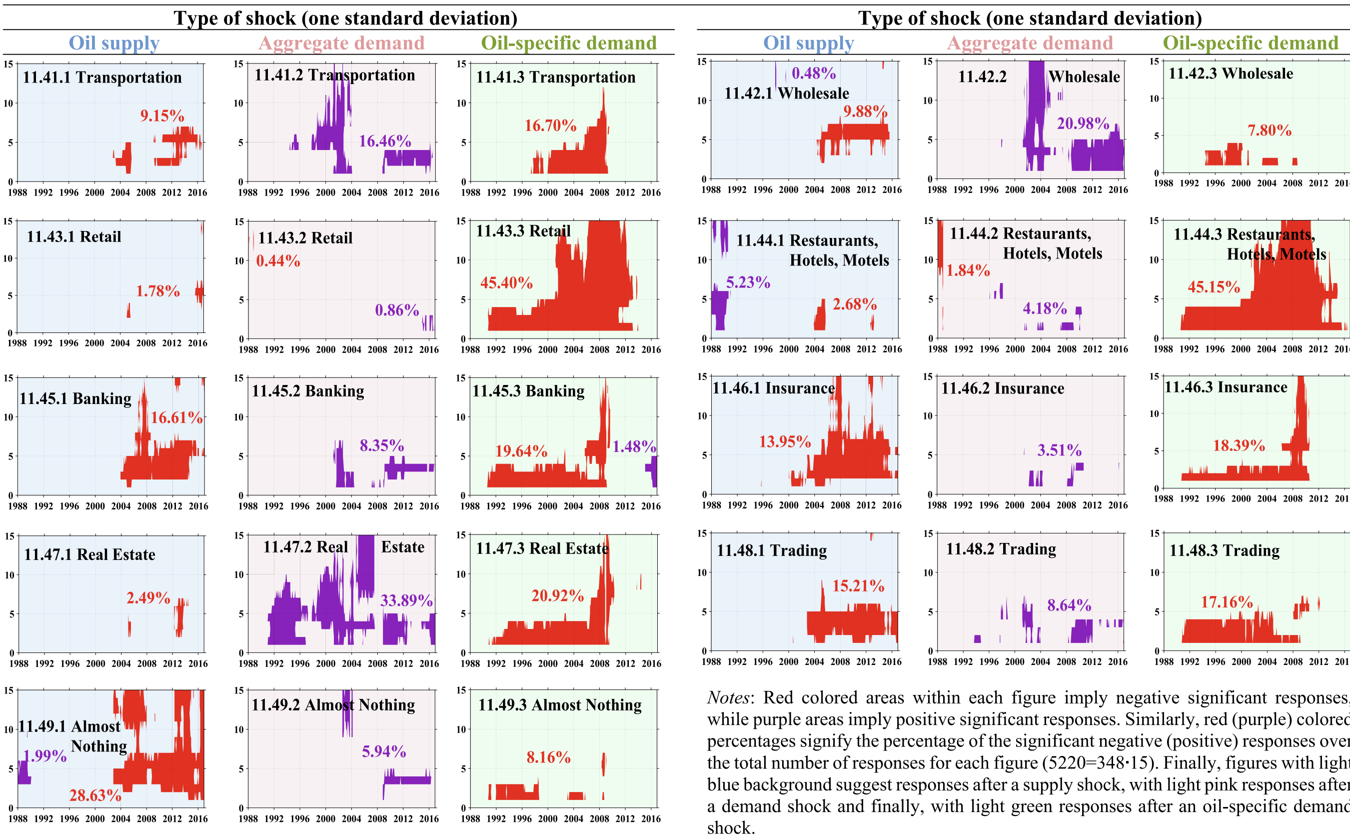


Fig. 11. (*continued*).

and the Texas Railroad Commission), and government policies.

In the future, the influence of non-economic forces may be damped by increased production of oil from tight formations in the U.S. Improved drilling technology which lowers the break-even price for tight oil and lowers world oil prices (Ansari and Kaufmann, 2019) may allow tight oil to serve as a backstop that blunts OPEC's control over the



Notes: Red colored areas within each figure imply negative significant responses, while purple areas imply positive significant responses. Similarly, red (purple) colored percentages signify the percentage of the significant negative (positive) responses over the total number of responses for each figure (5220=348·15). Finally, figures with light blue background suggest responses after a supply shock, with light pink responses after a demand shock and finally, with light green responses after an oil-specific demand shock.

Fig. 11. (*continued*).

marginal supply of crude oil and therefore its ability to influence price by opening/shutting in operable capacity (Kaufmann et al., 2004, 2008; Chevillon and Rifflart, 2009). As such, crude oil prices may become less volatile and the transmission of oil prices to other forms of energy is likely to decline. Under these conditions, the impacts of oil-related shocks on the stock market and the macroeconomy are likely to diminish.

For policy makers, sectoral analyses of the relation between oil shocks and the performance of the stock market suggest an alternative approach for analyzing the economic impacts of policies aimed at reducing carbon emissions. As described in the introduction, CGE models are used to analyze the impacts of policies to abate emissions in nations where such policies are not yet implemented, such as the U.S. But such evaluations are highly uncertain without empirical observations for the effects of such policy, or strong validations of the economic models used to analyze these policies.

Alternatively, the costs associated with policies to abate carbon emissions can be proxied *ex ante* by the effect of oil price shocks on stock prices. *Ceteris paribus*, the price for a share of stock should be positively related to the net present value of the firm's anticipated profit stream. If policy to reduce carbon emissions lowers a firm's anticipated profit stream, this reduction should be embodied in a lower price for a stock. Consistent with this hypothesis, Allen et al. (2009) argue that keeping climate change to a 2^{o} C warming would require a significant fraction of fossil fuel resources be left in the ground (i.e., unburnable carbon). This recognition reduced the share price for 63 of the largest U.S. oil and gas companies by 1.5% to 2% (Griffin et al., 2015).

This effect implies that it may be possible to analyze a carbon tax and/or tradeable permits as an oil-related shock and use the analysis presented here to trace its impact through the economy. Of the three types of shocks, oil supply, aggregate demand, and oil-specific demand, a carbon tax and/or tradeable permits are most similar to an oil supply shock, which is a reduction in the quantity of oil made available to the public. This tends to raise prices for and reduce consumption (and emissions) of fossil fuels. In the long run, the effects of an oil supply shock are similar to a reduction in the fraction of fossil fuel resources that can be burned.

Based on this parallel, the results of this analysis suggest that the economic costs of policy to reduce emissions may be relatively small. As described previously, a supply shock does not have a statistically measurable effect on an aggregate index for the U.S. stock market for the K&P or full sample (Fig. 5) or any of the rolling windows (Fig. 8). The same shock generally has little effect on individual sectors. Notable exceptions include a negative response in some windows by the banking, trading, and insurance sectors. Interestingly, these sectors are largely ignored by discussions of the economic impacts of policies to abate carbon emissions.

Conversely, oil supply shocks have a positive effect on the petroleum and gas sector in short forecast horizons for some rolling windows. But this positive effect probably will not be generated by a carbon tax and/or tradeable permits because the resultant price increases will not be captured by firms in the petroleum and gas sector. Beyond this sector, carbon taxes and/or tradeable permits are likely to reduce activity in the coal and utility sectors, which is consistent with the negative effects of an oil supply shock that are indicated by rolling windows towards the end of the sample period.

Finally, our disaggregated analysis does not fully describe the relation between the oil and stock markets. It may be possible to deepen the understanding of this relation by analyzing the relation for individual firms. For example, individual firms in the Petroleum and Natural Gas sector may respond differently to an oil supply or oil-specific demand shock. Such firm-specific effects are implied by our results. The Petroleum and Natural Gas sector responds positively to an aggregate demand shock, but the lack of a significant response by most rolling windows suggests few gains for the sector. However, this result may change if firms in upstream, midstream, and downstream sectors are analyzed separately (Kang et al., 2017). We leave such analysis in a dynamic framework for future research.

Credit author statement

Ioannis Arampatzidis Methodology, software, validation, formal analysis, investigation, resources, data curation, Writing - Original Draft.

Theologos Dergiades Methodology, software, validation, formal analysis, investigation, resources, data curation, Writing - Original Draft.

Robert K. Kaufmann Conceptualization, Writing- Original draft preparation, Writing- Reviewing and Editing.

Theodore Panagiotidis Conceptualization, Writing- Original draft preparation, Writing- Reviewing and Editing, Writing - Original Draft, Supervision.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105588.

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