Impact of State-Dependent Oil Price on U.S. Stock Returns using Local Projections*

Juan Equiza-Goñi (Universidad de Navarra, Spain)
Fernando Perez de Gracia (Universidad de Navarra, Spain)

Abstract

In this paper we investigate the impact of oil prices on both aggregate and industry U.S. real stock returns over the period 1973-2017. The empirical analysis contributes to the related literature introducing a state-dependent oil price (*high* and *low*) and the local projections approach initiated by Jordà (2005). Our main finding is that, depending on the nature of the shock and industry, the negative effects of oil price shocks become exacerbated -and the positive effects get moderated- if oil prices are already high.

Keywords: state-dependent oil price; U.S. stock returns; economic policy uncertainty; local projections
JEL classification: G12, Q43

* We thank the editor, David Peel and anonymous referee for helpful comments and suggestions. Juan Equiza and Fernando Perez de Gracia gratefully acknowledge financial support from the Ministerio de Economía y Competitividad (ECO2017-83187-R).

1-. Introduction

A number of studies have already analyzed the impact of oil prices on the stock returns (see, for example, Jones and Kaul, 1996; Huang et al., 1996 or the complete recent survey by Degiannakis et al., 2018 and references therein). This paper reexamines the nexus between oil prices and stock returns. In particular, we investigate the impact of state-dependent oil prices on U.S. aggregate and sector stock returns from 1973 to 2017 using local projections (LPs).[1] Two are the main contributions of the paper. First, our empirical strategy is based on the LPs approach initially proposed by Jordà (2005) rather than the vector autoregressions (VARs) used by previous empirical related literature (e.g., Park and Ratti, 2008; Cunado and Perez de Gracia, 2014; Messias Marques and Catalão-Lopes, 2015; Kang et al., 2017). Contrary to VARs, LPs does not impose a strong assumption on the data-generating process and can easily introduce non-linearities or state-dependent impulses (Tanaka, 2018). Second, instead of considering non-linear specifications of oil prices to capture the asymmetric relationship between stock returns and oil prices (Cunado and Perez de Gracia, 2014), we propose non-linearities that allow the impulse-responses to depend on the state of oil prices (*high* and *low*).

Furthermore, our empirical approach incorporates two relevant variables. Considering that stock returns across industries (or sector) do not respond similarly to oil price shocks (Elyasiani et al., 2011), we include both aggregate and sector stock returns. In addition, previous recent evidence have documented that uncertainty shocks have a substantial impact on firms (Bloom, 2009). We also introduce economic uncertainty as an additional explanatory variable in the LPs (Kang and Ratti, 2013; Kang et al., 2017). To the best of our knowledge, this is the first paper that uses LPs to

[1] For example, recently Carcel et al. (2018) investigate the monetary policy in Brazil using LPs.

investigate the state-dependent oil prices on U.S. disaggregated stock returns taking into account economic uncertainty.

The remainder of this paper is structured as follows. In Section 2, we describe methodology used and Section 3 presents the dataset. In Section 4, we discuss the empirical results. Section 5 concludes.

2. Empirical strategy

The LPs approach pioneered by Jordà (2005) consists in running sequential predictive regressions of the endogenous variable on a structural shock and a set of controls for an increasingly larger prediction horizon. Let y_t, x_t and $w_{i,t}$ be stationary time series observed from $t = 1, \dots, T$. Using LPs, we can estimate the impulse-response of y_{t+h} with respect to a change in the regressor x_t, for $h = 0, \dots, H$. In particular, the dynamic effect of x on y is obtained from the regression coefficient β_h in the following set of regressions:

$$y_{t+h} = \alpha_h + \beta_h x_t + \sum_{i=1}^{p} \gamma_{i,h} w_{i,t} + u_{h,t+h}, \qquad (1)$$

where $w_{i,t}$ is a set of controls that might contain lags of y_t, x_t or other variables, p is the maximum lag, and $u_{h,t+h}$ is a prediction error with variance σ_h^2.

Moreover, a regression like Equation (1) can be easily adapted to estimate a state-dependent model. In the case of a model that allows for impulse-responses to depend on whether the level of oil prices is *high* or *low*, Equation (1) would be modified to

$$y_{t+h} = \alpha_{0,h} + \beta_{0,h} x_t + \sum_{i=1}^{p} \gamma_{0,i,h} w_{i,t} + I_t\left[\alpha_{1,h} + \beta_{1,h} x_t + \sum_{i=1}^{p} \gamma_{1,i,h} w_{i,t}\right] + v_{h,t+h}, \quad (2)$$

where I_t is an indicator function that takes the value *1* if oil prices are above average at time *t* and *0* if they are below that threshold. Then, the coefficient is $\beta_{0,h}$ is the dynamic response when oil prices are *low*, whereas the response is $\beta_{0,h} + \beta_{1,h}$ when oil prices are *high*. We run each regression separately by OLS and use the Newey-West correction for the standard errors because the successive leading of the dependent variable induces serial correlation in the error terms.

Although we estimate responses to oil price shocks using Equations (1) and (2), we previously identify and estimate these disturbances following Kilian (2009). This seminal paper distinguishes between oil supply and demand shocks and, among the latter, also between those due to spurs of aggregate world demand for all industrial commodities or oil market-specific demand increases. Thus, x_t is in each case one of these three different types of oil shocks.

Therefore, our study considers a structural VAR model of order p to extract the separate supply and demand-side sources of oil price fluctuations:

$$A_0 Z_t = c_0 + \sum_{j=1}^{p} A_j Z_{t-j} + \varepsilon_t, \tag{3}$$

where $Z_t = (\Delta prod_t, rea_t, rpo_t, pu_t, ret_t)$ is a 5 by 1 vector of endogenous variables: changes in real world oil production ($\Delta prod$), real economic activity (rea), the real price of oil (rpo), the economic policy uncertainty index (pu), and real U.S. stock returns (ret). Moreover, A_0 is the matrix of contemporaneous coefficients while A_j are the autoregresive coefficient matrices, c_0 is a vector of constant terms, and ε_t stands for a vector of structural disturbances with diagonal variance-covariance matrix Σ.

Following Kilian (2009), we assume that A_0^{-1} has a recursive structure. Let e_t be the reduced-form error term obtained from regressing Z_t on its own lags and a constant. Then, assuming that e_t can be decomposed by $e_t = A_0^{-1}\varepsilon_t$, we impose the restriction that A_0^{-1} is a lower triangular matrix. This is equivalent to assuming that the only structural disturbance which may have a contemporaneous effect on both rpo and $\Delta prod$ is the one ordered first and, thus, we call it a supply (oil price) shock.

This restriction is equivalent to assuming that oil production cannot respond within a month to non-supply (i.e., demand) oil price shocks.

Moreover, the second variable in our system, real economic activity, only responds contemporaneously to both the oil supply shock and the second structural disturbance. Thus, the latter is the only demand shock that can have a contemporaneous effect on both rpo and rea, and we label it an aggregate demand (oil price) shock. As a result, the third shock is the last structural disturbance which may have a contemporanous effect on rpo. Since it does not affect global economic activity within a month, we call it an oil market-specific demand (price) shock. This is a reasonable assumption given the sluggishness of aggregate economic reaction.

By assumption, the fourth and fifth structural shocks cannot have an inmediate effect in rpo and, thus, are not of our interest. However, we control for economic policy uncertainty (pu) because it has been shown to have a significant impact on our three identifing variables and U.S. stock returns (see, for example, Kang and Ratti, 2013; Kang et al., 2017). Moreover, our main variable of interest, stock returns (ret) was also included in system (3) to make sure that our identified oil price shocks are clean of any response to lagged disturbances in the U.S. stock market.

3. Dataset

Our study uses monthly time series data on the crude oil market, global economic activity, an index of U.S. economic policy uncertainty, and U.S. stock returns over February 1973 to September 2017. Thus, our data spans back to the beginning of the sample period typically covered in the literature (e.g., Kilian and Park, 2009) and finishes in the latest currently available observation.

Data on the price of oil is based on U.S. refiner's acquisition cost of crude oil, as reported by the U.S. Department of Energy since January 1974, and extrapolated back to 1973 following Barsky and Kilian (2002). An index of aggregate demand based on shipping cargo freights constructed by Kilian (2009) is used as an indicator of global economic activity. The overall Index of U.S. Economic Policy Uncertainty is provided by Bloom (2009) since January 1985. We extended this series back to the beginning of our sample period based on the News-Based Historical Economic Policy Uncertainty series provided by the same author. The data source for aggregate and industry-specific U.S. stock returns is the Center for Research in Security Prices (CRSP). These variables are value-weighted returns on market portfolios including NYSE, AMEX, and Nasdaq stocks. Finally, oil prices, economic activity and stock returns are adjusted by the U.S. CPI available from the Bureau of Labor Statistics to obtain their real values.

4. Empirical Results

4.1. Aggregate Stock Returns

The first contribution of our paper is that we reexamine using LPs methods the linear response of real world oil production ($dprod$), real economic activity (rea), the real price of oil (rpo) and real U.S. aggregate stock returns (ret) to the different oil price shocks. In addition, these estimates are based on data series updated to September 2017 (the latest available observation). Figure 1 shows the reaction of these four variables along 24 months (for h = 0,…,23; thus H = 23). The number of lags used in the estimation of equation (1) is p = 12. We also report one- and two-standard deviation confidence bands constructed using recursive-design wild bootstrap; see Gonçalves and Kilian (2004). In the set of controls we include lags of all variables.[2]

[2] The results do not change if we include also as controls the contemporaneous value of those variables that according to our recursive assumptions cannot respond instantaneously to the specific type of shock

Notice that policy uncertainty is also included in the system, although their responses have not been reported.[3]

***** Insert Figure 1 about here *****

First, we find that an oil supply shock lowers real world production persistently and significantly for about 0.75%. This effect is aligned but smaller than that reported in Kilian (2009) and very close to that found by Kang and Ratti (2013). The effects in real economic activity and the real price of oil are mostly insignificant, as in Kilian (2009) that emphasized instead the importance of demand shocks. In contrast to Kilian (2009) and Kang and Ratti (2013), the real return on the aggregate U.S. stock market falls and, thus, motivates the study of whether this differences hold on an industry level.[4]

Demand price shocks tend to be accommodated by higher oil production at least within a year and mostly non-significantly, however production falls at a longer horizon similarly to Kilian (2009) for aggregate demand shocks and Kang and Ratti (2013) for oil-specific demand disturbances. As expected, both real economic activity and the real price of oil rise in respond to demand shocks, by relatively more the former if it is global than oil-specific. In contrast, *rea* increases relatively less than *rpo* if the spur in demand is oil-specific. Finally, the U.S. stock loses value (after a minor increase in the first five-six months) in response to both types of demand shocks.

***** Insert Figures 2a & 2b about here *****

For instance, if we estimate the dynamic effect of an aggregate demand shock at time *t* on real economic activity at time *t* also (*h*=0), we could include in w_t the real price of oil at time *t* (rpo_t) but do not include (the change in) real oil production at the time of the shock ($\Delta prod_t$).

[3] The results are very similar if we do not include policy uncertainty in the system, however often they become less significant or non-significant.

[4] Motivated by the minor role of oil supply shocks estimated by Kilian and Park (2009), Kang et al. (2016) revisit the study of their impact on U.S. stock returns and find it mostly non-significant. Their main contribution, however, is the distinction and identification of U.S. and non-U.S. supply shocks. They find that reductions in U.S. oil production reduce significantly the aggregate U.S. stock return. Our results, thus, point at an important role of negative supply shocks of U.S. origin during our sample period.

Figures 2a & b show the responses of aggregate U.S. stock returns to oil price shocks in the states of *low* and *high* oil prices: the former includes confidence bands for *low* price state while the latter shows them for the for *high* price state. First, we see that the reaction to supply shocks differs with the state: returns drop if oil prices were already at *high* level, whereas they rise in the *low* state. These responses are not significant but suggest that are mainly the reductions in oil supply at times of *high* oil prices that harm the U.S. stock market.

Regarding aggregate demand shocks, notice that the negative response of returns documented in Figure 1 is at odds with the literature. The intuitive reaction typically found is that increases in oil prices due to higher global economic activity have a positive effect on returns. Figure 2 shows that this holds in the *low* oil price state. In contrast, when oil prices are already *high*, U.S. stock returns fall, although not significantly. Finally, oil market-specific demand shocks have a negative impact on the U.S. stock market in both states: significantly (and intuitively) when oil prices are already *high*. The empirical results for oil market-specific demand are in line with Kang et al. (2015).

4.2. Industry stock returns

Figure 3 shows the reaction of sector stock returns studied by Kilian and Park (2009) and Kang and Ratti (2013). Our contribution, again, is that we use an up-to-date sample period and we use LPs methods to estimate the dynamic responses. Industry stock returns have been retrieved also from the CRSP database.

***** Insert Figure 3 about here *****

Then we proceed to use our state-dependent LPs model to differentiate between the responses when oil prices are already *high* or *low*. This a completely new analysis whose interest is raised by the different responses documented in Figure 2. Thus, Figure 4 presents the responses of U.S. stock returns in the *oil & gas*, *automobile, retail*, and *gold & precious metals* industries for *low* and *high* oil price states. Figure 4a includes confidence bands for *low* price state whereas Figure 4b shows them for the for *high* price state.

***** Insert Figures 4a & 4b about here *****

First, let's discuss the estimated responses to oil supply shocks. Figure 3 shows that the *oil & gas* industry is benefited, as documented by Kang and Ratti (2013). This reaction, though, is unclear and not significant during the first 12 months because returns tend to fall when oil prices are already *high* (although not significantly) as we see in Figure 4. The *auto* and *retail* sectors are overall significantly harmed and, especially, when oil prices are already *high*[5]. The *gold & precious metals* industry is significantly benefited as oil supply disruptions frequently follow political turmoil in producer countries and raises demand of safe assets like precious metals.

Regarding aggregate demand shocks, *oil & gas* and *gold & precious metals* industries are benefited whereas *automobile* and *retail* are harmed, exactly as in Kilian and Park (2009). The interpretation is that higher prices due to larger global economic activity obviously benefit in particular the producers of that more demanded oil. It also raises inflation expectations, thus benefiting alternative investment, like precious metal. The bleak side is that higher oil prices lowers income available for retail products and the demand for cars. Moreover, Figure 4 displays that the high state lowers the benefits of the former, and worsens the negative impact in the latter. In other words, all industries are less benefited (or more harmed) if this type of oil shock happens when oil prices are already *high*.

[5] For oil prices in *low* levels, returns of *automobile* and *retail* firms are insignificantly (and counterintuitively) benefited, but Kang and Ratti (2013) had this result.

Finally, U.S. stock returns fall significantly overall and across all industries in response to oil market-specific (price) surges. If the shock hits when oil prices are already *high*, the fall in returns of *automobile* and *retail* is aggravated, whereas the response of returns for *oil & gas* and *gold & precious metals* firms does not get worse. Similarly, Kilian and Park (2009) obtain that automobile sector depreciate whereas gold sector appreciates in response to oil market-specific shock.

5. Final Conclusions

This study is the first one that investigates the effect of state-dependent oil price on sectoral and aggregate U.S. real stock returns using LPs. Our empirical findings are the following.

When we analyze aggregate U.S. real stock returns, our results suggest that an oil supply (and also demand) shocks reduce stock returns. Taking into account the states of *low* and *high* oil prices, we find that stock returns drop if oil prices were already at *high* level, whereas they rise in the *low* state. Oil market-specific demand shocks have a negative impact on the U.S. stock market in both states (*high* and *low*).

In addition, we also focus on the impact of oil price shocks on industrial stock returns. Our findings support that *gold & precious metals* industry is significantly benefited as oil supply shocks while *oil & gas* and *gold & precious metals* firms are benefited from aggregate demand. The oil price state-dependent analysis suggest that all industries are less benefited (or more harmed) if this type of oil shock happens when oil prices are already *high*. Finally, U.S. stock returns fall significantly overall and across all industries in response to oil market-specific shock. We find these negative reactions to be aggravated by already *high* oil prices in the case of the *automobile* and *retail* industries.

Our findings have three main implications to global investors, financial managers and policy makers. First, our empirical results have suggested that investors, financial managers and policy makers should focus not only on oil prices (or oil price shocks) but also on the level of oil prices -*high* and *low*-. When oil prices are *high*, the negative impact of oil price shocks on stock returns is exacerbated. Hence, when oil prices fluctuate around high levels, hedging strategies against oil price risk should be revised conservatively. Second, our evidence has also demonstrated the relevance of the nature of the oil price shock (i.e., supply, global demand and specific demand). Finally, policy makers and financial markets participants should also consider that stock returns in all industries are more affected when oil prices are high.

References

Barsky, R.B., Kilian, L., (2002). Do we really know that oil caused the Great Stagflation? A monetary alternative. In B. Bernanke and K. Rogoff (eds.), *NBER Macroeconomics Annual* 2001, 137-183.

Bloom, N., (2009). The impact of uncertainty shocks. *Econometrica*, 77, 623-685.

Carcel, H., Gil-Alana, L., Wanke, P., (2018). Application of local projections in the monetary policy in Brazil. *Applied Economics Letters*, 25, 941-944.

Cunado, J., Perez de Gracia, F., (2014). Oil price shocks and stock market returns: Evidence for some European countries. *Energy Economics*, 42, 365-377.

Degiannakis, S., Filis, G., and Arora. V., (2018). Oil prices and stock markets: A review of the theory and empirical evidence. *Energy Journal*, 39, 85-130.

Elyasiani, E., Mansur, I., Odusami, B., (2011). Oil price shocks and industry stock returns. *Energy Economics*, 33, 966-974.

Gonçalves, S., Kilian, L., (2004). Bootstrapping autoregressions in the presence of conditional heteroskedasticity of unknown form. *Journal of Econometrics*, 123, 89-120.

Huang, D.R., Masulis, R.W., Stoll, H., (1996). Energy shocks and financial markets. *Journal of Futures Markets*, 16, 1-27.

Jones, C.M., Kaul, G., (1996). Oil and stock markets. *Journal of Finance*, 51, 463-491.

Jordà, O., (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95, 161-182.

Kang, W., Ratti, R.A., (2013). Oil price shocks, policy uncertainty and stock market return. *Journal of International Financial Markets, Institutions & Money* 26, 305-318.

Kang, W., Ratti, R.A., Yoon, K.H., (2015). The impact of oil price shocks on the stock market return and volatility relationship. *Journal of International Financial Markets, Institutions and Money*, 34, 41-54.

Kang, W., Perez de Gracia, F., Ratti, R. A., (2017). Oil price shocks, policy uncertainty, and stock returns of oil and gas corporations. *Journal of International Money and Finance*, 70, 344-359.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99, 1053-1069.

Kilian, L., Park, C., (2009). The impact of oil price shocks on the U.S. stock market. *International Economic Review*, 50, 1267-1287.

Messias Marques, S., Catalão-Lopes, M., (2015). Portuguese stock market returns and oil price variations. *Applied Economics Letters*, 22, 515-520.

Park, J., Ratti, R.A., (2008). Oil price shocks and stock markets in the U.S. and 13 European countries. *Energy Economics*, 30, 2587-2608.

Tanaka, M., (2018). Bayesian inference of local projections with roughness penalty priors. *Working Paper*. Cornell University Library.

Figures

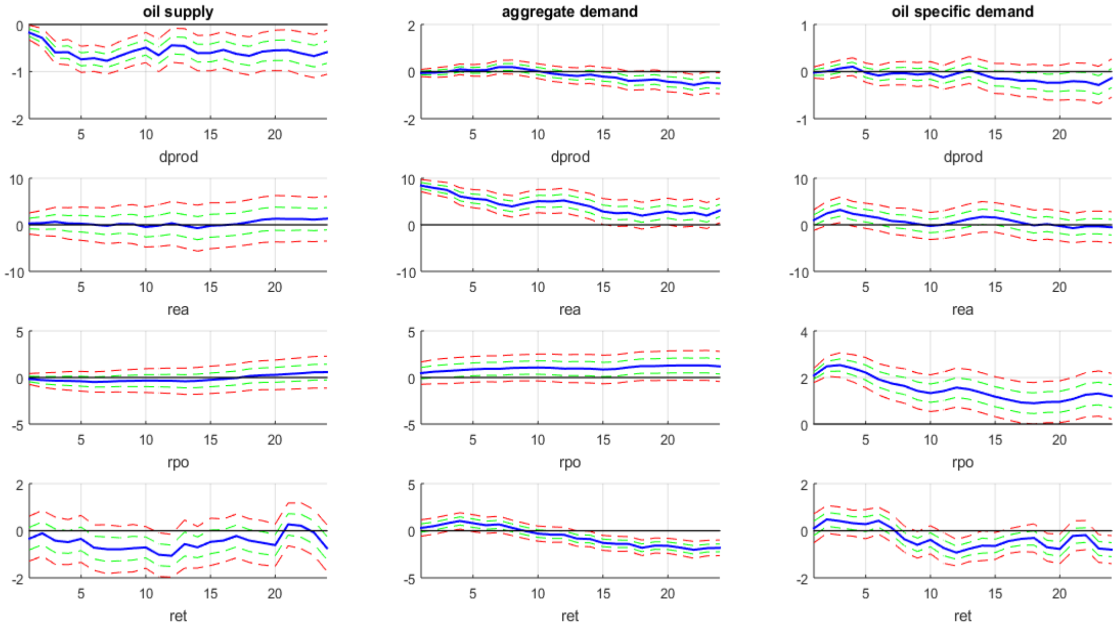

Figure 1. Linear effects of oil price shocks on (changes of) real world oil production ($dprod$), real economic activity (rea), the real price of oil (rpo) and real U.S. aggregate stock returns (ret). Dynamic responses have been estimated using local projection methods over 24 months (*h=0,…,23*). Following Kilian (2009), the identification distinguish supply and demand shocks, and among the latter between those due to aggregate or oil market-specific demand pressures. Green and red (dashed) lines are the one- and two-standard deviation confidence bands constructed using recursive-design wild bootstrap.

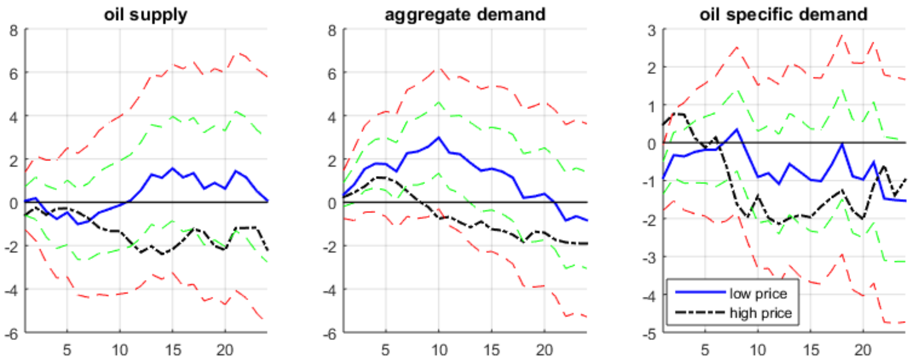

Figure 2a. Effect of oil price shocks on real U.S. aggregate stock returns (ret) for low (in blue, solid) and high (black, dash-dotted) oil price states. Dynamic responses have been estimated using local projection methods over 24 months (*h=0,…,23*). Following Kilian (2009), the identification distinguish supply and demand shocks, and among the latter between those due to aggregate or oil market-specific demand pressures. Green and red (dashed) lines are the one- and two-standard deviation confidence bands constructed using recursive-design wild bootstrap for responses in the *low* oil price state.

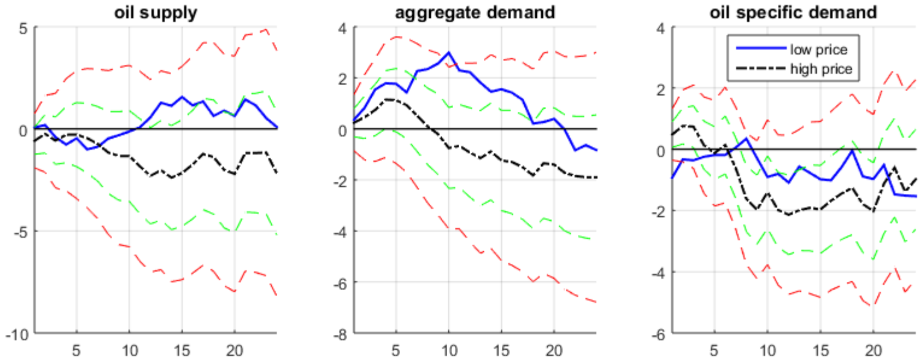

Figure 2b. Effect of oil price shocks on real U.S. aggregate stock returns (ret) for *low* (in blue, solid) and *high* (black, dash-dotted) oil price states. Dynamic responses have been estimated using local projection methods over 24 months (*h=0,…,23*). Following Kilian (2009), the identification distinguish supply and demand shocks, and among the latter between those due to aggregate or oil market-specific demand pressures. Green and red (dashed) lines are the one- and two-standard deviation confidence bands constructed using recursive-design wild bootstrap for responses in the *high* oil price state.

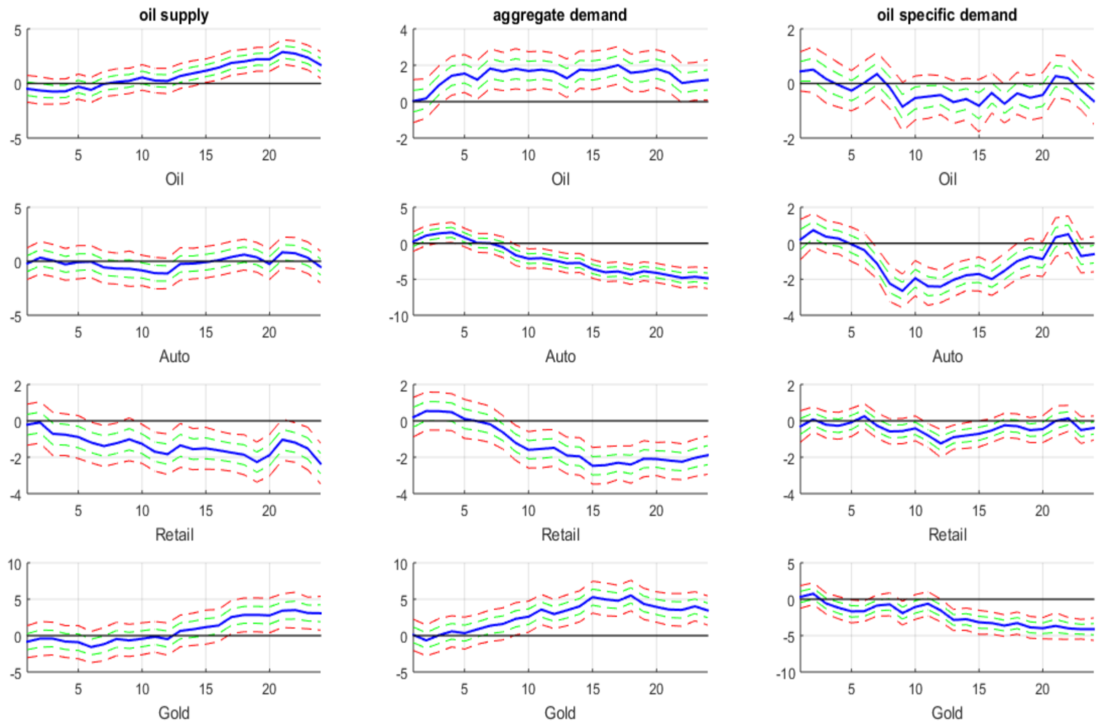

Figure 3. Linear effects of oil price shocks on real U.S. stock returns in the *oil & gas*, *automobile*, *retail*, and *gold & precious metals* industries. Dynamic responses have been estimated using local projection methods over 24 months (*h=0,…,23*). Following Kilian (2009), the identification distinguish supply and demand shocks, and among the latter between those due to aggregate or oil market-specific demand pressures. Green and red (dashed) lines are the one- and two-standard deviation confidence bands constructed using recursive-design wild bootstrap.

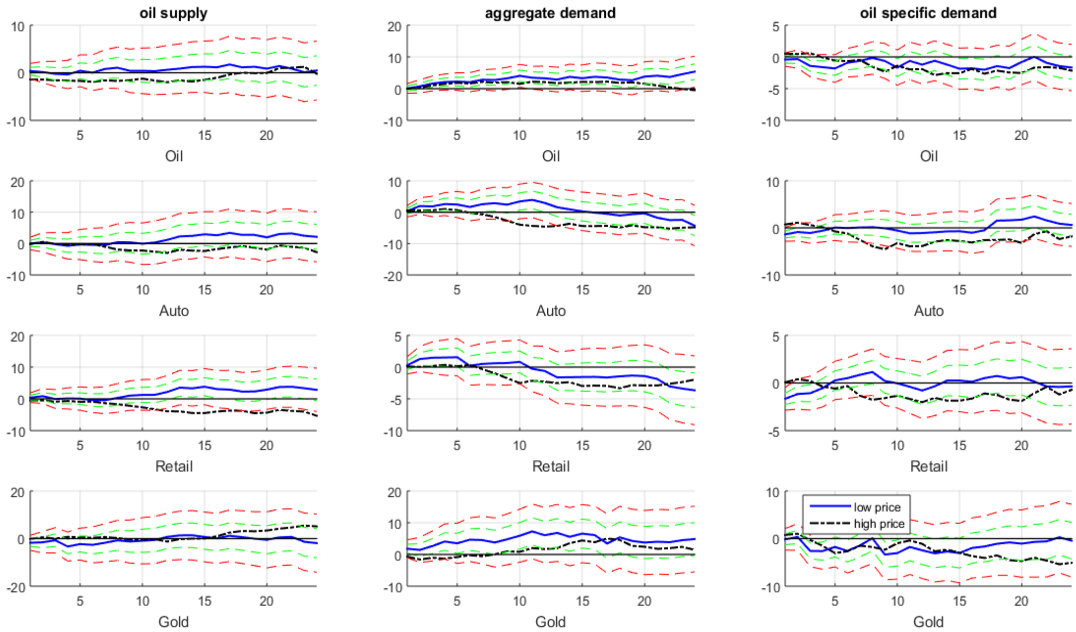

Figure 4a. Effects of oil price shocks on real U.S. stock returns in the *oil & gas*, *automobile*, *retail*, and *gold & precious metals* industries for low (in blue, solid) and high (black, dash-dotted) oil price states. Dynamic responses have been estimated using local projection methods over 24 months ($h=0,\ldots,23$). Following Kilian (2009), the identification distinguish supply and demand shocks, and among the latter between those due to aggregate or oil market-specific demand pressures. Green and red (dashed) lines are the one- and two-standard deviation confidence bands constructed using recursive-design wild bootstrap in the *low* oil price state.

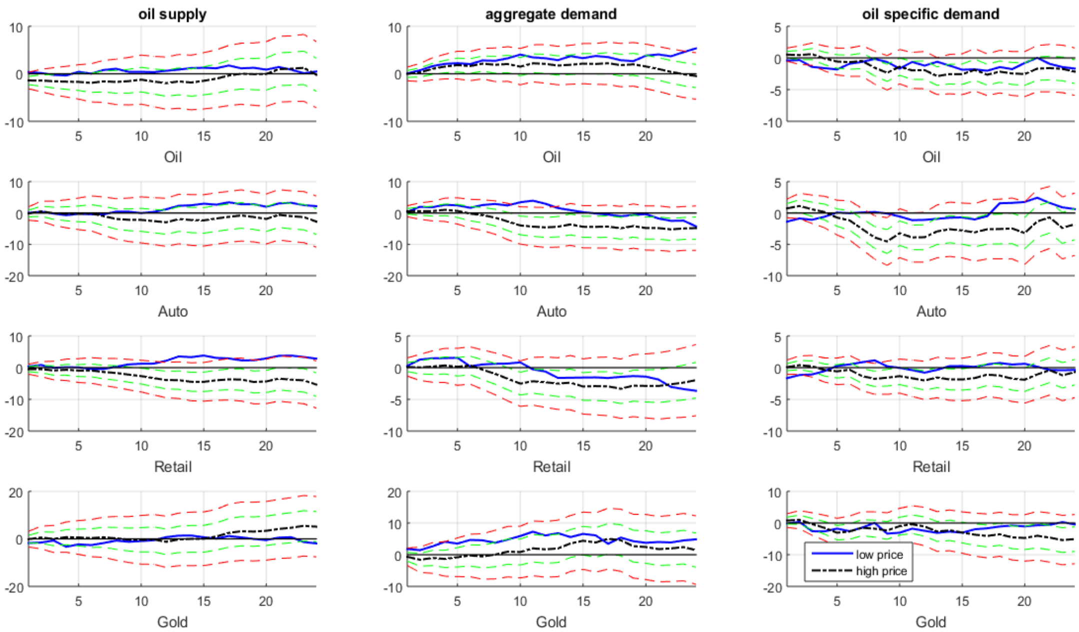

Figure 4b. Effects of oil price shocks on real U.S. stock returns in the *oil & gas*, *automobile*, *retail*, and *gold & precious metals* industries for *low* (in blue, solid) and *high* (black, dash-dotted) oil price states. Dynamic responses have been estimated using local projection methods over 24 months ($h=0,\ldots,23$). Following Kilian (2009), the identification distinguish supply and demand shocks, and among the latter between those due to aggregate or oil market-specific demand pressures. Green and red (dashed) lines are the one- and two-standard deviation confidence bands constructed using recursive-design wild bootstrap in the *high* oil price state.