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Abstract

This paper is set to reconcile the existent conflicting empirical evidence on the effect of oil prices on stock prices. We estimate various nonlinear models where the response changes according to a first-order Markov switching process. More importantly, we model the transition probabilities between the high- and low-response regimes to depend on state variables to allow us to explain the forces behind the asymmetry in the response. The results show statistically significant asymmetries that can be explained by economic recessions and to a lower extent depend on the magnitude of the oil price shift and on whether the shift is positive or negative. In the high response regime, the effect is positive and lasts longer. We also find evidence of asymmetries in the response of stock prices to crude oil supply shocks, global aggregate demand shocks, and oil-specific demand shocks.

Keywords: Asymmetric effects, Recession, Stock, Oil shocks, Regime-switching

JEL Classifications: C32, E32, G10, Q41

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1. Introduction

Fluctuations in crude oil prices have attracted the attention from policy makers and researchers alike, primarily due to effects of crude oil prices on stock market and the economy. Crude oil prices are often regarded as an essential factor for understanding variation in stock prices (see, e.g., Kilian and Park, 2009); however, the empirical evidence is mixed (see, e.g., Kling, 1985, and Jones and Kaul, 1996, who find a negative association, while Chen et al., 1986, and Huang et al., 1996, who find no link). This paper sets to reconcile prior conflicting empirical evidence by using nonlinear models in which the response of stock prices to oil prices is allowed to change over time. More importantly, our flexible empirical strategy allows explaining the forces behind the asymmetry in the response.

The empirical approach endogenously identifies the time variation in the response of stock prices to oil prices. The response switches between low and high-response regimes following a first-order Markov switching model. In the basic setup the model has fixed transition probabilities, but later on we model the transition probabilities to be a function of various state variables to explain the forces behind the asymmetric response. We study whether the magnitude of the oil price change, the sign of the oil price change, and being in a recession period play a role in explaining the observed asymmetries. The advantage of our approach is that it allows different manifestations of asymmetries to be modeled jointly, while it does not necessitate the time variation in the estimates to be matched to a single source of asymmetry, which is useful when different sources that explain the asymmetric response are correlated. Our structural representation of the trend and transitory components of stock prices allow of oil prices to impact stock price only in the short run. Studying transitory or short-run dynamics allows us to investigate the possibility that the market crashes are results of unusually large transitory shocks that are short-lived (see, e.g., Kim and Kim, 1996) and caused by the noise traders' misperceptions (see, e.g., De Long et al., 1990).

We find robust empirical support for time variation in the response. The effect of oil prices on stock prices switches between high and low response periods. The state-dependent impulse response functions show that during the high response regimes the effect is positive and lasts over a year, while economically significant evidence is lacking during the low response regime. When turning to explaining the asymmetry, our study finds empirical evidence that economic recessions increase the probability of being in a high-response regime. Moreover, the magnitude and the sign of oil price shifts also help explain the time variation, but to a lower extent. When plotting the filtered probabilities, we observe that higher probabilities of being in the high-response regime follow closely the NBER-dated recessions. This observation shows that the identification of the model comes across the historical episodes of recessions and not just from a small subset of the data.

The importance of fluctuations in oil prices and its effect on the economy is well known. The seminal work by Hamilton (1983) finds that oil price shocks are responsible for recessions in the United States. Using evidence from emerging markets, Fang and You (2014) argue that oil prices might affect economy through the real balance channel, income transfer channel and allocative channel. For the effect of oil prices on stocks, the existing empirical evidence is still inconclusive. On the one hand, various works found a negative effect. For example, Jones and Kaul (1996) study international stock markets to show a negative effect in the post-war period, while Sadorsky (1999) finds the same negative effect using a VAR. Additional studies that show a negative stock-oil relationship include Park and Ratti (2008) in international stock markets, Nandha and Faff (2008) with globally diversified industry portfolios, and Kilian and Park (2009) with VAR models and U.S. stock market data. On the other hand, work that found a positive effect includes Sadorsky (2001) who studies the Canadian stock market, and Gogineni (2007) that uses U.S. data and looks at aggregate demand shocks. Moreover, Sukchareon et al. (2014) find that international stock markets returns do not respond to oil market shocks. Likewise, Henriques and Sadorsky (2008) show similar evidence from U.S. alternative energy companies' indexes.

There are several theoretical explanations that support our nonlinear model specifications and the empirical results. Theoretically, higher oil prices lead to higher production costs, increases inflationary pressure, and lowers real consumption, all of which slows economic growth in the short run primarily through its impact on aggregate demand, or consumer spending and, hence, an adverse effect on corporate profits. In the late aftermath of 2007-2009 recession stock prices showed tendency to move, especially decline, along with oil prices. This was unanticipated given the usual presumption that a decline in oil prices is favorable news for the consumer as it boosts domestic income, which means more spending power and thus, leads to overall economic boom.[1]

The asymmetric effect of oil prices on financial markets has been attracting significant attention from researchers. Reboredo (2010) uses a Markov-switching, while Aloui and Jammazi (2009) use a two regime Markov-switching EGARCH. More recently, Sim and Zhou (2015) employ a quantile-on-quantile approach, and Zhu et al. (2017) considers asymmetries while separating the sources of oil price shocks. Kumar (2019) includes exchange rates and uses nonlinear Granger causality and nonlinear ARDL tests. Kocaarslan and Soytas (2019) further reports that ignoring the presence of nonlinear relations leads to misleading findings.[2] Our

[1] http://www.eia.gov/todayinenergy/detail.php?id=20752
[2] See also Filis et al. (2011), Chang and Yu (2013), and Zhang and Li (2016).

approach is different as we aim at explaining the factors behind the asymmetric response and we separate the sources of oil price shocks.

Other studies that looked at the stock-oil relationship using linear models include Sadorsky (1999) using a VAR model, and Basher and Sadorsky (2006) who focus on emerging economies. Cong et al. (2008) use data from China, and Nandha and Faff (2008) looks at various industries. More recently, Bams et al. (2017) uses variance risk premia extracted from options and futures contracts.

The remainder of the paper is organized as follows. Section 2 presents the data, while section 3 discusses the empirical approach. In section 4 we present the estimation results, followed by theoretical discussion on findings in section 5. Finally, section 6 concludes.

2. Data

To be able to examine any potential asymmetric responses of real stock prices to real oil prices we use monthly data between January 1974 and October 2016. We measure the real stock price with the monthly real price of S&P 500 index.[3] This data series is obtained from Datastream. For the crude oil price, we use the U.S. Crude Oil Composite Acquisition cost by Refiners, obtained from the Energy Information Administration.[4] The U.S.'s Consumer Price Index (CPI) deflates all nominal price series. We obtained the CPI from the Federal Reserve Bank of St. Louis on the monthly basis with 1982 (1982 = 100) as the base year. Following Kilian and Park (2009), we consider three different oil related shocks: oil supply shocks,

[3] S&P 500 is a benchmark index of 500 large capitalization value companies that are publicly traded in the United States.
[4] U.S. Crude Oil Composite Acquisition cost by Refiner is the weighted average of domestic and imported crude oil costs. It is reported in the U.S. Dollar per Barrel. This is the cost of crude oil, including transportation and other fees paid by the refiner. The refiner acquisition cost does not include the cost of crude oil purchased for the Strategic Petroleum Reserve (SPR). Source: Energy Information Administration (http://www.eia.gov/dnav/pet/pet_pri_rac2_dcu_nus_m.htm).

aggregate demand shocks, and oil-specific demand shocks. These shocks are constructed using data on crude oil production, a real economic activity index, and crude oil price. We retrieved global crude oil production from Datastream and real economic activity index from the Lutz Kilian website.[5]

[Table 1, about here]

Table 1 reports the descriptive statistics. The mean of the real stock price is $425.83, while the real oil price average around $22.55. REC is a dummy variable equal to one during an NBER-dated recession, otherwise zero. The mean of REC is 0.13 suggesting that NBER-dated recession periods are usually short-lived relative to our sample size. SIGN takes value of one if the shift in oil prices at time *t* is positive, zero otherwise. We have two measures to capture the size of the shifts. First, SIZE equals to one if the shift in oil prices is greater than one standard deviation, zero otherwise, and SIZE2 which is equal to one if the shift in oil prices is greater than 0.58 standard deviations, zero otherwise. We select 0.58 to make sure the average of SIZE2 is equal to 0.5 The SIGN average around 0.54 signifies that slightly more than half of the shifts in real oil prices are positive. On the other hand, the mean of SIZE at 0.11 indicates that few of the shifts in real oil prices fall outside one standard deviation. By construction, half of the values of SIZE2 will be one, and half will be zero. In addition, supply, aggregate demand, and oil-specific demand shocks are obtained from the structural VAR. Mean of aggregate demand shock is negative and highly volatile compared to supply shocks and oil-specific demand shocks.

[Figure 1, about here]

[5] http://www-personal.umich.edu/~lkilian/paperlinks.html

Figure 1 presents the real stock index and the real crude oil index along with the NBER recessions illustrated by shaded areas.[6] The NBER-defined recessions in our sample are January 1980 to July 1980, July 1981 to November 1982, July 1990 to March 1991, March 2001 to November 2001, and December 2007 to June 2009. From figure 1 we notice that most of the times the financial market appears to react negatively to bearish economic conditions. In addition, we observe falling stock prices prior to almost every recession start date. Economists have argued that many recessions are caused by rising oil prices: 1980-1981, 1990-1991, and 2007-2009 (see, e.g., Hamilton, 2009; Barsky and Kilian, 2004; Sharma and Escobari, 2018). In all these recessions, the oil price eventually fell as demand for energy collapsed. Overall, it is noticeable that oil prices rose for most of the period between early 1990s until the financial crisis in late 2007. This is partly due to the strong oil demand in emerging markets. However, China's recent efforts to focus on strengthening its domestic demand, while also transitioning from manufacturing to a service-oriented economy has weakened oil prices from demand side. Figure 1 shows how oil prices have rapidly plunged since 2014. Advancements in horizontal drilling and hydraulic fracturing (also known as fracking) are the United States' supply side technological innovations that have challenged traditional oil suppliers (e.g., OPEC). Our empirical specifications will not only be able to model asymmetric behavior in the effect of oil prices to stocks, but will also be able to separate between different oil related supply and demand shocks as motivated in Kilian and Park (2009).

Figure 1 is consistent with a changing pair-wise correlation between the stock market and oil prices, which supports our nonlinear specifications. During non-NBER-defined recessions,

[6] The NBER defines a recession as a significant decline in economic activity spread across the economy, lasting more than a few months, normally noticeable in real GDP, real income, employment, industrial production, and wholesale-retail sales.

there appears to be a positive correlation, which seems to be stronger during recessions. This association between stock and oil only seems to weaken during some periods. For example, weak association was observed in 2008 at the beginning of the recession and starting in mid-2014.

3. Empirical strategy

To model the dynamics of the real stock price and to empirically investigate the asymmetric effect of oil prices on stock prices, we first decompose the dynamics of the real stock price into the following two additively separable components:

$$stock_t = stock_t^P + stock_t^T, \tag{1}$$

where $stock_t$ is the logarithm of the real stock price (hereafter "stock price"). In addition, the first term on the right-hand side is the permanent (stochastic trend) component of stock price $stock_t^P$, while the second term is the transitory component, $stock_t^T$. Our specification of the permanent component is modeled as a random walk:

$$stock_t^P = \mu_t + stock_{t-1}^P + v_t, \tag{2}$$

This equation (2) controls for permanent shocks to stock prices and for a potential trend. In this random walk formulation, the autoregressive term is restricted to have a coefficient equal to one, making shocks v_t have a permanent effect on stock prices. The forecasting function will have a time-varying drift term captured by μ_t,

$$\mu_t = \mu_{t-1} + \omega_t, \tag{3}$$

which evolves as a driftless random walk.[7] The innovations v_t and ω_t are assumed to be normally and *independent and identically distributed (i.i.d.)* random variables.

The analysis of the response of the logarithm of the real stock price to the logarithm of the real oil price, oil_t (hereafter "oil price") is modeled with the following autoregressive process:[8]

$$\phi(L) \cdot stock_t^T = \gamma_0(L) \cdot oil_t + \gamma_1(L) \cdot oil_t \cdot S_t + \varepsilon_t, \tag{4}$$

$$\phi(L) = \sum_{k=0}^{K} \phi_k \cdot L^k ; \quad \phi = 1 ; \quad \gamma_i(L) = \sum_{j=0}^{J} \gamma_{j,i} \cdot L^j , \tag{5}$$

where all roots of $\phi(L)$ lie outside the unit circle.[9] As with previous innovations, we assume ε_t is an *i.i.d.* random variable that follows a normal distribution. The indicator variable S_t in equation (4) captures the regime changes in the responses of stock prices to oil prices. This construction follows Lo and Piger (2005) and Escobari (2013) and we will provide various specifications to be consistent with the empirical model of stock market response to oil price shocks in Kilian and Park (2009). In these specifications oil price can be treated as predetermined factor. Further, following Gerlach and Smets (1999), our approach expands the standard unobserved components model with an oil price variable, (oil_t). This formulation captures how fluctuations in the price of oil affects the transitory component of stock prices in different regimes while separately modeling the dynamics of the permanent component of stock prices. Previous literatures have proposed several methods of decomposing a time series into permanent and transitory components. Campbell and Mankiw (1987) employing an ARMA model, estimated the effect of a shock on long-run forecast to show comparative importance of

[7] This characterization of the drift aims to model low frequency shocks to the stochastic trend, which can include structural breaks in the growth rate of the trend.
[8] Clark (1987) and Watson (1986) discuss the decomposition of the unobserved component into stochastic trend and transitory component.
[9] Note that if we disregard oil_t in equation (4), the specification of equations (1) to (5) is basically the unobserved components decomposition of stock price into $stock_t^P$ and $stock_t^T$.

the two components. Others have examined the relative significance of two components within the framework of the state-space model with Markov regime-switching (see, e.g., Kim and Kim, 1996; Kim and Nelson, 1999).

In addition to our base model presented in equations (1) to (5) that focuses on the effect of real oil prices on real stock prices, we adopt Kilian and Park's (2009, henceforth KP) framework to study how different types of oil related shocks (i.e., oil supply shocks, global aggregate demand shocks, and oil-specific demand shocks) can have an asymmetric effect on real stock prices. Using a VAR model, Kang et al. (2015) show that the contribution of oil related shocks to stock return gradually rose during global financial crisis, where both the coefficients and the variance-covariance matrix provide evidence of time variation. With this motivation, we construct a structural VAR as in KP to capture oil related supply shocks, oil-specific demand shocks, and global aggregate demand shocks. The simplest form of this approach involves having $B_0 y_t = \alpha + \sum_{i=1}^{k} B_i y_{t-i} + \epsilon_t$ as the structural representation of our VAR, where y_t is a vector of response time series variables with *n* elements at time *t*, while α is a vector of constants. Furthermore, multiplying the model by B_0^{-1}, we obtain that $A_i = B_0^{-1} B_i$ are $n \times n$ matrices for each lag *i* for a total of *k* autoregressive matrices. Moreover, $I = B_0^{-1} B_0$ is just the identity matrix, whereas ϵ_t is a vector of serially uncorrelated innovations that have a covariance matrix Σ. The recursively identified structural VAR model has the following reduced form innovations:

$$e_t \equiv \begin{pmatrix} e_{1t}^{\Delta global\ oil\ production} \\ e_{2t}^{global\ real\ activity} \\ e_{3t}^{real\ price\ of\ oil} \end{pmatrix} = \begin{bmatrix} \mathrm{b}_{11} & 0 & 0 \\ \mathrm{b}_{21} & \mathrm{b}_{22} & 0 \\ \mathrm{b}_{31} & \mathrm{b}_{32} & \mathrm{b}_{33} \end{bmatrix} \begin{pmatrix} \epsilon_{1t}^{\Delta oil\ supply\ shock} \\ \epsilon_{2t}^{aggregate\ demand\ shock} \\ \epsilon_{3t}^{oil-specific\ demand\ shock} \end{pmatrix} \quad (6)$$

We then allow each of the reduced form shocks e_t obtained from equation (6) to influence the real stock price in regime switching models as presented in equations (1) to (5). Furthermore, to obtain the shocks e_t, we follow Kilian (2009) identifying restrictions in equation (6) which imply that (i) oil supply shocks are innovations from the oil supply; (ii) given the slowness in global real economic activity increases in real price of oil, determined by oil market specific shocks, will not impact global real economic activity in the short-run; and (iii) innovations to the real price of oil are shocks specific to the oil market, which cannot be explained by oil supply shocks or aggregate demand shocks.[10]

In order to model the time variation in the response, our nonlinear specification allows the response to change between regimes. The indicator variable S_t in equation (4) captures the regime. Whether, S_t is zero or one will be filtered from the data, and it is unobserved by the researcher. We follow Hamilton (1989) and model the transition between regimes to be captured by a first-order Markov process. In the time invariant or fixed transition probability (FTP) specification, S_t takes the values of 0 and 1 as modeled by:

$$P(S_t = 0 \mid S_{t-1} = 0) = \frac{\exp(c_0)}{1 + \exp(c_0)}$$

$$P(S_t = 1 \mid S_{t-1} = 0) = 1 - P(S_t = 0 \mid S_{t-1} = 0),$$

$$P(S_t = 1 \mid S_{t-1} = 1) = \frac{\exp(c_1)}{1 + \exp(c_1)}$$

$$P(S_t = 0 \mid S_{t-1} = 1) = 1 - P(S_t = 1 \mid S_{t-1} = 1). \tag{7}$$

This FTP of equations (7) essentially mean that the probability of switching regime (or staying in the same regime) is same throughout the period of study. A more flexible approach

[10] The nature and origin of the identifying assumptions regarding recursively identified structural model is explained in detail in KP.

would be to model the transition probabilities between regimes to be a function of some observables. To this extent, we adopt the specification in Filardo (1994) to have time-varying transition probabilities (TVTP) where the regime-switching process changes over time. Our TVTP model has the following logistic form:

$$P(S_t = 0 \mid S_{t-1} = 0) = \frac{\exp(c_0 + z_t' \cdot a_0)}{1 + \exp(c_0 + z_t' \cdot a_0)},$$

$$P(S_t = 1 \mid S_{t-1} = 1) = \frac{\exp(c_1 + z_t' \cdot a_1)}{1 + \exp(c_1 + z_t' \cdot a_1)}. \tag{8}$$

The state variables that govern the regime switch are included in the $q \times 1$ vector z_t, where $z_t = (z_{1t},\ z_{2t}, \dots, z_{qt})'$, whereas a_0 and $a_1$are the $q \times 1$ vectors of coefficients $(a_{01}, a_{02}, \dots, a_{0q})'$ and $(a_{11}, a_{12}, \dots, a_{1q})'$ associated with z_t at each state. The vector z_t will include three sources of asymmetries to capture the regime changes; asymmetry to capture the direction of oil price shift, asymmetry to capture the size of the oil price shift, and asymmetry to capture economic recessions. Various specifications of the z_t will allow us to analyze each asymmetric independently as well as to combine different sources of asymmetry in the response. This information is included in z_t in the form of different sets of the dummy variables REC, SIGN, SIZE, and SIZE2. Because these dummy variables in z_t are expected to capture dynamics of the asymmetry, we include J lags of each variable.

4. Results

To estimate the model presented in equations (1) to (5), (7) and (8) we use the logarithm of the monthly real S&P 500 index price, $stock_t$. For the price of oil our first set of results use the logarithm of the real oil price. To obtain the maximum likelihood estimates, first we find the state-space representation of the Markov-switching model by implementing the filtering and smoothing procedure described in Kim (1994). Due to the non-stationary nature of the transition equation, we use the Kalman filter portion of Kim's filter. We, therefore, initiated the filter where we place high variance on initial guesses. We compute the maximum likelihood only after twelve months of data to dissipate the effects of initial parameter guesses. This means that although our sample begins in January 1974, the estimation results will cover from January 1975 through October 2016. In addition to using real oil prices, further specification will follow KP to disentangle the real oil prices into oil-related global supply shocks, aggregate demand shocks, and oil-specific demand shocks. This allows to further study if there is an asymmetric response from any of these shocks to stock prices.

4.1.Testing for asymmetries in the response

The first step in the estimation is to examine if the regime-switching model is a significant improvement relative to the model that assumes a constant response. The improvement should be in terms of the model fit. To decide on the values of the lags *K* and *J* in equation (5), we estimate the FTP model with a maximum lag order of twelve for both *K* and *J* and start reducing the number of lags until a likelihood ratio finds a significant value of either ϕ_k or $\gamma_{j,i}$. This resulted in a lag order of $K = 2$ and $J = 1$, which we employ in all of the specifications.

To test for the significance of regime-switching model, we follow Hansen (1992), which basically tests the significance of the fixed transition probability model (or regime-switching model) versus the null hypothesis that the response coefficients are constant; that is, $\gamma_{j,0} = \gamma_{j,1}$ for all j. The importance in using Hansen (1992) to the fact that in this type of Markov-switching models, some parameters of interest are not identified under the null. Not being able to meet this regularity condition implies that the standard LR test has an unknown distribution for the null hypothesis. Hansen (1992) is useful as it provides an upper bound of the *p*-value; hence, we read it as a conservative test of the null.[11] When applied to our base model, the Hansen test yields a *p*-value of 0.01. We interpret significant upper bound *p*-value as a significant empirical evidence supporting the model time-varying coefficients. Similarly, we find strong evidence in favor of alternative hypothesis of regime-switching response coefficients, while using KP's oil-market related shocks. For the oil-related supply shock and the aggregate demand shock, we obtain a *p*-value of 0.01. For the oil-specific demand shock, the *p*-value is 0.05.

4.2. Modeling the sources of the asymmetric response

After finding evidence of asymmetry in the response, we turn to estimate the FTP model as well as various specifications of the TVTP for our baseline model. Table 2 reports the Schwarz Information Criteria (SIC), the Akaike Information Criteria (AIC), and the log likelihood of different specification of the z_t vector in the first three columns. The last column presents the *p*-values associated with the Likelihood Ratio tests of each of the TVTP models versus the FTP model. Within the time-varying transition probabilities specification, $P(S_t = 1|S_{t-1} = 1)$ is modeled not to depend on time as the estimation results from all the models that we consider suggest that $S_t = 1$ holds only for short periods of time. This means that z_t has a small contribution explaining the variation within $P(S_t = 1|S_{t-1} = 1)$. Thus, the modeling focuses on the how the transition probability $P(S_t = 0|S_{t-1} = 0)$ changes over time.

[Table 2, about here]

[11] Lo and Piger (2005) provide details on Hansen in a similar setting.

The first specification corresponds to the fixed transition probability model where equations (8) can just be written as equations (7). Table 2 describes the FTP model where z_t is empty, as well as models in which $\mathrm{SIGN_t}$, $\mathrm{SIZE_t}$, and $\mathrm{REC_t}$ are included, one at the time, in z_t. First, we model the specification where z_t contains the variables characterizing the direction of change; that is, $z_t = (\mathrm{SIGN_{t-1}}, \mathrm{SIGN_t})'$. The *p*-value presented in the last column shows evidence that at the 0.004 level, the direction of the shift in real oil prices is helpful for explaining regime shifts. The specification that follows considers the case where z_t contains the dummy variables capturing the magnitude of the change in real oil prices, i.e., $z_t = (\mathrm{SIZE_{t-1}}, \mathrm{SIZE_t})'$. The LR test statistic for the null hypothesis of the fixed transition probabilities model has a *p*-value of 0.068.

We interpret this as empirical evidence that this measure of the size of the shift helps explain the different responses of stock prices to shifts in the price of oil. However, when $z_t = (\mathrm{SIZE2_{t-1}}, \mathrm{SIZE2_t})'$, we have that the associated LR test *p*-value is 0.1960. This is evidence that the SIZE2 model does not represent an improvement in terms of fit over the FTP model. Hence, we have mixed evidence on the role of size when explaining the asymmetric effect. When comparing the *p*-values, we see that this evidence is weaker than when $\mathrm{SIGN_t}$ explains the asymmetric response. Finally, the last specification reported in Table 2 models z_t to contains the dummy variables that capture the NBER recession dates, i.e., $z_t = (\mathrm{REC_{t-1}}, \mathrm{REC_t})'$. The log likelihood statistics and the likelihood ratio test reported for NBER recession (REC) periods signifies that REC specification is our preferred model when compared to the FTP or the other TVTP specifications reported in Table 2. In subsequent section, we focus on the results for this preferred specification.

4.3. Model estimates and interpretation

The model selection described earlier suggests that the response of stock prices to oil prices varies amid regimes. Moreover, the regime changes can be modeled by different asymmetries. In this section we move to present the estimates for various specification of the z_t vector in equations (8). The maximum likelihood estimates reported in Table 3 have the FTP model in the first column, while the TVTP specifications appear in columns 2 through 4. We do not further explore the role of SIZE2 as it does not represent an improvement in terms of fit over the FTP model. Across all specification, the parameters of the trend component of the $stock_t^P$ suggest that growth of real stock prices is well recognized as being mainly constant, with sporadic shifts that can capture episodes of stock market crashes. Precisely, σ_ω is statistically significant, i.e., the trend component is categorized by low frequency innovations, which have a permanent effect on the growth rate of the trend. Nevertheless, σ_v is not statistically significant, which means that once low frequency innovations are modeled, there are no further permanent innovations to real stock prices.

[Table 3, about here]

Figure 2 presents the transitory component of the real stock price ($stock_t^T$) for the REC model of column 4, along with the highlighted areas that characterize NBER dated recession periods (i.e., $\mathrm{REC_t} = 1$). This figure illustrates the sharp decline in stock prices during NBER-dated recessions. In addition, there is empirical evidence of a negatively skewed $stock_t^T$, as negative deviations are larger than the positive deviations from the permanent component.

[Figure 2, about here]

In order to visually inspect $stock_{t+j}^T$ as modeled by equation (4) and the results captured by the regime-switching response coefficients, $\gamma_{0,0}$, $\gamma_{1,0}$, $\gamma_{0,1}$, and $\gamma_{1,1}$, Figure 3 provides the impulse response functions (IRFs) that depend on the state for the REC specification (column 4, Table 3), with the cumulative responses reported on the right-hand side. The indicator variable S_t divides the oil price innovations that have large effects from innovations that have relatively smaller effects. The real oil price shift at $t-1$ is set to be equal to its historical standard deviation of 0.1108. The impulse response functions only depend on the values of S_t and S_{t+1}, because *J* = 1 in equation (5). Thus, we compute IRFs under four possible realizations of the indicator variables: $S_t = S_{t+1} = 0$; $S_t = 1$ and $S_{t+1} = 0$; $S_t = 0$ and $S_{t+1} = 1$; and $S_t = S_{t+1} = 1$. In addition, while computing the impulse responses, we assume that $stock_{t+1}^T = stock_{t+2}^T = 0$, $\varepsilon_{\mathrm{t+j}} = 0$, $\forall j$ and $oil_{t-j} = 0, j \neq 0$. The state-dependent IRFs show that there is a positive effect for the high-response regime, with the response being larger and lasting longer when $S_t = 1$ and $S_{t+1} = 1$. A one standard deviation rise in oil prices increases stock prices by about 0.31% at three-month periods during high response regime (i.e., $S_t = S_{t+1} = 1$). When $S_t = 0, S_{t+1} = 1$ or $S_t = 1, S_{t+1} = 0$ the maximum response of real stock price is still positive, but it is about half the size. Finally, during the low-response regime (when $S_t = 0$ and $S_{t+1} = 0$) the effect on stock prices is negligible. The cumulative responses reported on the right-hand side show a similar story. The maximum accumulated effect on stock prices after a one standard deviation shift in oil prices reaches a maximum of about 2.8% increase after about a year and a half.

[Figure 3, about here]

In addition, results in Figure 3 are an illustration of a case under the assumption of a constant response of real stock prices to real oil prices obscure interesting features of the data. For example, Figure 3 shows that the estimated response of stock prices to a positive real oil price shift is close to null in the low response regime, i.e., $S_t = S_{t+1} = 0$. Furthermore, when looking at the responses with regime transitions (i.e., $S_t = 1, S_{t+1} = 0$; and $S_t = 0, S_{t+1} = 1$)

and for the high response regime ($S_t = S_{t+1} = 1$), the effect is positive. This indicates that the response of the real stock price to the real oil prices is different in terms of sign and magnitude when we allow for nonlinear effects. Thus, when having a more flexible approach we expose the concealed component of regime varying relationship between the real stock price and the real oil price.

When replacing equations (7) with equations (8) in the estimation of the model, we can obtain the estimated coefficients $\hat{c}_0$, $\hat{c}_1$, $\hat{a}_{01}$, and $\hat{a}_{02}$ to allow us asses how transition probabilities vary over time. From the estimates in column 4 of Table 3, we have $\hat{c}_0 = 2.3081$, which results in $P(S_t = 0|S_{t-1} = 0) =$ $\exp(\hat{c}_0)$ / $(1 + \exp(\hat{c}_0))$ = 0.91. This suggests that if the economy has not been in a recession in the recent past ($REC_{t-1} = REC_t = 0$) and we were in a low response regime last period ($S_{t-1} = 0$), we will remain in the current period in the low response regime ($S_t = 0$) with a relatively high probability. The probability of switching to a high response regime is just 0.09.

Alternatively, when the economy is currently in a recession and was in a recession in the previous period ($REC_{t-1} = REC_t = 1$), from the same column in Table 2, we observe that $\hat{a}_{01}$ is relatively large, negative, and statistically significant, while $\hat{a}_{02}$ is small and statistically insignificant. Using these values in the corresponding equation (8) we have that $P(S_t = 0|S_{t-1} = 0)$ decreases to $\exp(\hat{c}_0 + \hat{a}_{01})$ / $(1 + \exp(\hat{c}_0 + \hat{a}_{01})) = 0.01$. This means that the probability of switching from a low to a high response regime increases to $P(S_t = 0|S_{t-1} = 0) = 0.99$ during recessions. Combining these results with the regime dependent IRFs results discussed earlier, we can say that during recessions oil prices will be more likely to have large positive effects on stock prices than outside recessions. The parameters defining $P(S_t = 1|S_{t-1} = 1)$ indicate that the $S_t = 1$ regime holds only for short bursts.

[Figure 4, about here]

Figure 4 visually summarizes the previous discussion by showing the filtered probability that $S_t = 1$, which we denote by $P(S_t = 1|t)$, for the REC specification of the vector z_t. The filtered probabilities are obtained using the TVTP specification presented in equations (1) to (5) and (8). The shaded areas in Figure 4 correspond to the NBER-dated recession periods. This figure illustrates how the model identifies two separate regimes, when $P(S_t = 1|t)$ is almost zero, and during brief and infrequent periods when it is almost one. These brief periods coincide for most part with the shaded areas. This is further evidence that REC helps in explaining the time variation in the transition probabilities. It is interesting to observe that there is at least one period in which $P(S_t = 1|t)$ jumps up around every NBER recession after 1990. Moreover, there is a consistent pattern where REC and $S_t = 1$ corresponds throughout the sample period, which is evidence that the model identification comes from the variation observed in various recession episodes.

4.4. Combined asymmetries

We now conduct additional model specifications to further study the factors that affect the asymmetric response. We first study the $\mathrm{SIGN_t}$ and $\mathrm{SIZE_t}$, one at the time, along with $\mathrm{REC_t}$. The model selection statistics for these two additional specifications are reported in Table 4. The likelihood ratio statistics in the fourth column tests the null of the FTP model, while the last column tests the null of the REC in the model (i.e., our preferred model from Table 2). The z_t vector in the first specification is given by $z_t = (\mathrm{REC_{t-1}}, \mathrm{REC_t}, \mathrm{SIGN_{t-1}}, \mathrm{SIGN_t})'$, with a corresponding *p*-value of 0.1186 on the LR test over the $z_t = (\mathrm{REC_{t-1}}, \mathrm{REC_t})'$ model and a near zero *p*-value on the LR test over the FTP model. We interpret this as evidence that a model with

REC and SIGN is a considerable improvement over the model with constant transition probabilities, but it is not significantly better than a model with simply REC.

[Table 4, about here]

The lower part of Table 4 presents two specifications that assess the degree to which SIGN and SIZE play a role in explaining the asymmetric response while being in an NBER-defined recession. This specification allows us to study whether SIGN and SIZE, while unconditionally significant, can be significant conditionally on the economy being in an NBER-defined recession. This involves estimating two alternative models for the vector z_t, i.e., $z_t = (\mathrm{REC_t}, \mathrm{REC_{t-1}}, \mathrm{SIZE_t} \times \mathrm{REC_t}, \mathrm{SIZE_{t-1}} \times \mathrm{REC_{t-1}})'$ and $z_t = (\mathrm{REC_t}, \mathrm{REC_{t-1}}, \mathrm{SIGN_t} \times \mathrm{REC_t}, \mathrm{SIGN_{t-1}} \times \mathrm{REC_{t-1}})'$. Based on the LR tests both specifications are preferred to the FTP model. Moreover, the LR test of the null of having only REC is rejected at the 5% significance level in favor of the SIGN specification (*p*-value of 0.039), but we fail the reject the null for the SIZE specification (*p*-value of 0.607). Furthermore, the AIC and SIC show consistent results as both also prefer the specification where SIGN within recessions explain the asymmetric response. Overall we observe that conditional on being in a recession period, the direction of shift in oil prices further helps to explain the asymmetric response.

[Figure 5, about here]

Figure 5 plots the regime-dependent impulse response functions for our preferred specification of Table 4, i.e., with $z_t = (\mathrm{REC_t}, \mathrm{REC_{t-1}}, \mathrm{SIGN_t} \times \mathrm{REC_t}, \mathrm{SIGN_{t-1}} \times \mathrm{REC_{t-1}})'$. The solid black lines illustrate the IRFs during the high-response regime (cumulative response on the right-hand side). There is a positive effect of oil prices on stock prices. The marginal effect is at its maximum three months out with a 0.41% effect on stock prices given a one standard deviation increase in oil prices. On the right-hand side panel, we observe that the cumulative effect during the high-response regime increase in oil prices by about 3.6% beyond the 18-month mark (for a one-standard deviation change in oil prices). This is consistent with the left-hand side IRF where the effect completely dies out after about two years. When either $S_t = 1$ and $S_{t+1} = 0$, or $S_t = 0$ and $S_{t+1} = 1$, the effects are smaller and have a shorter duration. In the latter case the maximum marginal effect for a one-standard deviation change in oil prices is achieved at the 3-month mark (with 0.32%) and the cumulative effect reaches a maximum of about 3.7% after about 18 months. On the other hand, if the low-response regime prevails (i.e., $S_t = 0$ and $S_{t+1} = 0$), the dashed black line shows how the marginal and the cumulative effect are economically insignificant. Overall these set of results are consistent with the previous findings when the asymmetric response was purely explained by recession periods. In both of these specifications, as presented in Figures 3 and 5, there is significant evidence of asymmetry in response of stock prices to oil prices. In a high-response regime ($S_t = S_{t+1} = 1$), the effects are positive, while in the low-response regime ($S_t = 0$ and $S_{t+1} = 0$), the effects are negligible.

[Figure 6, about here]

Figure 6 reports the filtered probabilities $P(S_t = 1|t)$ to examine the time at which the model experiences a regime change. The periods in which $P(S_t = 1|t)$ spikes up are observed to be highly correlated with dates defined as an NBER recession, shown as the shaded areas in the figure. Note that $P(S_t = 1|t)$ spikes in every recession and gets to be close to one in two of the recessions (July 1990 to March 1991, and December 2007 to June 2009). This filtered probability provides further evidence in support to our model specification and highlights the importance of recession periods in explaining the asymmetric response.

4.5 Alternative measures of oil-specific shocks and robustness test

Following the work of KP, we now turn to study whether the underlying cause behind the oil price change plays a role on the effect of oil prices changes on stock prices. Combining our model from equations (1) to (5) and (8) with structural VAR of equation (6), we extend KP to further study whether oil supply shocks, an aggregate demand shocks, and oil-specific demand shocks have a nonlinear effect on stock prices. The VAR structure in equation (6) that serves to identify the three different oil-related shocks also helps us to define changes in the oil market as exogenous factors to the U.S. stock market (see, e.g., Kilian, 2009, and KP).

[Table 5, about here]

The three panels presented in Table 5 show the results for each of the shocks filtered from equation (6).[12] In each of the panels we present results for the FTP specification as well modeling z_t to depend on sign, size, and recessions. We observe that for oil supply shocks, aggregate demand shocks, and oil-specific demand shocks (reported in Panels A, B, and C, respectively), SIGN and SIZE do not represent a significant improvement over the FTP model. However, given the associated likelihood ratio p-values of 0.0002, 0.0035, and 0.0227, we observe that for all three alternative measures of oil-specific shocks, being in a recession (REC) helps explain the asymmetry in the response. Only in high response regimes oil supply shocks have a small negative effect, aggregate demand shocks have a positive effect, while oil-specific demand shocks have a negligible negative economic effect. There are no statistically significant effects during low-response regimes. While these is consistent with Kilian and Park (2009), it is

[12] The Hansen test finds strong evidence in favor of the models with regime-switching response coefficients for all three shocks in KP.

difficult to directly compare the results as for most of our sample, when we are out of a recession, there is no response.[13]

Comparison across the different LR tests tells us that REC is the preferred model for each of the alternative measures of oil-specific shocks. Overall, the findings in Table 5 provide additional evidence that recessions play an important role on the nonlinear effect of oil prices on stocks, this time considering various causes for the underlying oil price changes. Moreover, these findings also extend the work of Zhu et al. (2017), to further explain that the transition between high- and low-response regimes can be explained by recession periods.

The findings presented in this paper can help us answer policy questions in light of oil related shocks having larger effects during recessions. This information might be used by regulators if they are aiming to stabilize stock prices by trying to affect oil supply particularly before (or during) recessions. There is a plausible behavioral explanation behind recessions driving the asymmetric response of stock to oil related shocks. It is an observed phenomenon that during periods of recession, consumer behavior changes as a result of changes in expectations and disposable income. As the economy enters a recession, investors update their beliefs about future stock returns, which in our case can explain how stock market participants react differently as they observe oil price changes. In addition, Massey and Wu (2005) argue that the ability of consumers to correctly identify the onset of a new regime can mean the difference between overreaction and underreaction. Investors' beliefs about the state of the economy influences their reaction to oil price changes. It is likely that consumers overreact to any information during the onset of recession periods. Likewise, during recovery periods consumers are likely to underreact or respond slowly to the recovery due to incumbent fear of losing an

[13] We show in the appendix how the responses differ by industry.

investment. Sharma (2017) show recession plays major role while explaining shifting relationship between oil and ADR stocks, while Sharma and Rodriguez (2019) document a diminishing hedging role of oil for stock market as a result of growing financialization after 2007-2009 crisis. Yeh et al. (2012) show that changes in international oil prices have a significant impact on industrial production. It is reasonable to expect consumers to respond (overreact or underreact) to changing oil prices as commodity price directly impacts industrial production, disposable income, spending power and, hence, has an immediate effect on corporate profits. Alternatively, Basak and Pavlova (2016) find that the presence of institutional investors in the marketplace causes high correlations between futures returns of commodities and stock returns. Datta et al. (2018) shows equity and oil are positively correlated from 2008 to 2017, because of a historically low short-term nominal interest rate. Similarly, Silvennoinen and Thorp (2013) show significantly positive stock-oil correlations after 2008 in contrast to earlier years. This is consistent with stock market responses to oil price shocks being higher during recession periods.

One constraint in the estimation of our nonlinear model is that we rule out feedback from stock prices to oil shocks. However, there is evidence that oil prices have responded to the same economic forces that drive stock prices. This is not causality evidence, but evidence of endogeneity. Hence, we need to assess if ruling out this feedback is reasonable in our setting. One candidate could be to test for linear Granger causality, but this test is too restrictive as it does not account for nonlinearities. Baek and Brock (1992) present a nonparametric statistical nonlinear Granger causality test that uses correlation integral between the series. In Baek and Brock's test, the time series are assumed to be mutually and individually independent and identically distributed. Hiemstra and Jones (1994) relax this assumption and develop a modified test statistic for nonlinear causality where each series is allowed to display short-term temporal dependence.

[Table 6, about here]

We employ the Hiemstra and Jones (1994) nonlinear Granger nonparametric statistic to test the null hypothesis that stock prices do not nonlinear Granger cause oil shocks. The results reported in Panel A of Table 6 show strong evidence that we fail to reject the null for the oil specific demand shocks, aggregate demand shocks, and oil supply shocks at various lags. These results support our nonlinear specifications that include the structural VAR.

Panel B of Table 6 serves as a sensitivity analysis to the functional forms imposed by our nonlinear response methods. The reported statistics assess if there exists a nonlinear Granger causality from the different types of oil shocks to stocks. The relatively low p-values across all three shocks and at various lags are largely consistent with causality going from oil shocks to stock prices, consistent with causality modeled in our nonlinear approach.

Conclusion

This paper estimates various flexible nonlinear specifications that allow us to reconcile existing conflicting empirical evidence on the relationship between oil prices and stock prices. The empirical approach employs a first-order Markov process where the transition between regimes is endogenously determined from the data. More importantly, it allows us to include state variables in the transition probabilities to explain the sources of the asymmetric response. The reassessment of the effect of oil prices on stock prices is additionally important given the recent volatility in oil prices and the changes on the structure of the supply side of the oil industry (i.e., increase in fracking). Building on the seminal work of Kilian and Park (2009), our empirical strategy additionally allows us to assess potential asymmetries in the response of stock prices to different sources of oil shocks.

The results provide strong support for the existence of an asymmetric response. In our baseline model the high response regime shows a positive and significant effect in the response of stocks to oil prices. The positive effect is greater and lasts longer when the high response regime is prevalent. Moreover, in the low response regime our estimates and the state-dependent impulse responses find no significant effect. Filtered probabilities provide further support to our models as they show a clear match between recessions and the spikes in the probabilities of switching to a high response regime.

To explain the asymmetry in the response, we used various specifications that included state variables in the transition probabilities. We tested whether the regime shift can be explained by the sign of the oil price change, the size of the oil price change, and whether the economy is in a recession. In addition, we explored if the regime shift can be explained by various combinations of the sources of asymmetries. The empirical findings show statistically significant support that regime changes are explained by recessions and the sign of the oil price change. In particularly, shifts in oil prices during recessions have a greater impact. The filtered probabilities provide support that this outcome is consistent throughout various recessions' episodes. Overall, there is only mild evidence that the size of the shift in oil prices affect the asymmetry in the response. Our approach and result complement the findings in Mo et al. (2019), Mishra et al. (2019) and Balcilar et al. (2019). Mo et al. report that the effects of oil prices on economic growth may vary during different investment horizon, whereas, Balcilar et al. indicate that stock markets become sensitive to oil price fluctuations during periods of economic downturns. Mishra et al. report positive effects of oil price fluctuations on Islamic stocks in short run, but oil prices exert a negative influence in the long run. This is consistent with our positive stock market response to oil related shocks during economic downturns, which is relatively short lived.

Furthermore, following Kilian and Park (2009) to separate different types of shocks, we find asymmetries in the response of stock prices to crude oil supply shocks, global aggregate demand shocks, and oil-specific demand shocks. In all these cases recession periods explain the asymmetry in the response. These results are consistent with market participants changing their expectations during recessions, where consumers are more susceptible and are likely to respond to even small price shifts. Taking into consideration the rise in price of a high demand energy commodity, such as crude oil, the response can be swift during recessions. Such reaction can immediately effect consumer spending, overall aggregate demand, and the stock market. Therefore, during contractionary periods it is crucial for policy makers to take essential steps to stabilize crude oil prices by, e.g., subsidizing domestic producers, reducing tariffs on energy imports, and/or subsidizing industry sectors that are directly related to oil related shocks. These policy actions may assist in minimizing effects of crude oil related shocks on stock markets.

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Table 1. Descriptive Statistics

Variable	Observation (1)	Mean (2)	Std. Dev (3)	Min (4)	Max (5)
Real stock price	514	425.8304	240.7443	111.4974	903.3837
Real oil price	514	22.5517	11.1986	5.9672	58.9135
REC	514	0.1275	0.3339	0	1
SIGN	514	0.5398	0.4989	0	1
SIZE	514	0.1096	0.3127	0	1
SIZE2	514	0.5000	0.5005	0	1
Supply shock	514	0.0034	1.5104	-9.0219	5.6594
Aggregate demand shock	514	-0.0294	7.1718	-35.1057	34.4863
Oil demand shock	514	0.0048	1.2983	-7.0437	4.7031

Notes: The monthly stock price series is obtained from Datastream, while the crude oil price is obtained from Energy Information Administration (EIA). Supply, aggregate demand, and oil demand shocks are obtained from the structural VAR from equation (6). REC (NBER recession) is equal to one if the economy is in an NBER-dated recession, otherwise zero. SIGN takes the value of one if the shift in oil prices at time t is positive, one otherwise. Similarly, SIZE equals to one if the shift in oil prices is greater than one standard deviation, zero otherwise and SIZE2 is equal to one if the shift is grater that 0.58 standard deviations, zero otherwise The Consumer Price Index (CPI) is obtained from the Federal Reserve Bank of St. Louis. Nominal price series are deflated using the CPI with 1982 (1982 = 100) as the base year as provided by Federal Reserve Bank of St. Louis. The sample spans from January 1974 to October 2016.

Table 2. Model Selection for TVTP Specifications

Elements of z_t	SIC (1)	AIC (2)	Log Likelihood (3)	LR Test (FTP) [d] (4)
FTP				
None	-2.7362	-2.8305	703.0520	
TVTP				
SIGN	-2.7335	-2.8449	708.5803	0.0040[a]
SIZE	-2.7218	-2.8333	705.7356	0.0683[c]
SIZE2	-2.7184	-2.8203	704.6819	0.1960
REC	-2.7353	-2.8468	709.0381	0.0025[a]

Notes: SIC, Schwarz information criterion; AIC, Akaike information criterion; LR, Likelihood ratio; FTP, Fixed transition probabilities; TVTP, Time-varying transition probabilities; LR test, p-values for a test of the null of the FTP. This table contains model selection statistics for the estimated model in equations (1) to (5) and (8); under various specifications for the vector of explanatory variables, (z_t). The oil price, oil_t , is measured as a shift in real oil price. The adjusted sample spans from January 1975 to October 2016. [a], [b], and [c] represent significance at 1%, 5% & 10% level. [d] p-value for a test of the null of the FTP model.

Table 3. Parameter Estimates

	FTP	TVTP		
Elements of z_t:	None	SIGN	SIZE	REC
Parameter	(1)	(2)	(3)	(4)
σ_v	0.0000	0.0000	0.0002	0.0001
	(0.0003)	(0.0005)	(0.0025)	(0.0039)
σ_ε	0.0544	0.0536	0.0554	0.0536
	(0.002)	(0.0019)	(0.0018)	(0.0018)
σ_ω	0.0017	0.0019	0.0020	0.0019
	(0.0006)	(0.0006)	(0.0007)	(0.0006)
φ_1	1.4697	1.4045	1.4057	1.4061
	(0.0403)	(0.0394)	(0.04)	(0.0396)
φ_2	-0.54	-0.4823	-0.4851	-0.4804
	(0.0296)	(0.0393)	(0.0389)	(0.0424)
$\gamma_{0,0}$	-0.4869	-0.0943	-0.0560	-0.0954
	(0.2292)	(0.0722)	(0.0602)	(0.0678)
$\gamma_{1,0}$	-0.1038	0.0812	0.1438	0.0783
	(0.2293)	(0.0913)	(0.0572)	(0.0594)
$\gamma_{0,1}$	0.7619	1.0201	1.3250	1.0038
	(0.2057)	(0.2389)	(0.2647)	(0.2229)
$\gamma_{1,1}$	0.4173	1.0605	0.0703	1.1186
	(0.2603)	(0.3968)	(0.2084)	(0.3336)
c_0	0.342	3.5841	10.2186	2.3081
	(0.3157)	(0.7813)	(10.7623)	(0.9876)
c_1	1.3138	0.8548	0.9000	-0.7113
	(1.0838)	(0.757)	(1.0555)	(0.0913)
a_{01}		-1.0696	-3.5715	-7.5634
		(1.7155)	(9.6469)	(1.0356)
a_{02}		0.3000	-4.0524	0.9196
		(1.4877)	(8.4317)	(3.8328)
Log likelihood	703.0520	708.5803	705.7356	709.0381

Notes: This table contains model selection statistics for the estimated model in equations (1) to (5) and (8); under various specifications for the vector of explanatory variables, (z_t). The oil price, oil_t, is measured as a shift in real oil price. The adjusted sample spans from January 1975 to October 2016. FTP, Fixed transition probabilities; TVTP, Time-varying transition probabilities. The numbers in parentheses are standard errors.

Table 4. Model Selection for the Combined Asymmetries

Elements of z_t:	SIC (1)	AIC (2)	Log Likelihood (3)	LR Test (FTP)[d] (4)	LR Test (REC)[e] (5)
TVTP					
REC, SIGN	-2.7228	-2.8514	711.1697	0.0003[a]	0.1186
REC, SIZE	-2.7129	-2.8415	709.7510	0.0012[a]	0.4902
REC, REC × SIGN	-2.7384	-2.8770	712.2886	0.0001[a]	0.0387[b]
REC, REC × SIZE	-2.7120	-2.8406	709.5372	0.0015[a]	0.6071

Notes: SIC, Schwarz information criterion; AIC, Akaike information criterion; LR, Likelihood ratio; FTP, Fixed transition probabilities; TVTP, Time-varying transition probabilities; LR test, p-values for a test of the null of the FTP. This table contains model selection statistics for the estimated model in equations (1) to (5) and (8); under various specifications for the vector of explanatory variables, (z_t). The oil price, oil_t, is measured as a shift in real oil price. The adjusted sample spans from January 1975 to October 2016. [a], [b], and [c] represent significant at 1%, 5% & 10% level. [d] p-value for a test of the null of the FTP model. [e] p-value for a test of the null of the REC model.

Table 5. Model Selection for the TVTP Specifications (Oil Specific Shocks)

Elements of z_t	SIC (1)	AIC (2)	Log Likelihood (3)	LR Test (FTP)[d] (4)
Panel A. Supply shock				
None	-2.2758	-2.3697	593.9425	
SIGN	-2.5130	-2.3622	594.1118	0.8443
SIZE	-2.5130	-2.3622	594.1061	0.8491
REC	-2.2858	-2.3967	602.5875	0.0002[a]
Panel B. Aggregate demand shock				
None	-2.9096	-3.0035	749.8596	
SIGN	-2.8853	-2.9962	750.0759	0.8055
SIZE	-2.8853	-2.9962	750.0761	0.8053
REC	-2.8825	-3.0105	755.5215	0.0035[a]
Panel C. Oil-specific demand shock				
None	-2.6559	-2.7498	687.4519	
SIGN	-2.6376	-2.7485	689.1371	0.1854
SIZE	-2.6314	-2.7423	687.6122	0.8519
REC	-2.6421	-2.7530	691.2374	0.0227[b]

Notes: SIC, Schwarz information criterion; AIC, Akaike information criterion; LR, Likelihood ratio; FTP, Fixed transition probabilities; TVTP, Time-varying transition probabilities; LR test, [d]p-values for a test of the null of the FTP. The estimated model is based on equations (1) to (5) and (8); under different characterizations of the elements in z_t.

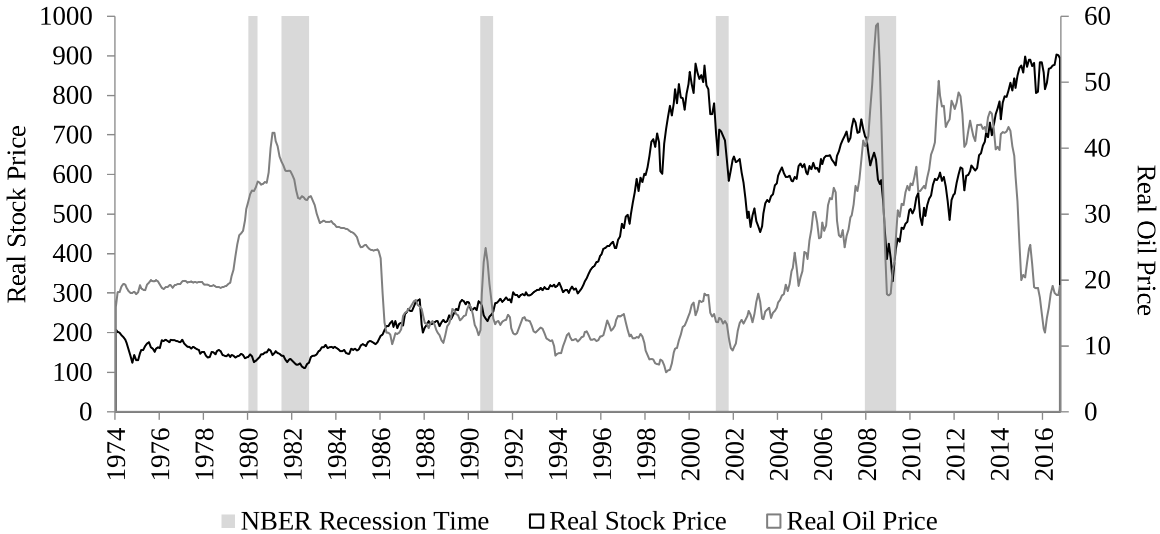
Table 6. Nonlinear Granger Causality Tests, Hiemstra and Jones (1994)

Panel A.	H_o: Changes in stock prices do not cause oil supply shock		H_o: Changes in stock prices do not cause aggregate demand shock		H_o: Changes in stock price do not cause oil-specific demand shock	
Lags	CS (1)	TVAL (2)	CS (3)	TVAL (4)	CS (5)	TVAL (6)
2	1.0000	-0.0144	0.9995	0.2189	1.0000	0.0082
4	1.0000	-0.0047	1.0000	0.1124	1.0000	0.0051
6	1.0000	-0.0013	0.9236	0.4657	1.0000	0.0036
8	1.0000	-0.0006	0.9986	0.0327	1.0000	0.0015

Panel B.	H_o: Oil supply shocks do not cause stock price changes		H_o: Aggregate demand shocks do not cause stock price changes		H_o: Oil-specific demand shocks do not cause stock price changes	
Lags	CS (1)	TVAL (2)	CS (3)	TVAL (4)	CS (5)	TVAL (6)
2	0.0000	14.3247**	0.0000	-5.0687**	0.9801	-0.5235
4	0.0000	5.4976**	0.0244	-1.5227	0.0000	-4.6904**
6	0.0000	5.1259**	0.0358	-1.6645	0.0000	-3.0177**
8	0.0837	-1.2799	0.0588	-1.8251	0.0000	-3.2051**

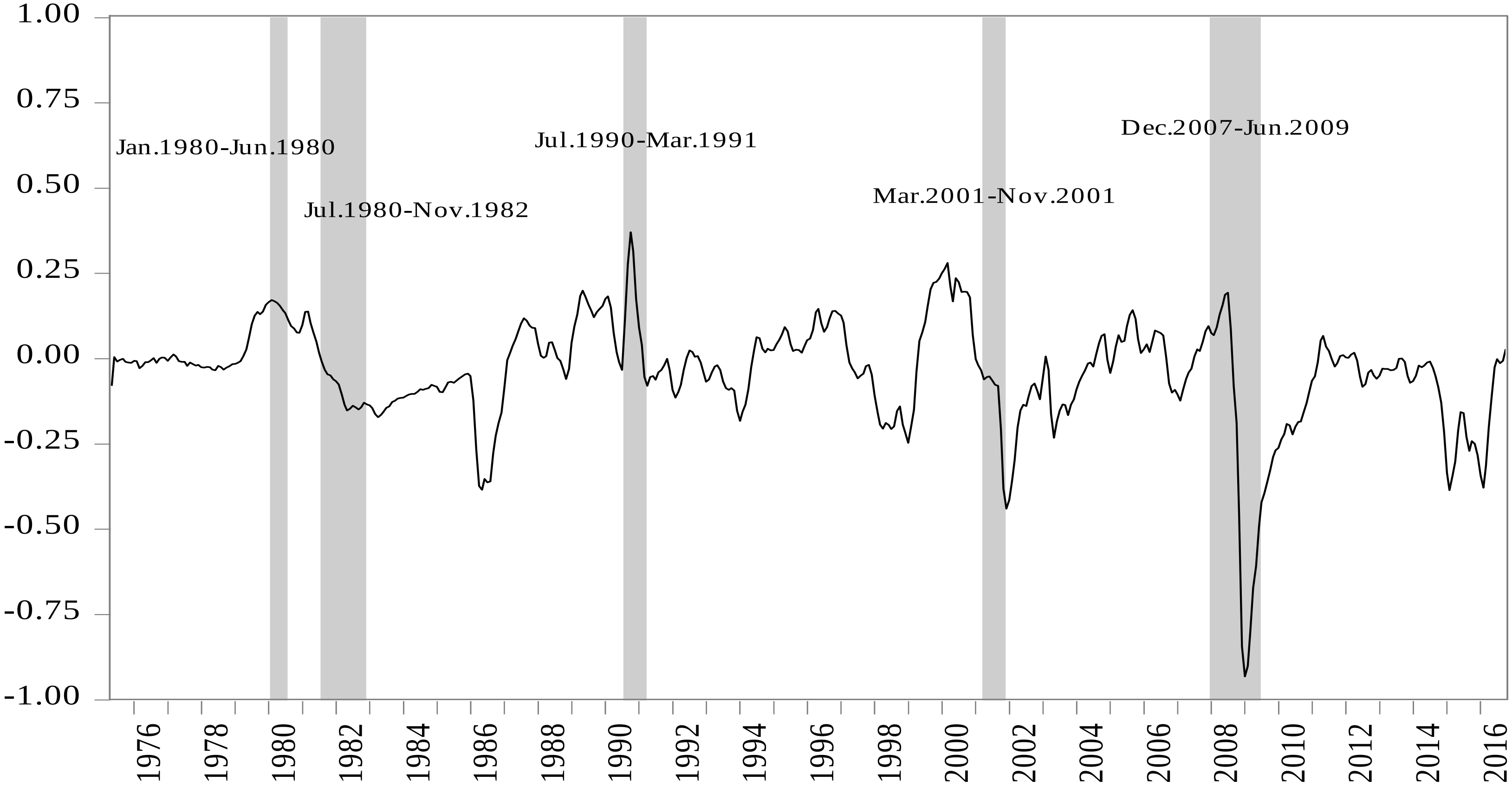
Note: **Significance at 1 percent level and *significance at 5 percent level. Sample spans from January 1975 to October 2016. Lags is the number of lags on the residual series used in the test. CS and TVAL denote the differences between the two conditional probabilities and the standardized test statistic, respectively. Please see Hiemstra and Jones (1994) equations (8) and (10) for details. The test statistics is asymptotically distributed N(0,1), under the null hypothesis of nonlinear Granger non-causality.

Figure 1. Real S&P 500 and Oil Price with NBER recession timeline.



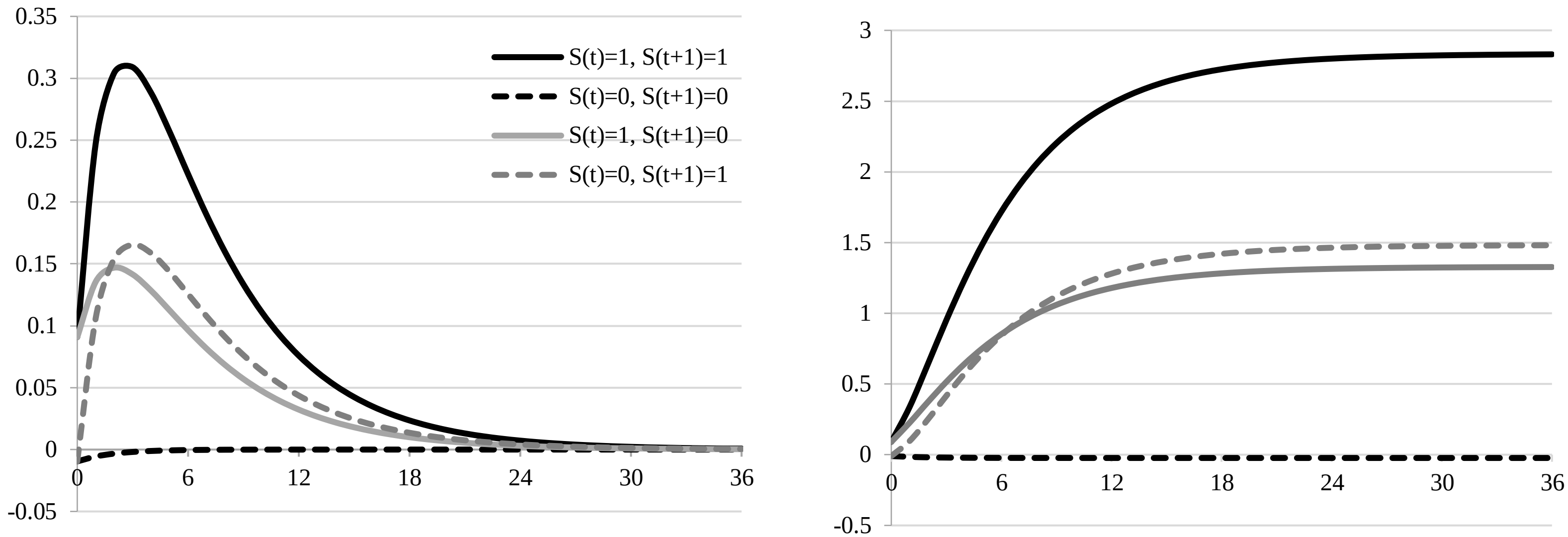
Notes: The shaded regions are NBER recession timeline and given time series are real S&P 500 and real Crude oil index. The sample spans from January 1974 to October 2016.

Figure 2. Estimated transitory component, $stock_t^T$.



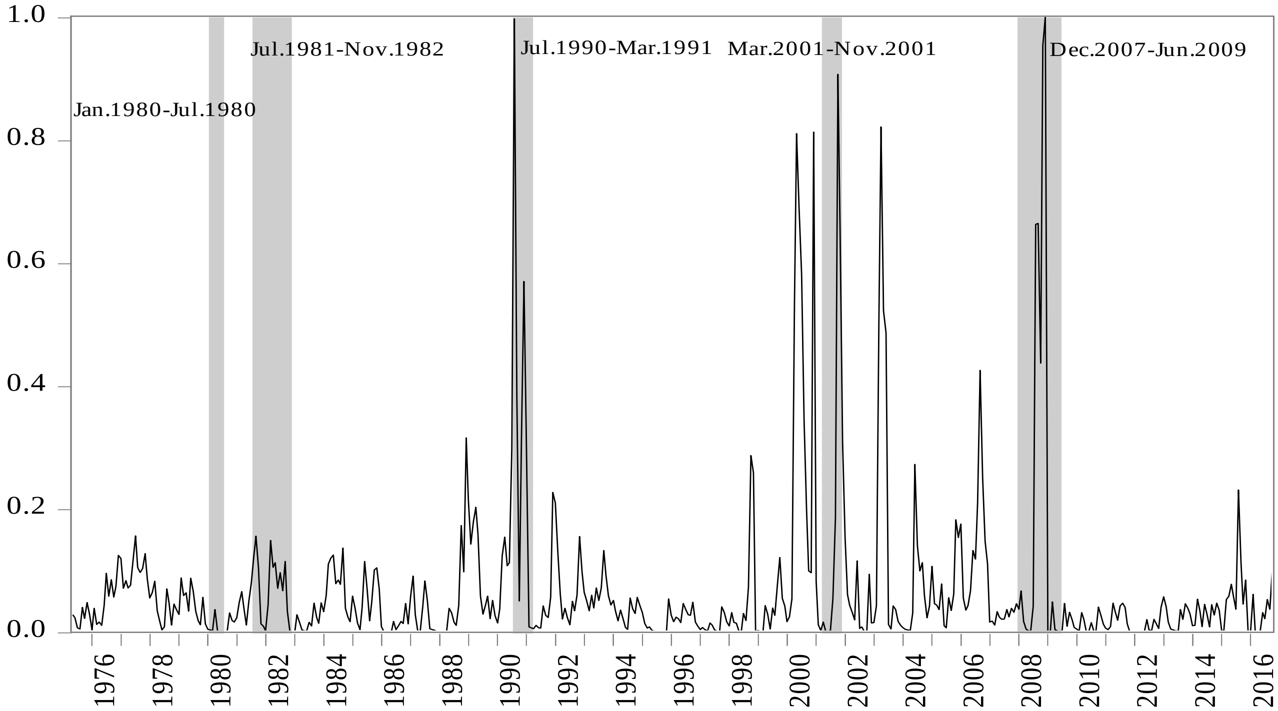
Notes: This figure presents the filtered transitory component $stock_t^T$, from the specification in equations (1) to (5) and (8), when $z_t = (REC_{t-1}, REC_t)'$ and the oil price variable, oil_t, is measured as a shift in real oil price. The shaded areas show the NBER-dated recessions ($\mathrm{REC_t} = 1$). The adjusted sample spans from January 1975 to October 2016.

Figure 3. Impulse response functions of $stock_t^T$ to oil prices.



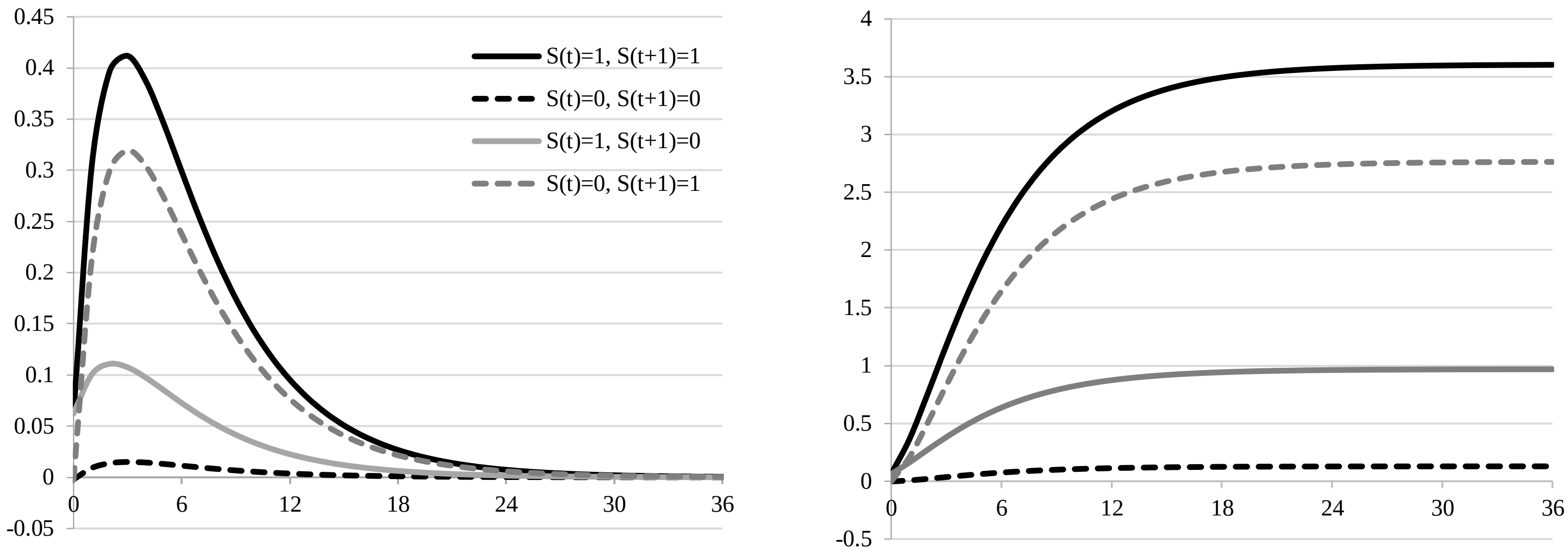
Notes: The left-hand side shows the IRF of the transitory component, $stock_t^T$, to a positive shock to the shift in real oil price at time $t-1$. The right-hand side presents the cumulative IRF of the transitory component, $stock_t^T$, to a positive shock to the shift in real oil price at time $t-1$. Both IRFs are regime dependent and are constructed for the specification $z_t = (\mathrm{REC}_{t-1}, \mathrm{REC}_t)'$. The size of the shock is equal to one standard deviation of historical real oil prices.

Figure 4: Filtered probability, $P(S_t = 1|t)$



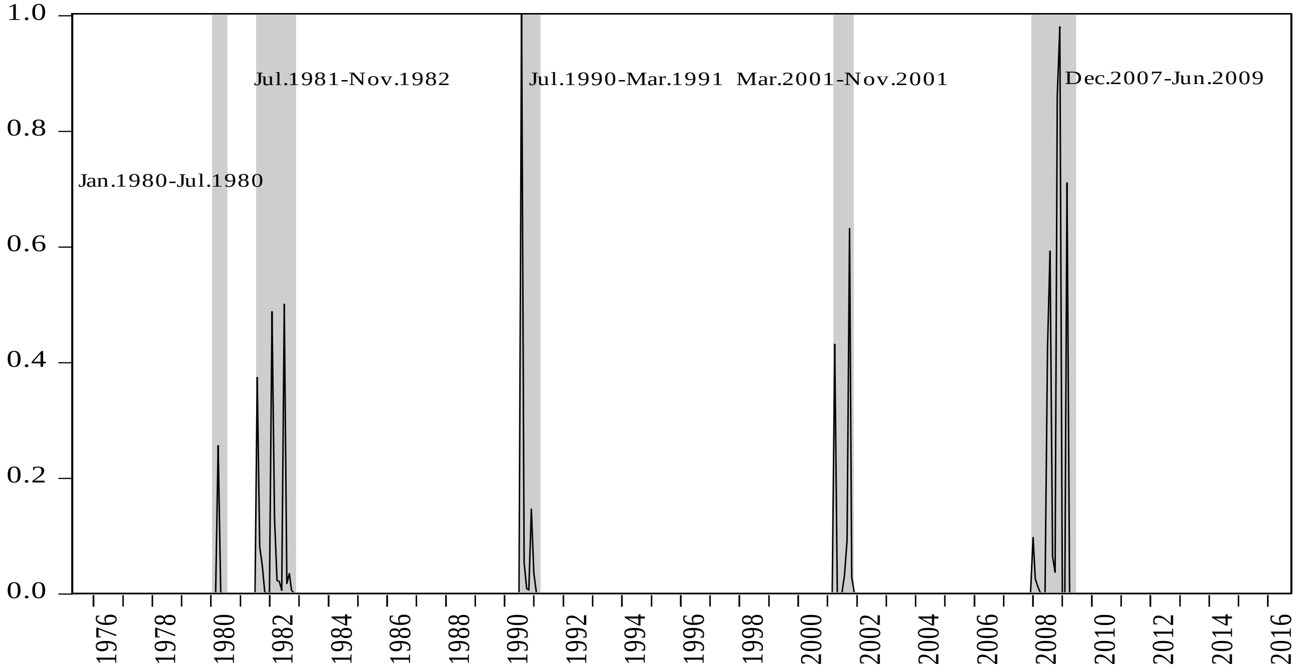
Notes: This figure presents the filtered probability that $S_t = 1$, $P(S_t = 1|t)$, from the specification in equations (1) to (5) and (8), when $z_t = (\mathrm{REC_{t-1}}, \mathrm{REC_t})'$ and the oil specific shock variable, rop_t, is measured as a shift in real oil price. The adjusted sample spans from January 1975 to October 2016 and the shaded areas represent NBER recession periods.

Figure 5. Impulse response function of $stock_t^T$ to oil prices.



Notes: The left-hand side shows the IRF of the transitory component, $stock_t^T$, to a positive shock to the shift in real oil price at time $t-1$. The right-hand side presents the cumulative IRF of the transitory component, $stock_t^T$, to a positive shock to the shift in real oil price at time $t-1$. Both IRFs are regime dependent and are constructed for the specification $z_t = (\mathrm{REC_t}, \mathrm{REC_{t-1}}, \mathrm{SIGN_t} \times \mathrm{REC_t}, \mathrm{SIGN_{t-1}} \times \mathrm{REC_{t-1}})'$. The size of the shock is equal to one standard deviation of historical real oil prices.

Figure 6: Filtered probability, $P(S_t = 1|t)$.



Notes: This figure presents the filtered probabilities that $S_t = 1, P(S_t = 1|t)$, from the specification in equations (1) to (5) and (8), when $z_t = (\mathrm{REC_t}, \mathrm{REC_{t-1}}, \mathrm{SIGN_t} \times \mathrm{REC_t}, \mathrm{SIGN_{t-1}} \times \mathrm{REC_{t-1}})'$ and the oil specific shock variable, oil_t, is measured as a shift in real oil price. The adjusted sample spans from January 1975 to October 2016 and the shaded areas represent NBER recession periods.

Appendix

Shocks to in the crude oil market are likely to differ by industry. For example, energy consumption sectors (e.g., automobile, retail) are likely to be negatively impacted by oil-market specific demand shocks, while energy supply sectors are likely to be positively impacted. In this appendix we assess potential differences.

We first retrieve industry specific portfolios from Kenneth French website along with SIC codes. These portfolios are constructed using NYSE, AMEX, and NASDAQ stocks at the end of June of the corresponding year and based on four-digit SIC codes. From Table A1 we see that manufacturing, energy, chemicals, business equipment, and utilities are positively correlated with oil price.

We then estimate various structural VAR models to assess for a potential different effect from the oil related shocks. Overall, we find that the responses for the positively correlated portfolios are similar to the responses of the S&P 500. For the portfolios that are negatively correlated, to a large extent, we observe that the responses to the different types of shocks are mostly negative.

Table A1: Industry details and SIC codes

Industry	SIC Codes	Correlation with Oil Price	Crude oil related shocks		
			Supply	Aggregate demand	Oil-specific demand
		(1)	(2)	(3)	(4)
Consumer Nondurables (nodur) -- Food, Tobacco, Textiles, Apparel, Leather, Toys	0100-0999; 2000-2399; 2700-2749; 2770-2799; 3100-3199; 3940-3989	N	N	N	N
Consumer Durables (durbl) -- Cars, TVs, Furniture, Household Appliances	2500-2519; 2590-2599; 3630-3659; 3710-3711; 3714-3714; 3716-3716; 3750-3751; 3792-3792; 3900-3939; 3990-3999	N	N	N	N
Manufacturing (manuf) -- Machinery, Trucks, Planes, Off Furn, Paper, Com Printing	2520-2589; 2600-2699; 2750-2769; 3000-3099; 3200-3569; 3580-3629; 3700-3709; 3712-3713; 3715-3715; 3717-3749; 3752-3791; 3793-3799; 3830-3839; 3860-3899	P	N	P	P
Oil, Gas, and Coal Extraction and Products (enrgy)	1200-1399; 2900-2999	P	N	P	P

Chemicals and Allied Products (chems)	2800-2829; 2840-2899	P	N	P	P
Business Equipment (buseq) -- Computers, Software, and Electronic Equipment	3570-3579; 3660-3692; 3694-3699; 3810-3829; 7370-7379	P	N	P	P
Telephone and Television Transmission (telcm)	4800-4899	N	N	N	P
Utilities (utils)	4900-4949	P	P	P	P
Wholesale, Retail, and Some Services - Laundries, Repair Shops (shops)	5000-5999; 7200-7299; 7600-7699	N	N	N	N
Healthcare, Medical Equipment, and Drugs (hlth)	2830-2839; 3693-3693; 3840-3859; 8000-8099	N	N	P	N
Money Finance (money)	6000-6999	N	N	P	N
Other (other) -- Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment		N	N	P	P

Notes: Monthly industry specific portfolio data from January 1975 to October 2016 were retrieved from Kenneth R. French website. Portfolios are constructed using NYSE, AMEX, and NASDAQ stocks at the end of June based on its four-digit SIC code at that time. N (P) denotes negative (positive) correlations, in column 1, or impulse responses, in columns 2 to 4.