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Oil price shocks and stock market activity

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Abstract

Results from a vector autoregression show that oil prices and oil price volatility both play important roles in affecting real stock returns. There is evidence that oil price dynamics have changed. After 1986, oil price movements explain a larger fraction of the forecast error variance in real stock returns than do interest rates. There is also evidence that oil price volatility shocks have asymmetric effects on the economy.

JEL classifications: Q43; E44

Keywords: Oil prices; Stock returns; Volatility

1. Introduction

The effect that oil price shocks have on OECD countries cannot be downplayed. As stated in Adelman (1993, p. 537)

> "Oil is so significant in the international economy that forecasts of economic growth are routinely qualified with the caveat: 'provided there is no oil shock.'"

In a seminal paper, Hamilton (1983) showed that oil price increases were at least partly responsible for every post-World War II US recession except the one in 1960. Since then, Hamilton's basic findings have been tested using alternative data and estimation procedures (see for instance, Burbidge and Harrison, 1984; Gisser and Goodwin, 1986; Loungani, 1986). More recently, the focus has been on the role

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that asymmetric oil price shocks have on the economy (Mork, 1989; Mork et al., 1994; Lee et al., 1995; Ferderer, 1996).

In sharp contrast to the volume of work investigating the link between oil price shocks and macroeconomic variables, there has been relatively little work done on the relationship between oil price shocks and financial markets. Two notable exceptions are Jones and Kaul (1996) and Huang et al. (1996).

Jones and Kaul (1996) use quarterly data to test whether the reaction of international stock markets to oil shocks can be justified by current and future changes in real cash flows and/or changes in expected returns. Using a standard cash-flow dividend valuation model (Campbell, 1991)) they find that the reaction of Canadian and US stock prices to oil price shocks can be completely accounted for by the impact of these shocks on real cash flows. The results for Japan and the UK are, however, not as strong.

Huang et al. (1996), used a vector autoregression (VAR) approach to investigate the relationship between daily oil futures returns and daily US stock returns. They found that oil futures returns do lead some individual oil company stock returns but oil future returns do not have much impact on broad-based market indices like the S & P 500.

Using quarterly data from 1947 to 1991, Jones and Kaul (1996) found that oil prices do have an effect on aggregate stock returns. In contrast, Huang et al. (1996) used daily data from 1979 to 1990 and found no evidence of a relationship between oil futures prices and aggregate stock returns.

In this paper, the interaction between oil prices and economic activity was investigated further. Of particular interest was the impact that oil price shocks may have on stock market returns. Monthly data were used and the approach used to estimating oil price shocks was different from either Jones and Kaul (1996) or Huang et al. (1996).

This paper is organised as follows. Section 2 discusses the time series properties of the data; Section 3 presents a generalised autoregressive conditional heteroskedastic (GARCH) model of oil price volatility; Section 4 presents empirical results from a vector-autoregression (VAR) while Section 5 reports the dynamic effects of shocks. The VAR approach is useful for examining the dynamic interaction between oil prices and other economic variables. Results are presented for oil price shocks, asymmetric oil price shocks, oil price volatility shocks and asymmetric oil price volatility shocks. Like Mork (1989), Mork et al. (1994), Lee et al. (1995) and Ferderer (1996) it was found that oil price shocks have asymmetric effects on the economy. In addition, it was found that the dynamics of oil price shocks have changed across time. It was also found that oil price shocks had a significant impact on real stock returns although this impact was strongest after 1986; Section 6 concludes.

2. Data

The natural logarithms of US industrial production (IP) (a measure of output), interest rates, and real oil prices are denoted as lip, lr and lo. Interest rates were measured using the 3-month T-bill rate. Oil prices were measured using the producer price index for fuels. Real stock returns, denoted as rsr, are the difference between the continuously compounded return on the S & P 500 and the inflation rate which is calculated using the consumer price index. The data definitions are the same as those used by Jones and Kaul (1996). The data are monthly and cover the period 1947:1–1996:4. All data come from the DRI/McGraw-Hill data base. All data definitions are discussed in Appendix A.

Table 1 reports the results from Phillips and Perron (1988) unit root tests. Because industrial production and oil prices both exhibit positive upward trends the alternative hypothesis for these two time series is stationarity about a linear time trend. For the interest rate and real stock return series the alternative hypothesis is stationarity in levels. All test regressions include intercepts.

The test results from Table 1 indicate that, for the variables in levels, only real stock returns are stationary at the 5% level of significance. Table 1 also shows that the first difference of each variable is stationary. The results from Table 1 suggest that each series is best described as being stationary in first differences with the exception of real stock returns which are stationary in levels.

The estimation period for this study covers the somewhat turbulent time of the 1970s. Consequently, it is important to check the data for structural breaks. This was done by using the testing procedure of Zivot and Andrews (1992). In this testing procedure, the null hypothesis is a unit root process without any structural breaks and the relevant alternative hypothesis is a trend stationary process with possible structural change occurring at an unknown point in time. Zivot and Andrews (1992) suggest estimating the following augmented Dickey and Fuller (1979) regression:

Table 1
Unit root tests [Phillips and Perron, 1988 test regression ($y_t = \mu + \alpha y_{t-1} + u_t$, t = 1950:1–1996:4)][a]

Variable	$Z(t\hat{\alpha})$
In levels	
lip	−3.17*
lo	−1.39
lr	−2.65*
rsr	−18.35***
In first differences	
Δlip	−15.69***
Δlo	−13.32***
Δlr	−15.87***
Δrsr	−51.81***

[a]*Notes.* ***, ** and * denote that a test statistic is significant at the 1, 5, and 10% level of significance, respectively. Critical values for the test statistics are from Hamilton (1994). The truncation lag parameter for the Bartlet Kernel correction for serial correlation is set at 5.

$$x_t = \mu + \theta DU_t(\lambda) + \beta t + \gamma DT_t(\lambda) + \alpha x_{t-1} + \sum_{l=1}^{k} c_l \Delta x_{t-l} + \varepsilon_t \tag{1}$$

where

$\lambda = T^B/T$ is the break fraction;
$DU_t(\lambda) = 1$ if $t > T\lambda$;
$DU_t(\lambda) = 0$ otherwise;
$DT_t(\lambda) = t - T\lambda$ if $t > T\lambda$;
$DT_t(\lambda) = 0$ otherwise; and
X_t is the time series being tested.

The tth regression allows both the slope and intercept to change at date T^B. Hence it can accommodate both a discontinuous jump in the trend line and a continuous trend with a kink at date $t = T^B$. Eq. (1) estimated with γ equal to zero allows for a break in the intercept, while Eq. (1) estimated with θ equal to zero allows for a break in the slope.

The estimation strategy is to estimate Eq. (1) allowing both the break points T^B and the lag length k to vary endogenously. Eq. (1) was estimated by ordinary least squares with the break points ranging from 1955:1 to 1993:12. Allowing for differences and lags, estimation of Eq. (1) was over the period 1950:1–1996:4. For each value of λ, the number of extra regressors, k, was determined endogenously and the t statistic for testing $\hat{\alpha} = 1$ computed. The minimum t statistic reported is the minimum overall break point regressions from 1955:1 to 1993:12. The lag length, k, was determined by the same selection procedure as used in Perron (1989) and Zivot and Andrews (1992). Working backwards from $k = 13$, the first value of k is chosen such that the t statistic on $\hat{c}_k$ was greater than 1.6 in absolute value and the t statistic on $\hat{c}_1$ for $1 > k$ was less than 1.6 in absolute value.

Table 2 reports the minimum t statistics from testing trend stationarity around a broken trend for each of lip, lo and 1r. The results from Table 2 indicate that at the 1% level of significance, none of the time series are trend-stationary around a broken trend. The industrial production series does, however, suggest some evidence of trend stationarity at the 5% level of significance. This may not be too much of a problem because, as Zivot and Andrews (1992) suggest, the asymptotic critical values are in general too small in absolute value. Consequently, we can proceed under the assumption that each of these series can best be described as difference stationary.

The results from Tables 1 and 2 indicate that lip, lr and lo each have stochastic trends. To investigate whether these variables have common stochastic trends we follow the approach suggested by Johansen (1991). The λ_{max} and trace tests reported in Table 3 indicate no evidence of cointegration between lip, lr and lo.[1]

[1] The robustness of the cointegration tests was checked by re-estimating the VAR with 6 and 24 lags. In neither case could cointegration be found.

Table 2
Minimum t statistics[a]

	Rank					
	t-statistic	Year	t-statistic	Year	t-statistic	Year
lip	−5.26**	1964:10	−5.10**	1963:12	−5.08**	1964:3
lo	−4.15	1973:8	−4.08	1973:10	−3.99	1973:9
lr	−4.46	1984:9	−4.49	1984:8	−4.42	1985:3

[a]All t statistics estimated from a break in intercept model. Critical values from Table 2 of Zivot and Andrews (1992); 1, 5 and 10% critical values are −5.34, −4.80 and −4.58, respectively.

Consequently the four variable system (Δlip, Δlr, Δlo, rsr), where Δ is the first difference operator, may be modelled as a vector autoregression.

3. Variability in oil prices

Figure 1 shows a time series plot of real oil prices. Real oil prices were fairly constant up to the early 1970s after which time they exhibit an upward trend. The 1986 oil price shock marks the first time there was a major oil price decrease. Due to the Persian Gulf crises, the early 1990s were a time characterized by both large oil price increases and large oil price decreases.

Recent work by Lee et al. (1995) and Ferderer (1996) suggests that oil price volatility may play an important role in affecting economic activity. Since the sample autocorrelation function for real oil prices (not shown) dies out rather slowly, it might be worthwhile to fit a low order generalised autoregressive conditional heteroskedastic (GARCH) model (see Bollerslev, 1986) to the growth rate of oil prices. A GARCH model can then be used to construct the conditional variation in oil price changes which in turn can be used to compute normalised

Table 3
Tests for cointegration using the Johansen procedure

$$\Delta x_t = \mu + \sum_{\tau=1}^{p-1} \overline{\Pi}_\tau \Delta x_{t-\tau} + \overline{\Pi} x_{t-p} + \varepsilon_t, \quad -\overline{\Pi} = \alpha\beta'$$

$$x_t' = \{\text{lip, lo, lr}\}$$

1950:1–1996:4: $p = 12$ is chosen using likelihood ratio tests.
Eigenvalues 0.01913 0.0065 0.0054
The test statistics for r equal to the number of cointegrating vectors

Hypothesis	$r = 0$	$r \leq 1$	$r \leq 2$
Trace test	17.391	6.653	3.040
λ max test	10.718	3.614	3.040

***, **, * denotes rejection of the null hypothesis at the 1, 5 and 10% level of significance, respectively. Critical values from Hamilton (1994).

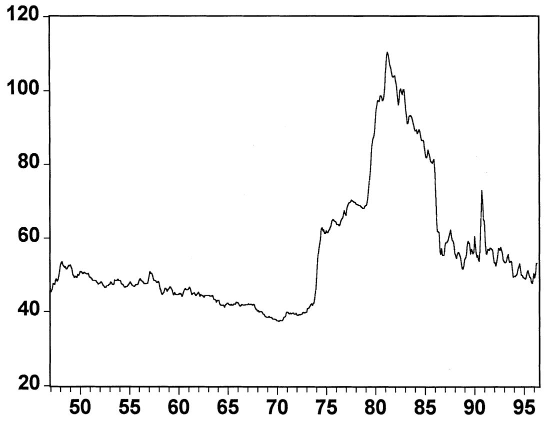


Fig. 1. Real oil prices.

unexpected movements in oil prices. These normalised unexpected movements in oil prices should be well suited to modelling the relationship between oil price shocks and stock returns.[2]

Consider the following GARCH(1,1) model.[3,4]

$$\Delta lo_t = \beta_0 + \sum_{i=1,3,6,7} \beta_i \Delta lo_{t-i} + \varepsilon_t, \varepsilon_t | I_{t-1} \sim N(0.h_t), \quad t = 1,...,T \tag{2}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} \tag{3}$$

Denote I_{t-1} as the information set available at time $t-1$ and E as expectation operator. If the residuals from Eq. (2) are denoted as $\hat{\varepsilon}_t$, ($\hat{\varepsilon}_t = \Delta \text{lo}_t - E(\Delta \text{lo}_t \mid I_{t-1})$, then a measure of an unexpected oil price shock which reflects both the magnitude and volatility of the forecast error $\hat{\varepsilon}_t$ can be defined as:

$$\hat{v}_t = \hat{\varepsilon}_t / \hat{h}_t^{1/2} \tag{4}$$

The variable $\hat{v}_t$ can then be included in the model. Table 4 reports estimates from the GARCH(1,1) model. All of the reported parameter estimates are statisti-

[2] Lee et al. (1995), use a similar technique in their investigation into the relationship between oil price shocks and the macroeconomy.

[3] Bollerslev et al. (1992, p. 10, 20) strongly suggest the use of low-order GARCH models, and in particular they recommend GARCH(1,1).

[4] Given the large body of research suggesting that oil price changes are exogenous to the US economy, the regressors were confined to just include lag values of the dependent variable. Preliminary research based on parameter fit, and absence of serial correlation suggested that the model in Eq. (2) is adequate.

Table 4
GARCH(1,1) model estimates

Parameter	Estimate	Standard error
β_0	−0.0003	0.0004
β_1	0.4011	0.0434
β_3	0.0760	0.0374
β_6	−0.1613	0.0420
β_7	0.1064	0.0422
α_0	6.69E-6	1.69 E-6
α_1	0.2039	0.0342
α_2	0.7785	0.0314

$\overline{R}^2 = 0.2464$ S.E.E. = 0.0159 D.W. = 1.746
Ljung- Box Q-statistics (residuals) for serial correlation.
$Q(6)$: P-value = 0.66
$Q(12)$: P-value = 0.12
$Q(24)$: P-value = 0.13
Ljung–Box Q-statistics (squared residuals) for serial correlation.
$Q(6)$: P-value = 0.93
$Q(12)$: P-value = 0.75
$Q(24)$: P-value = 0.95

cally significant at the 5% level and, based on the Ljung–Box Q statistics, there is no evidence of serial correlation in the standardised residuals or the squared standardised residuals. Consequently, the GARCH(1,1) model, reported in Table 4, appears adequate. The correlation coefficient between Δlo and $\hat{v}$ is 0.77. As a result, the models that are estimated will include either Δlo or $\hat{v}$ but not both.

4. Empirical model

In order to investigate the interaction between oil prices, stock returns and economic activity, an unrestricted vector autoregression model was estimated. The system is identified by using Choleski factorisation and placing the 3-month T-bill rate variable first in the ordering followed by either oil prices or the GARCH measure of oil price volatility, industrial production and stock returns. This ordering assumes that monetary policy shocks are independent of contemporaneous disturbances to the other variables. As in Ferderer (1996), this ordering also assumes that changes in interest rates influence oil prices. Finally, real stock returns are placed last in the ordering. As will be discussed later on, the empirical results are not very sensitive to these ordering assumptions.

The reduced form VAR may be written as

$$\mathbf{X}_t = \sum_{i=1}^{p} \mathbf{A}_i \mathbf{X}_{t-i} + \varepsilon_t, \tag{5}$$

where $\mathbf{X}_t = (\Delta \mathrm{lr}_t, \Delta \mathrm{lo}_t, \Delta \mathrm{lip}_t, \mathrm{rsr}_t)$ Here Δ is the first difference operator. and ε is the vector of innovations to the disturbances $(\varepsilon^r, \varepsilon^o, \varepsilon^p, \varepsilon^k)$ with $E(\varepsilon_t \varepsilon_t') = \Sigma$. The disturbances ε^r, ε^o, ε^p, and ε^k are interpreted as shocks to interest rates, oil prices, industrial production and real stock returns, respectively. In Eq. (5), the ε's are the impulses while the **A**'s characterise the propagation mechanism. On the basis of likelihood ratio tests, and absence of serial correlation, the order, p, is chosen to be 12.

Table 5 presents the estimated variance–covariance matrix from the unrestricted VAR. The results in Table 5 clearly show the negative correlation between changes in oil prices and stock returns. Table 5 also reports negative correlations between stock returns and interest rates.

5. Dynamic effects of the shocks

This section characterises the dynamic effects of the shocks on the endogenous variables. Both variance decompositions and impulse response functions are presented and discussed.

Estimated coefficients from structural VAR models often appear to be lacking in statistical significance, According to Sims (1986) this may be due to the inaccuracy of the technique in estimating standard errors. Consequently, it is often suggested that a better test of a model's specification is the pattern of impulse response functions. Impulse response functions are dynamic simulations showing the response of an endogenous variable over time to a given shock.

Variance decompositions give the contributions of each source of shock to the variance of the n-period ahead forecast error for each endogenous variable. Results are presented for both oil price shocks and oil price volatility shocks.

5.1. Oil price shocks

From Table 6, the variance decompositions for the T-bill rate show that after 24 periods, shocks to interest rates, industrial production, real stock returns, and oil prices account for approximately 87, 6, 5, and 2%, of the variation in the T-bill rate. Monte Carlo constructed standard errors (from 1000 replications) are shown in parentheses.

Table 5
Estimated variance–covariance/correlation matrices from the unrestricted VAR(1950:1–1996:4)

	Δlr	Δlo	Δlip	rsr
Δlr	0.44e-2	0.48e-1	0.13	−0.64e-1
Δlo	0.49e-4	0.23e-3	0.28e-1	−0.16
Δlip	0.75e-4	0.37e-5	0.74e-4	0.98e-2
rsr	−0.13e-3	−0.72e-4	0.25e-5	0.89e-3

Table 6
Variance decomposition of forecast error variance after 24 months

Step	Shocks to			
	ε^r	ε^o	ε^p	ε^k
Ordering (Δlr, Δlo, Δlip, rsr), 1950:1–1996:4				
Δlr	87.79	1.65	6.00	4.57
	(3.17)[a]	(1.54)	(2.17)	(2.02)
Δlo	2.69	95.25	1.13	0.93
	(2.13)	(2.83)	(1.31)	(1.32)
Δlip	10.33	4.29	78.76	6.61
	(2.88)	(2.21)	(3.89)	(2.70)
rsr	5.69	4.96	3.34	86.01
	(2.12)	(2.01)	(1.53)	(3.11)
Ordering (Δlr, Δlo, Δlip, rsr), 1950:1–1985:12				
Δlr	86.23	3.04	4.71	5.93
	(3.54)	(2.02)	(2.05)	(2.28)
Δlo	6.38	89.33	1.50	2.78
	(3.64)	(4.30)	(1.74)	(2.00)
Δlip	10.41	8.88	73.84	6.87
	(3.08)	(3.29)	(4.50)	(2.67)
rsr	7.23	6.43	4.29	82.05
	(2.58)	(2.49)	(1.98)	(3.89)
Ordering (Δlr, Δlo, Δlip, rsr), 1986:1–1996:4				
Δlr	72.26	9.27	12.76	5.29
	(7.90)	(5.94)	(5.71)	(3.94)
Δlo	3.50	79.84	12.60	4.09
	(4.68)	(7.24)	(5.32)	(3.74)
Δlip	13.53	17.93	61.30	7.25
	(5.39)	(5.91)	(6.84)	(4.13)
rsr	9.89	16.16	11.35	62.60
	(5.13)	(6.16)	(4.58)	(7.18)

[a] Monte Carlo constructed standard errors are shown in parentheses.

For the oil price variable, almost all of the variance decomposition comes from movements in itself. This suggests that oil price movements can influence US economic variables but changes in US economic variables have little impact on oil prices.

For the industrial production variable, own shocks account for most of the forecast error variance. After 24 months, industrial production, T-bill rate, real stock returns, and oil prices, account for approximately 79, 10, 7, and 4% of the industrial production forecast error variance, respectively.

The variance decompositions for real stock returns show that stock return fluctuations account for over half of the forecast error variance. This result is similar to Lee (1992) who finds that real stock returns are primarily explained by innovations to real stock returns. I also find that oil price fluctuations and interest rates account for approximately 5 and 6% of the stock return forecast error variance.

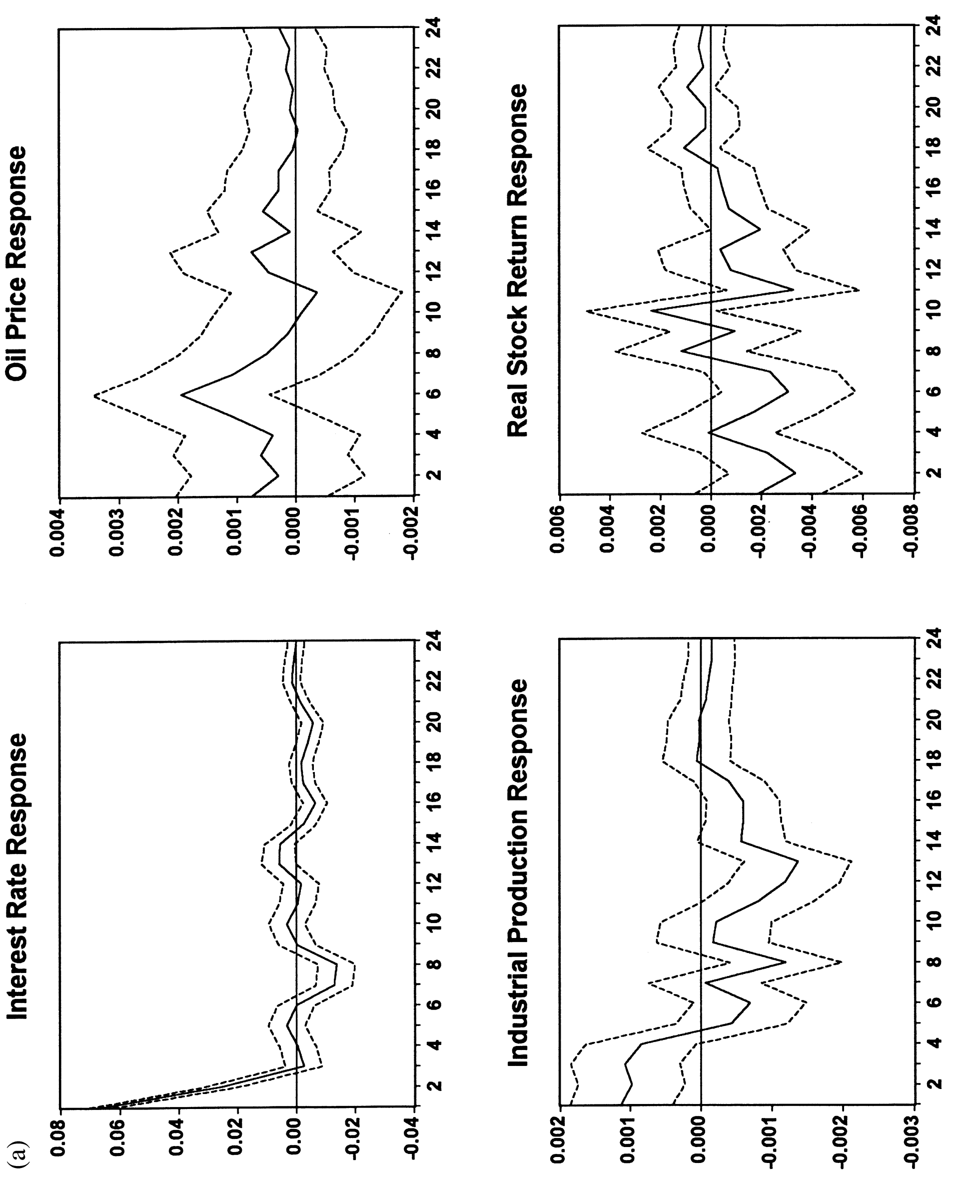
Figure 2a–d show the impulse responses resulting from a 1 S.D. shock to interest rates, oil prices, industrial production, and stock return disturbances. Monte Carlo constructed 95% confidence bounds are provided to judge the statistical significance of the impulse response functions. Also, the impulse response functions for interest rates, oil prices, industrial production, and real stock returns are reported in rates. Multiplying these values by 100 gives percentage values.

Figure 2a shows that an interest rate shock has a large and statistically significant negative impact on stock returns. This illustrates the importance that interest rate shocks have on the stock market. Changes in interest rates affect stock returns for three reasons. First, changes in interest rates are changes in the price charged for credit which is a major influence on the level of corporate profits. This affects the price investors are willing to pay for equities. Second, movements in interest rates alter the relationship between competing financial assets. Third, some stocks are purchased on margin. Changes in the cost of carrying margin debt influence the desire and/or ability of investors to speculate. Consequently, increases in interest rates dampen stock returns. Figure 2a also shows that interest rate shocks have a negative impact on industrial production although this occurs, as in Ferderer (1996), only after an initial positive impact. The industrial production impulse turns down after 4 months while the oil price response turns down after 6 months. These results are fairly consistent with the pattern observed by Ferderer (1996) and Christiano et al. (1996).

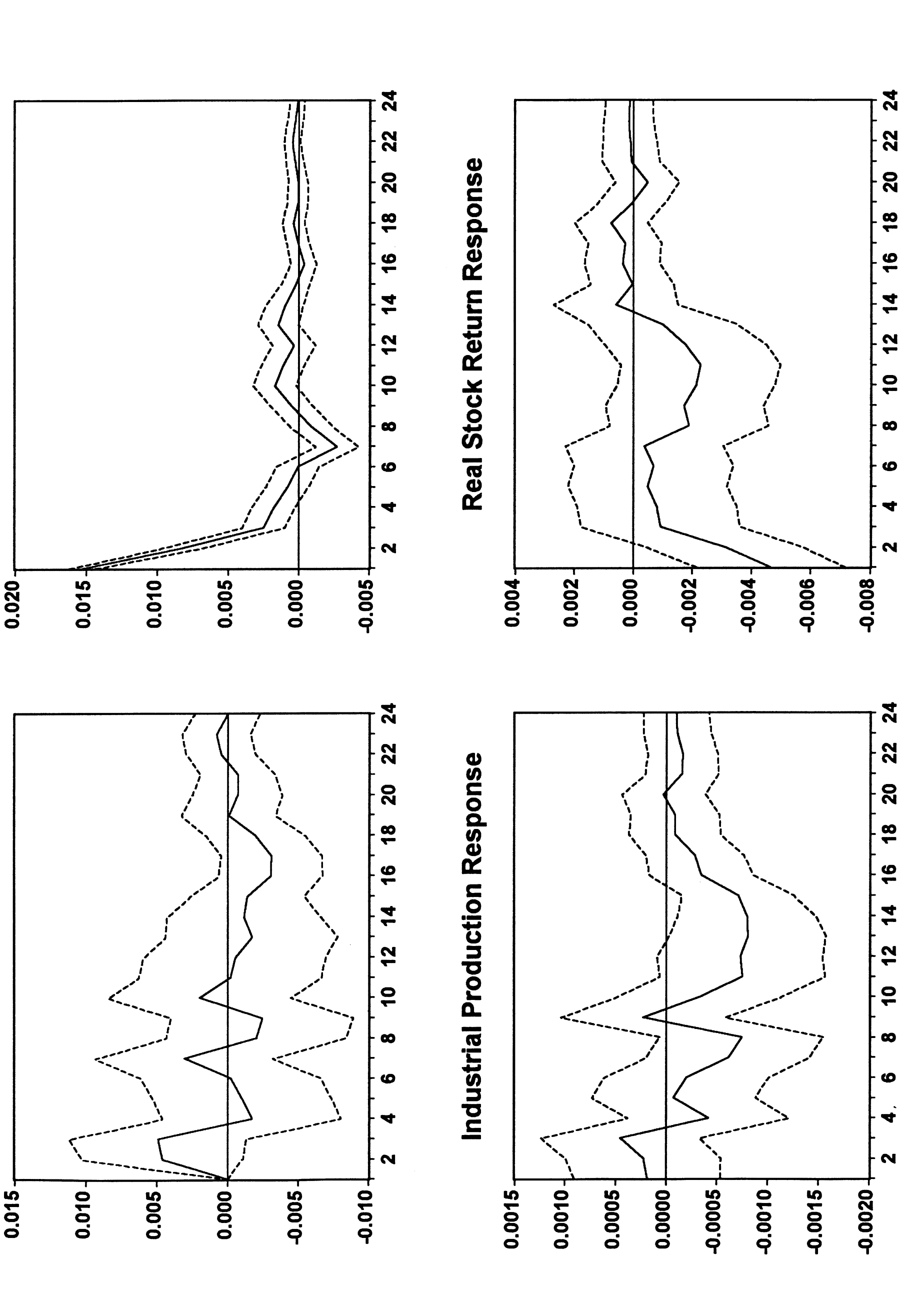
Figure 2b shows that, initially, an oil price shock has a negative and statistically significant initial impact on stock returns. If oil price changes affect economic activity, as measured by either industrial production or GDP, then it will affect the earnings of companies for which oil is a cost of production. Consequently, an increase in oil prices will cause earnings to decline. If the stock market is efficient this increase in oil prices will cause an immediate decline in stock prices. If the stock market is not efficient then an increase in oil prices will bring about a lagged decline in the stock market. Figure 2b shows that while the real stock returns impulse does respond immediately to an oil price shock, the effect lasts for 3 months.

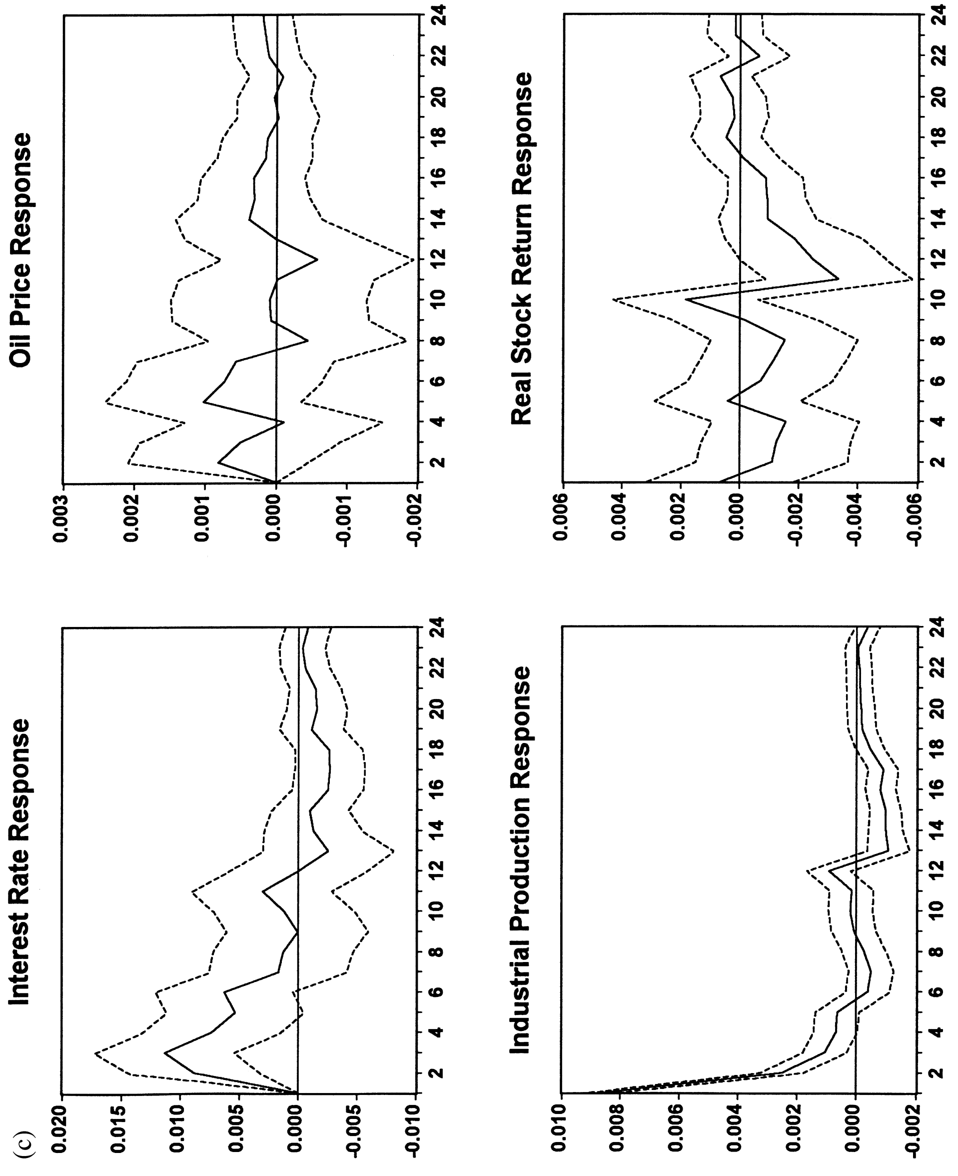
Initially, an oil price shock has a positive impact on interest rates. This result is consistent with the idea that increases in oil prices are often indicative of inflationary pressure in the economy which in turn could indicate the future of interest rates and investments of all types.

Figure 2c shows the dynamic responses to a one-standard deviation industrial


(a)
Interest Rate Response
Oil Price Response
Industrial Production Response
Real Stock Return Response

(b)


Interest Rate Response
Oil Price Response
Industrial Production Response
Real Stock Return Response


(c)
Interest Rate Response
Oil Price Response
Industrial Production Response
Real Stock Return Response

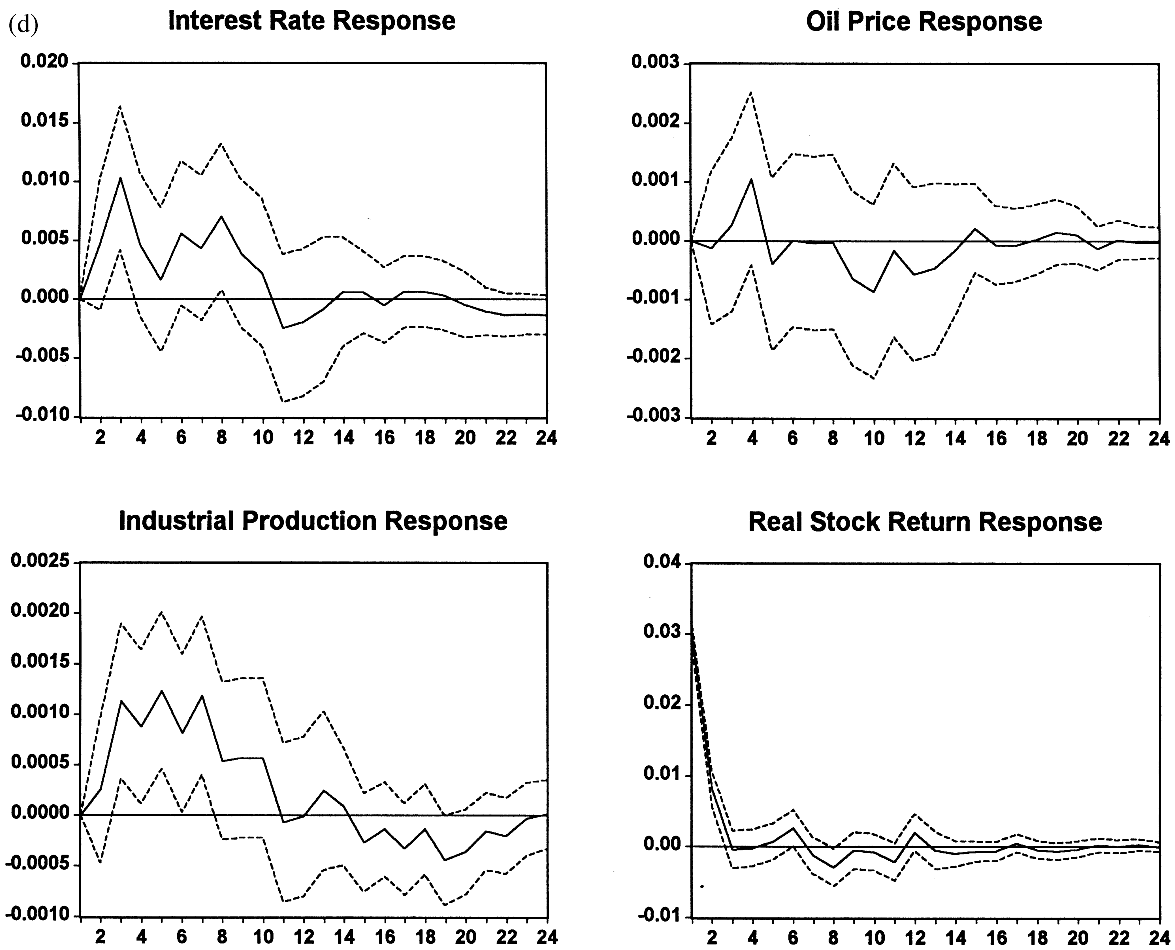


Fig. 2. (a) Response to a one-standard deviation interest rate shock; (b) response to a one-standard deviation oil price shock; (c) response to a one-standard deviation industrial production shock; (d) response to a one-standard deviation real stock return shock.

production shock. Theoretically, a positive production shock could generate a stronger economy. A stronger economy implies higher profits and higher dividends which should raise stock prices. Higher economic activity, however, raises interest rates which depending on the reaction of the Federal Reserve, could either dampen or accommodate higher stock returns (see Blanchard, 1997, chapter 9).

Figure 2c shows that, as expected, a positive industrial production shock increases industrial production. Interest rates respond positively to this shock which is consistent with the predictions from a stronger economy. Figure 2c also shows that a positive industrial production shock has little impact on real stock returns or oil prices.

Figure 2d shows that a real stock return shock has a positive impact on interest rates. Like Lee (1992), I find that a real stock return shock has little impact on prices. I also find that industrial production responds positively to stock return shocks. This is consistent with the empirical results in Lee (1992) and the suggestions made by Fama (1981) and Geske and Roll (1983) that the stock market is a leading indicator of real economic activity.

The estimated results shown in Figure 2a–d also suggest that individual shocks to oil prices depress real stock returns while shocks to stock market returns have a positive effect on industrial production. This is consistent with the notion that positive oil price shocks dampen stock markets, presumably over fears of inflation, while positive stock return shocks increase economic activity by increasing industrial production.[5]

Table 6 also reports the VAR decompositions from splitting the sample at 1986. Following Huang et al. (1996), the split occurs at January 1 1986 so that the period of large oil price declines is separated from the earlier period. Here, there are several things worth noting. In the second sub-period the own effect of a variable on its variance decomposition is considerably less than in the first sub-period. For instance, in the first (second) sub-period the own effect of a variable on its variance decompositions is approximately 86% (73%). 89% (80%), 74% (61%) and 82% (62%) for the variables, interest rates, oil prices, industrial production -and real stock returns, respectively. Also over the second sub-period, oil price shocks have a larger impact on stock returns than do interest rates. This suggests that either the dynamics of oil price shocks or the structure of the economy changed after 1986.

To further investigate this possibility, I estimate variances of the residuals from the VAR. The estimated error variances from the interest rate, oil price, industrial production and real stock return equations over the pre-1986 (post-1986) sub-periods are 0.51E-2 (0.86E-3), 0.87E-4 (0.51E-3), 0.85E-4 (0.15E-4), and 0.85E-2 (0.54E-3), respectively. The variance of the errors from the oil price equation increases across the two sub-periods while the variances of the other three equations decreases across the two sub-periods. This pattern may have resulted from an increase in the magnitude of the own shocks to oil prices or from a change in the

[5]The results that I have presented for the period 1950–1996 are fairly robust to varying the lag lengths in the VAR and changing the ordering in the VAR decomposition.

response of the system to shocks. A change in the response of the system to shocks, which is a change in structure, seems unlikely given that my results from Section 2 indicate no evidence of trend stationarity in the data.

A somewhat different approach to examining the change in structure vs. change in dynamics issue is to compare the change in the forecast errors of real stock returns across the two sub-periods under different assumptions about the underlying model and the associated variance–covariance matrix. Panel A of Table 7 shows the actual change in the real stock return forecast standard error between the two sub-periods. The actual change in standard errors (calculated as pre-1986 minus post-1986 and shown in column 2) are positive indicating that the forecast errors for rsr were larger in the pre-1986 period. Columns 3–6 show the contribution of each innovation to the real stock return forecast standard error. Panel A shows that the contribution of real stock return innovations were larger in the pre-1986 period while the contributions of the other innovations were larger in the post-1986 period.

Panels B and C report the change in rsr forecast standard errors resulting from a change in structure. Here, for example, the entries in Panel B (C) were computed from variance decompositions using the pre-1986 (post-1986) variance–covariance matrices in both sub-periods. The results from column 2 of Panels B and C indicate that after 24 periods the change in rsr forecast standard errors are negative indicating that a change in structure would have actually resulted in higher forecast errors in the post-1986 period. This is the opposite of what was actually observed in Panel A.

Table 7
Change in forecast error of real stock returns with oil price shocks

Step	Change in standard error	ε^r	ε^o	ε^p	ε^k
A. Actual change (pre-1986–post-1986)					
1	0.586e-2	−0.443e-3	−0.894e-3	−0.428e-3	−0.762e-2
12	0.247e-2	−0.579e-3	−0.193e-2	−0.228e-2	0.725e-2
24	0.154e-2	−0.744e-3	−0.305e-2	−0.221e-2	0.753e-2
B. Change in structure given Σ^{pre}					
12	−0.168e-2	−0.597e-2	0.153e-2	−0.130e-1	0.445e-2
24	−0.146e-1	−0.751e-2	0.147e-2	−0.134e-1	0.481e-2
C. Change in Structure given Σ^{post}					
12	−0.524e-3	−0.177e-2	0.844e-2	−0.289e-2	−0.326e-2
24	−0.379e-3	−0.216e-2	0.773e-2	−0.302e-2	−0.294e-2
D. Change in Dynamics given pre-1986 parameter estimates					
12	0.194e-2	0.119e-1	−0.104e-1	0.611e-3	0.105e-1
24	0.194e-2	0.142e-2	−0.108e-1	0.817e-3	0.105e-1
E. Change in dynamics given post-1986 parameter estimates					
12	0.154e-1	0.539e-2	−0.346e-2	0.107e-1	0.279e-2
24	0.162e-1	0.677e-2	−0.450e-2	0.112e-1	0.272e-2

Panels D and E report changes in rsr forecast standard errors computed using the estimated parameters from the pre-1986 (post-1986) VAR. The results from column 2 of Panels D and E indicate that after 24 periods, the change from pre-1986 to post-1986 shocks decreased the rsr forecast standard errors. Panels D and E also show that shocks to interest rates, industrial production and real stock returns (reported in columns 3, 5 and 6, respectively) had a lesser impact after 1986 while shocks to oil prices (column 4) had a larger impact after 1986. The larger impact that oil price shocks had on the real stock returns variance decompositions is due to an increase in the magnitude of the oil price shocks (partially due to the 1986 oil price drop and the 1990 Gulf crisis) and a decrease in the magnitude of the shocks to interest rates, industrial production and real stock returns, rather than a change in the response of the system to these shocks.

5.2. Asymmetric oil price shocks

Asymmetric oil price shocks can be investigated by decomposing the variable Δlo into one variable which represents positive shocks, Δlo^{+}, and one variable which represents negative shocks, Δlo^{-}. For example, Δlo^{+} is equal to the positive values of Δlo and zero elsewhere while Δlo^{-} is equal to the negative values of Δlo and zero elsewhere. VAR forecast error decompositions (not presented) show that for the full sample, positive shocks explain more of the forecast error variance in Δlr, Δlip and rsr than do negative shocks.

In comparison, summary statistics for the variables Δlo^{+} and Δlo^{-} were also computed. Over this full sample period 51% of the shocks were negative and 49% were positive. The average value of a negative shock was -0.012 while the average value of a positive shock was 0.010. These summary statistics indicate that there are more negative shocks than positive shocks and the average value of a negative shock is 20% larger in absolute value than the average value of a positive shock. In contrast, the variance decompositions computed using asymmetric oil price shocks suggests that positive oil price shocks have a larger impact on the economy. Consequently, oil price shocks appear to have asymmetric effects on economic activity.

Over the first sub-period, positive oil price shocks explain more of the forecast error variance in industrial production and real stock returns than do negative shocks.[6] Over the second sub-period, positive and negative oil price shocks explain approximately the same fraction of the forecast error variance in real stock returns.[7]

5.3. Oil price volatility shocks

Several authors have suggested that oil price volatility shocks may play an important role in explaining economic activity (see for instance, Lee et al., 1995;

[6]Over the 1950:1–1985:12 sub-period, 50% of the Δlo were positive with an average value of 0.010 while the average value of a negative shock was -0.008.

Ferderer, 1996). In the finance literature, Ross (1989) suggests that volatility of price changes may be an accurate measure of the rate of information flow in financial markets. Consequently, oil price volatility shocks may have impacts on real stock returns.[7]

Table 8 reports 24-period VAR decompositions for asymmetric oil price volatility shocks over the full sample 1950:1–1996:4 as well as the two sub-periods, 1950:1–1985:12 and 1986:1–1996:4. From Section 3 the measure of oil price volatility is $\hat{\upsilon}$. The results reported in Table 8 indicate that oil price volatility shocks do have some impact on economic activity, but as in the case of oil prices, the largest impact is observed in the second sub-period.[8,9]

5.4. Asymmetric oil price volatility shocks

Asymmetric oil price volatility shocks are investigated by splitting the variable $\hat{\upsilon}$ into $\hat{\upsilon}^+$ and $\hat{\upsilon}^-$, where $\hat{\upsilon}^+$ represents the positive values of $\hat{\upsilon}$ and $\hat{\upsilon}^-$ represents the negative values of $\hat{\upsilon}$. Forecast error variance decompositions (not presented) show that over the full sample and the two sub-samples, positive oil price volatility shocks explain a larger proportion of the forecast error variance in industrial production and real stock returns than do negative oil price volatility shocks. Over the post-1986 period, positive oil price volatility shocks explain a larger proportion of the real stock return forecast error variance than do interest rates.

These results are consistent with those reported by Lee et al. (1995) and Ferderer (1996), who find that oil price (and oil price volatility) shocks exhibit asymmetric effects on industrial production. Two possible explanations for the asymmetric impact of positive and negative oil price shocks on the economy can be found in the literature on sectorial shocks, which suggests that it is the magnitude of relative price changes that matter, and the literature on irreversible investment under uncertainty, which stresses there is an option value associated with waiting to invest.

Hamilton (1988) constructs a multi-sector model of an economy where it is costly to shift labour and capital inputs between sectors (due to labour mobility and training costs). In such a model Hamilton (1988) shows that relative price shocks can reduce aggregate employment by inducing workers in adversely affected sectors to remain unemployed while they wait for labour conditions to improve in their sector rather than moving to a sector which is not adversely affected.

In the literature on irreversible investment, discussed in Pindyck (1991) a firm may be faced with the choice of adding energy-efficient capital or energy-ineffi-

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[7]Over the 1986:1–1996:4 sub-period, 56% of the shocks were negative while 44% of the shocks were positive. The average value of the negative (positive) shocks was −0.023 (0.021).

[8]Impulse response functions from a model with interest rates, oil price volatility, industrial production and real stock returns show patterns similar to those reported in Figure 2a–d.

[9]The change in the forecast error of real stock returns using oil price volatility shocks are qualitatively similar to the results presented in Table 7.

Table 8
Oil price volatility (variance decomposition of forecast error variance after 24 months)

Response	Shocks to			
	ε^r	ε^o	ε^p	ε^k
Ordering ($\Delta lr, \hat{v}, \Delta lip$, rsr), 1950:1–1996:4				
Δlr	88.01	2.25	5.69	4.04
	(3.06)[a]	(1.50)	(2.11)	(1.89)
$\hat{v}$	4.03	92.88	1.67	1.42
	(1.74)	(2.27)	(1.11)	(1.19)
Δlip	10.55	5.80	77.55	6.10
	(2.83)	(2.24)	(3.88)	(2.56)
rsr	5.58	4.58	3.47	86.37
	(1.98)	(2.03)	(1.62)	(3.22)
Ordering ($\Delta lr, \hat{v}, \Delta lip$, rsr), 1950:1–1985:12				
Δlr	86.17	3.48	4.52	5.83
	(3.54)	(1.91)	(2.13)	(2.34)
$\hat{v}$	6.73	88.84	1.80	2.63
	(2.39)	(3.10)	(1.41)	(1.60)
Δlip	11.11	7.53	74.33	7.02
	(3.34)	(2.78)	(4.55)	(2.88)
rsr	7.40	5.41	4.48	82.72
	(2.60)	(2.37)	(2.05)	(3.81)
Ordering ($\Delta lr, \hat{v}, \Delta lip$, rsr), 1986:1–1996-4				
Δlr	70.01	12.83	11.87	5.29
	(8.33)	(6.83)	(5.33)	(4.09)
$\hat{v}$	4.44	79.63	10.21	5.71
	(4.03)	(6.77)	(4.60)	(4.21)
Δlip	12.62	16.95	61.68	8.74
	(5.45)	(6.00)	(7.06)	(4.54)
rsr	11.53	11.22	9.31	68.12
	(4.93)	(5.83)	(4.31)	(6.89)

[a] Monte Carlo constructed standard errors are shown in parentheses.

cient capital. Increased energy price uncertainty due to higher volatility in energy prices raises the option value associated with waiting to invest. Decreases in energy prices can also be offset by increases in uncertainty.

6. Concluding remarks

Oil price movements are an important and interesting topic to study because increases in oil prices are often indicative of inflationary pressure in the economy which in turn could indicate the future of interest rates and investments of all types.

Results from a vector autoregression confirm that oil prices and oil price volatility both play important roles in affecting economic activity. My results suggest that changes in oil prices impact economic activity but, changes in economic activity have little impact on oil prices. Impulse response functions show that oil price movements are important in explaining movements in stock returns. The estimated results suggest that positive shocks to oil prices depress real stock returns while shocks to real stock returns have positive impacts on interest rates and industrial production. There is evidence that oil price dynamics have changed. After 1986, oil price movements explain a larger fraction of the forecast error variance in real stock returns than do interest rates. There is also evidence that oil price volatility shocks have asymmetric effects on the economy.

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Appendix A.

All data are from the DRI/McGraw Hill data base. Variable definitions and code names are as follows.

1. Index of industrial production, 1982 = 100, seasonally adjusted (IP).
2. Three-month T-bill rate (FYGM3).
3. Producer price index of fuels, 1982 = 100 (PWFUEL), seasonally unadjusted.
4. S & P 500 common stock price index, 1967 = 100, seasonally unadjusted (FPS6US).
5. Consumer price index, 1982–1984 = 100 (PZUNEW), seasonally unadjusted. The variables PZUNEW and PFUEL were seasonally adjusted and PZUNEW was transformed so that 1982 = 100. These two new variables are PZUNEW* and PFUEL*.
6. Real oil prices, PWFUEL*/PZUNEW* $\times$ 100.
7. Real stock returns, Δ1(FPS6US) $-$ Δl(PZUNEW*).

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