What is an Oil Shock?*

James D. Hamilton

Department of Economics, 0508

University of California, San Diego

La Jolla, CA 92093-0508

jhamilton@ucsd.edu

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ABSTRACT

This paper uses a flexible approach to characterize the nonlinear relation between oil price changes and GDP growth. The paper reports clear evidence of nonlinearity, consistent with earlier claims in the literature– oil price increases are much more important than oil price decreases, and increases have significantly less predictive content if they simply correct earlier decreases. An alternative interpretation is suggested based on estimation of a linear functional form using exogenous disruptions in petroleum supplies as instruments.

A large body of research suggests that there is a significant effect of energy supply disruptions on economic activity. A clear negative correlation between energy prices and aggregate measures of output or employment has been reported by Rasche and Tatom (1977, 1981), Hamilton (1983), Burbidge and Harrison (1984), Santini (1985, 1994), Gisser and Goodwin (1986), Rotemberg and Woodford (1996), Daniel (1997), Raymond and Rich (1997) and Carruth, Hooker, and Oswald (1998), among others. Most recently, Muellbauer and Nunziata (2001) successfully predicted the U.S. recession of 2001 from a multivariate analysis in which oil prices featured prominently. Analyses of microeconomic data sets at the level of individual industries, firms, or workers also demonstrate significant correlations between oil price shocks and output, employment, or real wages (Keane and Prasad, 1996; Davis, Loungani, and Mahidhara, 1996; Davis and Haltiwanger, 2001; Lee and Ni, 2002), and certainly oil shocks are a major factor driving fluctuations in the international terms of trade (Backus and Crucini, 2000). Nevertheless, the suggestion that oil price shocks contribute directly to economic downturns remains controversial, in part because the correlation between oil prices and economic activity appears to be much weaker in data obtained since 1985; (see Hooker, 1996).

A number of authors have attributed this instability of the empirical relation between oil prices and output to misspecification of the functional form. Loungani (1986), Davis (1987a,b), Mork (1989), Lee, Ni and Ratti (1995), Hamilton (1996), Davis, Loungani, and Mahidhara (1996), Davis and Haltiwanger (2001), Balke, Brown, and Yücel (1999), and Cuñado and de Pérez (2000), among others, have suggested that the relation between oil prices and economic activity is nonlinear. Insofar as there has been a shift in the process generating oil prices, a linear approximation to the relation between oil prices and economic activity may appear unstable over time, even if the underlying nonlinear relation is stable.

One problem with suggesting that this is indeed what happened is that there is an unbounded universe of alternative nonlinear specifications. How does one decide which nonlinear specification is the right one to use, and how can we distinguish between a statistically significant nonlinear relation and the outcome of determined data-mining?

This paper applies a methodology recently developed by Hamilton (2001) to address these questions. This approach provides a valid test of the null hypothesis of linearity against a broad range of alternative nonlinear models, consistent estimation of what the nonlinear relation looks like, and formal comparison of alternative nonlinear models. The results generate strong support for the claim of a nonlinear relation along the lines suggested in the literature: oil price increases affect the economy whereas decreases do not, and increases that come after a long period of stable prices have a bigger effect than those that simply correct previous decreases.

These results are exclusively concerned with characterization of the functional form of the conditional expectation of GDP given past GDP and past oil prices. Establishing these facts would seem to be of considerable interest, though it leaves open the question of whether this correlation should be given a causal interpretation. To address this issue, the paper attempts to isolate an exogenous component of oil price movements by measuring the oil supply curtailed by five separate military conflicts during the postwar period. Insofar as these conflicts were indeed exogenous with respect to developments in the U.S. economy, a correlation between this component of oil price movements and subsequent changes in GDP should be given a causal interpretation. I find that the nonlinear transformation of oil prices suggested by the functional form of the conditional expectation function is in fact quite similar to the first-stage least-squares fit from a regression of oil price changes on these exogenous supply disturbances, and that the dynamic multipliers from the nonlinear relation are similar to those coming from a linear relation estimated by instrumental variables. I conclude that the basic fact being summarized by the nonlinear analysis is the historical tendency of the U.S. economy to perform poorly in the wake of these historical conflicts

The plan of the paper is as follows. The first section discusses why an investigation of the linearity of the relationship might be important both for econometric inference and economic interpretation. Section 2 reviews the methodology applied in this paper. Empirical results are presented in Section 3. Section 4 discusses structural stability of the suggested nonlinear formulations. Section 5 proposes a measure of the exogenous component of oil price movements and suggests an alternative interpretation of the results in terms of instrumental variable estimation. Conclusions are offered in Section 6.

1 Why functional form matters.

Many economic analyses of the effects of oil shocks[1] begin with a production function relating output to inputs of capital, labor, and energy. An exogenous decrease in the supply of energy reduces output directly by lowering productivity and indirectly to the extent that lower wages induce movement along a labor supply schedule (Rasche and Tatom, 1977, 1981; Kim and Loungani, 1992), changes in business markups (Rotemberg and Woodford, 1996), or capacity utilization rates (Finn, 2000). These models imply that the log of real GDP should be linearly related to the log of the real price of oil. One implication of this linearity is that if the price of oil goes down, then output should go up; if an oil price increase brings about a recession, then an oil price decline should induce an economic boom by the same mechanism operating in the reverse direction.[2]

These models view recessions as supply driven rather than demand driven. According to these models, an oil price increase produces a recession because it makes cars more costly to manufacture. This seems contrary to reports in the trade and business press, in which the problem is invariably perceived as a reduction in the number of cars consumers are willing to buy; see for example the trade press accounts in Lee and Ni (2002).

A number of early analyses focused instead on demand-side effects of an oil price increase. In these models, an increase in oil prices would increase the overall price level, which, given

[1] Useful reviews of the different mechanisms by which oil shocks could affect economic performance are provided by Bohi (1989) and Mork (1994).

[2] Atkeson and Kehoe (1999) offered an interesting extension of this class of models by assuming putty-clay investment technology. In their formulation, an oil price decrease still produces an increase in output, though the output boom from a large oil price decline is smaller in magnitude than the output decline that follows an oil price increase of the same logarithmic magnitude.

the Keynesian assumption of rigid wages, reduces employment. Examples of such models include Pierce and Enzler (1974), Solow (1980), and Pindyck (1980). Mork and Hall (1980) demonstrated the potential for interactive effects between wage rigidities and supply-side effects. These models again all maintain the existence of a linear relation between the log of the price of oil and the log of GDP, so that again an oil price decline is expected to produce an economic boom.

These models also have the characteristic that there is nothing all that special about oil. The basic economic inefficiency is the familiar Keynesian mismatch between the aggregate wage and the aggregate price level, and oil price disruptions are just one of many developments that might contribute to such a mismatch.

Surely the price and availability of gasoline matter for car sales not simply because they affect the overall price level but further because they are key inputs in how cars get used. Is your next car going to be a small foreign car or a large sport-utility vehicle? Your decision depends in part on what you think about gasoline availability. If you are very unsure about where gas prices are headed, you might be inclined to postpone a new purchase until you have a better idea of where the market stands.

Energy prices and availability may be quite relevant for a host of other durable goods purchases, including housing. How long a commute to work are you willing to put up with? How energy-efficient should your appliances, windows, and insulation be? What equipment and industrial techniques should a firm build a new factory around? When energy prices and availability are as uncertain as they were in early 1974, it is rational to postpone such commitments until better information is available.

Oil shocks may matter for short-run economic performance precisely because of their ability temporarily to disrupt purchases of large-ticket consumption and investment goods, as in Bernanke (1983). A major disruption in oil supplies makes people uncertain about the future, with the result that spending on cars, housing, appliances, and investment goods temporarily falls. A variety of microeconomic evidence suggests that oil shocks have substantial potential to exert such effects. Bresnahan and Ramey (1993) documented that the oil shocks of 1974 and 1980 caused a significant shift in the mix of demand for different size classes of automobiles with an attendant reduction in capacity utilization at U.S. automobile plants. Sakellaris (1997) found that changes in the stock market valuation of different companies in response to the 1974 oil shock were significantly related to the vintage of their existing capital. Davis and Haltiwanger (2001) discovered a dramatic effect of oil price shocks on the rate of job loss in individual economic sectors, with the job destruction rising with capital intensity, energy intensity, product durability, and plant age and size. See also Loungani (1986), Davis (1987a,b), Hamilton (1988a,b), Santini (1992), and Davis, Loungani, and Mahidhara (1996), and Lee and Ni (2002) for related evidence and discussion.

These studies have further noted that, if allocative disturbances are indeed the mechanism whereby oil shocks affect economic activity, then there is no reason to expect a linear relation between oil prices and GDP. An oil price increase will decrease demand for some goods but possibly increase demand for others. If it is costly to reallocate labor or capital between sectors, the oil shock will be contractionary in the short run. Note moreover that an oil price decrease could also be contractionary in the short run. A price decrease also depresses demand for some sectors, and unemployed labor is not immediately shifted elsewhere. Furthermore, if it is primarily the postponement of purchases of energy-sensitive big-ticket items that produces the downturn, then an oil price decrease could in principle be just as contractionary as an oil price increase.

Of course, an oil price decrease is not all bad news, by virtue of the production function and inflation effects noted earlier. But surely it is unreasonable to assume that an oil price decrease would produce an economic boom that mirrors the recession induced by an oil price increase.

As a simple statistical illustration of how the specification of functional form can matter in practice, consider the following example. Let y_t denote the growth rate of real GDP and let o_t denote the percentage change in the price of oil. Let us assume that the effect of oil prices on output is given by

$$y_t = f(o_t) + \varepsilon_t \tag{1.1}$$

where ε_t is a regression error term. Suppose that every one percent increase in oil prices produces a β percent decrease in real GDP, but that a decrease in oil prices has no effect on GDP. Then the function $f(o_t)$ takes the form

$$f(o_t) = \begin{cases} \alpha & \text{if } o_t \leq 0 \\ \alpha - \beta o_t & \text{if } o_t > 0 \end{cases} . \tag{1.2}$$

I simulated 50 observations from equations (1.1) and (1.2) with a critical precondition–

all of the o's in the sample were positive.[3] Thus for this particular sample the data satisfy the classic linear regression assumptions. Ordinary least squares (OLS) regression produces excellent inference about the values of α and β (standard errors in parentheses):

$$y_t = \underset{(0.47)}{2.29} - \underset{(0.044)}{0.117}\, o_t. \tag{1.3}$$

Oil prices are inferred to have a strong and statistically significant effect on the economy, with a t-statistic of -2.66. The simulated data, estimated relation, and true relation are displayed in Figure 1.

Now let us double the sample size but allow both positive and negative values for o_t, as displayed in Figure 2. The OLS regression estimates now turn out to be

$$y_t = \underset{(0.16)}{1.65} - \underset{(0.015)}{0.029}\, o_t. \tag{1.4}$$

The result of using the larger sample is that oil prices are only imputed to have 1/4 as big an effect as they seemed to have in the smaller sample, and this effect is no longer statistically significant. The reason is that if equation (1.2) represents the true model and if the sample includes negative values for o, then regression (1.4) is misspecified and is not providing a consistent estimate of the parameter β.

Mork (1989) argued that this is essentially what is going on with the historical U.S. experience.[4] In the postwar data up until 1980, there was very little experience with falling

[3] The simulation used $\alpha = 2$, $\beta = 0.1$, $u_t \sim N(0, 2.25)$, and $o_t \sim N(0, 100)$, where (o_t, y_t) pairs were thrown out if $o_t \leq 0$ until 50 pairs of observations were generated. These values were chosen to correspond to rough magnitudes that might characterize the actual U.S. relation.

[4] Actually, Mork estimated separate coefficients for oil price increases and decreases, and found that the coefficients on decreases were insignificantly different from zero. The argument as presented in the text here jumps to the conclusion in a single step. Mork, Olsen and Mysen (1994) reported more qualified support for this idea in the experience of other countries.

oil prices, so that the sample was essentially like that in Figure 1. After 1980, however, there are a lot of observations of big oil price decreases, so that the sample becomes more like that shown in Figure 2. The result is that when more observations are added to the sample, the estimated effect becomes smaller in magnitude and loses statistical significance.

Specifically, to get away from simulated data and turn to the actual numbers, consider the results of regressing each quarter's GDP growth (y_t) on four lags of GDP growth and four lags of the percent change in the nominal price of crude petroleum (o_{t-j}). When this regression is estimated for data from 1949:II to 1980:IV, the result is

$$\begin{aligned} y_t \;=\; & \underset{(0.19)}{1.19} + \underset{(0.09)}{0.20}\, y_{t-1} + \underset{(0.09)}{0.06}\, y_{t-2} - \underset{(0.09)}{0.09}\, y_{t-3} - \underset{(0.09)}{0.20}\, y_{t-4} \\ & - \underset{(0.027)}{0.003}\, o_{t-1} - \underset{(0.027)}{0.030}\, o_{t-2} - \underset{(0.027)}{0.036}\, o_{t-3} - \underset{(0.028)}{0.064}\, o_{t-4}. \end{aligned} \tag{1.5}$$

When one calculates the impulse-response function, this regression implies that a 10% increase in oil prices will result four quarters later in a level of GDP that is 1.4% lower than it otherwise would be. Because of the imposed linearity, the regression also requires that a 10% decrease in oil prices will result in a 1.4% higher level of GDP.

When the same regression is reestimated using data from 1949:II to 2001:III, the result is

$$\begin{aligned} y_t \;=\; & \underset{(0.11)}{0.72} + \underset{(0.07)}{0.28}\, y_{t-1} + \underset{(0.07)}{0.13}\, y_{t-2} - \underset{(0.07)}{0.06}\, y_{t-3} - \underset{(0.07)}{0.12}\, y_{t-4} \\ & - \underset{(0.006)}{0.003}\, o_{t-1} - \underset{(0.006)}{0.003}\, o_{t-2} - \underset{(0.006)}{0.004}\, o_{t-3} - \underset{(0.007)}{0.016}\, o_{t-4}. \end{aligned} \tag{1.6}$$

The coefficient on o_{t-4} is about 1/4 of its value in the smaller sample, though it remains statistically significant at the 5% level. The reason the coefficient on o_{t-4} is much smaller in the larger sample is that an oil price decrease of 10% does not add 1.4% to the level of GDP. In order for a linear relation to be consistent with what happened after the oil price declines since 1980, a smaller coefficient is needed.

As evidence in support of Mork's claim that the historical regressions (1.5) and (1.6) are reflecting the same factors as the simulated regression (1.3) and (1.4), consider imposing the functional form (1.2) directly. Define

$$o_t^+ = \begin{cases} 0 & \text{if } o_t \leq 0 \\ o_t & \text{if } o_t > 0 \end{cases}. \tag{1.7}$$

When o_{t-j} in (1.6) is replaced by o_{t-j}^+, the estimated relation over 1949:II to 2001:III is

$$\begin{aligned} y_t = & \underset{(0.13)}{0.88} + \underset{(0.07)}{0.26}\, y_{t-1} + \underset{(0.07)}{0.12}\, y_{t-2} - \underset{(0.07)}{0.07}\, y_{t-3} - \underset{(0.07)}{0.14}\, y_{t-4} \\ & - \underset{(0.009)}{0.011}\, o_{t-1}^+ - \underset{(0.009)}{0.005}\, o_{t-2}^+ - \underset{(0.009)}{0.007}\, o_{t-3}^+ - \underset{(0.009)}{0.023}\, o_{t-4}^+. \end{aligned} \tag{1.8}$$

The estimated effects of oil price increases are considerably larger than those implied by the linear relation (1.6).

Although the functional form in equation (1.2) seems consistent with the empirical evidence in regressions (1.5), (1.6), and (1.8), Mork's interpretation has recently been challenged on two grounds. First, Hooker (1996) argued that even the asymmetric relation (1.8) offers a relatively poor fit to data since 1986. Second, if the mechanism is indeed that an oil price increase causes postponement of certain major purchases, then equation (1.2) is surely too crude– consumers' behavior should be based not just on whether oil prices went up, but further on what they believe the increase means for the future. Most of the quarters in which oil prices went up since 1986 followed a quarter in which oil prices had gone down even more, so that the increases were simply partial corrections to a chronic downward trend. Several authors have suggested alternative functional forms that might better represent the true relation. Ferderer (1996) argued that oil price volatility itself depresses spending. Lee, Ni, and Ratti (1995) suggested that what matters is how surprising an oil price increase is based on the observed recent changes.[5] Hamilton (1996) claimed that the key question is whether the oil price increase is big enough to reverse any decreases observed in the immediately preceding quarters. Davis, Loungani, and Mahidhara (1996) and Davis and Haltiwanger (2001) focused on whether the oil price increase was sufficient to raise the price above its previous 5-year average.

All of these specifications have a certain plausibility. One logical way to sort out the various alternatives would be to leave the function $f(o_t)$ in equation (1.1) totally unrestricted, and let the data tell us which of the various nonlinear alternatives is best supported by the data. This paper pursues that idea using a flexible approach to nonlinear modeling recently suggested by Hamilton (2001). The basic technique is described in the following section.

[5] Lee, Ni and Ratti constructed a variable $e_t^* = e_t/\sqrt{h_t}$ where e_t is the error in forecasting the real price of oil based on past observations and $\sqrt{h_t}$ is the standard error of this forecast as estimated by a GARCH model. The GARCH specification assumes that e_t is distributed $N(0, h_t)$, so the probability of observing an increase in oil prices during quarter t as large or larger than what was actually observed is $1 - \Phi(e_t^*)$, where $\Phi(\cdot)$ is the cumulative distribution function for a standard Normal variate. Thus the statement that the effect of an oil price increase depends on e_t^* is equivalent to the statement that the effect of an oil price increase depends on how surprisng that increase is, given the recent behavior of oil prices.

2 A flexible approach to nonlinear inference.

Consider a nonlinear regression model of the form

$$y_t = \mu(\mathbf{x}_t) + \boldsymbol{\delta}'\mathbf{z}_t + \varepsilon_t \tag{2.1}$$

where y_t is a scalar dependent variable, $\mathbf{x}_t$ and $\mathbf{z}_t$ are k- and p-dimensional vectors of explanatory variables, and ε_t is an error term. The form of the function $\mu(.)$ is unknown, and we seek to represent it using a flexible class. On the other hand, there may be some subset of variables $\mathbf{z}_t$ for which the researcher is willing to assume linearity, and, if so, significant efficiency gains can be obtained by imposing this restriction. In the application below, $\mathbf{z}_t = (y_{t-1}, y_{t-2}, y_{t-3}, y_{t-4})'$ contains lagged values of GDP growth while $\mathbf{x}_t = (o_{t-1}, o_{t-2}, o_{t-3}, o_{t-4})'$ contains lagged changes in oil prices. The approach suggested by Hamilton (2001) is to view the function $\mu(.)$ itself as the outcome of a random field.[6] That is, if $\boldsymbol{\tau}_1$ denotes an arbitrary, nonstochastic k-dimensional vector, then the value of the function $\mu(.)$ evaluated at $\boldsymbol{\tau}_1$, denoted $\mu(\boldsymbol{\tau}_1)$, is regarded as a random variable. Hamilton (2001) treats this random variable as being Normally distributed with mean $\alpha_0 + \boldsymbol{\alpha}'\boldsymbol{\tau}_1$ and variance λ^2, where α_0, $\boldsymbol{\alpha}$, and λ are population parameters to be estimated. Note that if $\lambda = 0$, then model (2.1) becomes a simple linear regression model $y_t = \alpha_0 + \boldsymbol{\alpha}'\mathbf{x}_t + \boldsymbol{\delta}'\mathbf{z}_t + \varepsilon_t$. The larger λ, the more the model (2.1) is allowed to deviate from a linear regression model.

The other item one needs to know about the random field $\mu(.)$ is how the random variable

[6] The general approach of viewing $\mu(.)$ as stochastic has a very old and extensive tradition in the statistics literature. The particular form for the random field used here is, to my knowledge, original– see Hamilton (2001) for references.

$\mu(\boldsymbol{\tau}_1)$ is correlated with $\mu(\boldsymbol{\tau}_2)$, for $\boldsymbol{\tau}_1$ and $\boldsymbol{\tau}_2$ again arbitrary k-dimensional vectors. We assume that $\mu(\boldsymbol{\tau}_1)$ is uncorrelated with $\mu(\boldsymbol{\tau}_2)$ if $\boldsymbol{\tau}_1$ is sufficiently far away from $\boldsymbol{\tau}_2$, specifically, that

$$E\{[\mu(\boldsymbol{\tau}_1) - \alpha_0 - \boldsymbol{\alpha}'\boldsymbol{\tau}_1][\mu(\boldsymbol{\tau}_2) - \alpha_0 - \boldsymbol{\alpha}'\boldsymbol{\tau}_2]\} = 0$$

if $(1/2)\left[\Sigma_{i=1}^k g_i^2(\tau_{i1} - \tau_{i2})^2\right]^{1/2} > 1$, where τ_{i1} denotes the ith element of the vector $\boldsymbol{\tau}_1$ and $g_1, g_2, ..., g_k$ are k additional population parameters to be estimated. The closer that $\boldsymbol{\tau}_1$ gets to $\boldsymbol{\tau}_2$, specifically, the smaller the value of the scalar $h_{12} = (1/2)\left[\Sigma_{i=1}^k g_i^2(\tau_{i1} - \tau_{i2})^2\right]^{1/2}$, the higher the correlation between $\mu(\boldsymbol{\tau}_1)$ and $\mu(\boldsymbol{\tau}_2)$, with the correlation going to unity as h_{12} goes to zero. If the nonlinear part of the model includes $k = 4$ explanatory variables, then the correlation is assumed to be given by

$$\text{Corr}(\mu(\boldsymbol{\tau}_1), \mu(\boldsymbol{\tau}_2)) = \begin{cases} H_4(h_{12}) & \text{if } 0 \leq h_{12} \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

where

$$H_4(h_{12}) = 1 - (2/\pi)\left[(2/3)h_{12}(1 - h_{12}^2)^{3/2} + h_{12}(1 - h_{12}^2)^{1/2} + \sin^{-1}(h_{12})\right]. \tag{2.2}$$

See Hamilton (2001) for the motivation behind this specification. Note that $H_k(.)$ is not a parameterization of the functional relation $\mu(.)$ itself, but rather a parameterization of the correlation between the random variables $\mu(\boldsymbol{\tau}_1)$ and $\mu(\boldsymbol{\tau}_2)$; a given realization of $\mu(.)$ from this random process can take on any of a variety of different forms, and this is what gives the approach its flexibility. The parameter g_i governs the likely variability of the nonlinear function $\mu(\boldsymbol{\tau})$ as the value of τ_i varies; as g_i becomes small, the value of $\mu(\boldsymbol{\tau})$ changes little when τ_i changes. If $g_i = 0$, then the function $\mu(\boldsymbol{\tau})$ is linear with respect to τ_i.

The above specification can be written in the form

$$\begin{aligned} y_t &= \alpha_0 + \boldsymbol{\alpha}' \mathbf{x}_t + \boldsymbol{\delta}' \mathbf{z}_t + \lambda m(\mathbf{x}_t) + \varepsilon_t \\ &= \alpha_0 + \boldsymbol{\alpha}' \mathbf{x}_t + \boldsymbol{\delta}' \mathbf{z}_t + u_t \end{aligned} \tag{2.3}$$

where $m(.)$ denotes the realization of a scalar-valued Gaussian random field with mean zero, unit variance, and covariance function given by (2.2) and where $u_t = \lambda m(\mathbf{x}_t) + \varepsilon_t$. If the regression error ε_t is assumed to be i.i.d. $N(0, \sigma^2)$ and if the regressors $(\mathbf{x}_t', \mathbf{z}_t')$ are strictly exogenous, then this specification implies a GLS regression model of the form

$$\mathbf{y}|\mathbf{X} \sim N(\mathbf{X}\boldsymbol{\beta}, \mathbf{P}_0 + \sigma^2 \mathbf{I}_T)$$

where $\mathbf{y} = (y_1, y_2, ..., y_T)'$, T is the sample size, $\mathbf{X}$ is a $(T \times (1+k+p))$ matrix whose tth row is given by $(1, \mathbf{x}_t', \mathbf{z}_t')$, $\boldsymbol{\beta}$ is the $(1+k+p)$-dimensional vector $(\alpha_0, \boldsymbol{\alpha}', \boldsymbol{\delta}')'$, $\mathbf{I}_T$ is the $(T \times T)$ identity matrix, and $\mathbf{P}_0$ is a $(T \times T)$ matrix whose row s, column t element is given by $\lambda^2 H_k(h_{st}) \delta_{[h_{st}<1]}$ where $h_{st} = (1/2) \left[\Sigma_{i=1}^k g_i^2 (x_{is} - x_{it})^2 \right]^{1/2}$, x_{is} denotes the value of the ith explanatory variable for observation s, and the function $H_k(.)$ is as specified in (2.2) when $k = 4$. Nonlinearity of the functional form $\mu(.)$ implies a correlation between u_t and u_s, the residuals of the linear specification, whenever $\mathbf{x}_t$ and $\mathbf{x}_s$ are close together.

The population parameters of the model thus consist of the linear part of the regression function $(\alpha_0,\ \boldsymbol{\alpha}, \boldsymbol{\delta})$, the variance of the nonlinear regression error σ^2, the parameter governing the overall importance of the nonlinear component λ^2, and the parameters governing the variability of the nonlinear component with respect to each explanatory variable $(g_1, g_2, ..., g_k)$. The nonlinear regression function $m(.)$ itself does not involve any parameters but instead is regarded as a random outcome whose probability law is to be modeled along with the observed data as described above. Conditional on the parameters, the likelihood function is simply that of a GLS Gaussian regression, and numerical Bayesian methods described in Hamilton (2001) can be used to evaluate the posterior distribution of any statistics of interest; the specific priors used in this study are detailed in Appendix A. Conditional on the parameters, the optimal inference of the value of the unobserved function $\mu(\mathbf{x}^*)$ at some arbitrary point $\mathbf{x}^*$ is given by

$$\hat{\mu}(\mathbf{x}^*) = \boldsymbol{\alpha}'\mathbf{x}^* + \mathbf{q}'(\mathbf{P}_0 + \sigma^2\mathbf{I}_T)^{-1}(\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) \tag{2.4}$$

where $\mathbf{q}$ denotes a $(T \times 1)$ vector whose tth element is given by $\lambda^2 H_k(h_t^*)\delta_{[h_t^*<1]}$ for $h_t^* = (1/2)\left[\Sigma_{i=1}^k g_i^2(x_{it} - x_i^*)^2\right]^{1/2}$ where x_{it} denotes the ith element of $\mathbf{x}_t$ and x_i^* denotes the ith element of $\mathbf{x}^*$. The inference thus modifies the linear estimate $\boldsymbol{\alpha}'\mathbf{x}^*$ by taking a linear combination of residuals u_t for those observations with $\mathbf{x}_t$ close to $\mathbf{x}^*$. Hamilton shows that the inference $\hat{\mu}(\mathbf{x}^*)$ converges to the true value $\mu(\mathbf{x}^*)$ for $\mu(.)$ any function from a broad class of continuous functions satisfying a certain smoothness condition. Monte Carlo investigation by Christian Dahl (1998) confirms that the procedure is useful in small samples for a variety of nonlinear time series models. One can calculate a 95% probability region for this inference by generating values of α_0, $\boldsymbol{\alpha}$, $\boldsymbol{\delta}$,σ, λ, and $\mathbf{g}$ from their posterior distributions and calculating the inference (2.4) along with its known standard error for each given parameter vector, and examining the resulting distribution of inferences.

The framework also suggests a simple test of the null hypothesis that the true relation is linear ($H_0 : \lambda = 0$). Hamilton suggests fixing the smoothing parameters g_i for purposes of this test on the basis of the sample standard deviation of the ith explanatory variable,

$$g_i = 2\left[k\left(T^{-1}\Sigma_{t=1}^{T}(x_{it} - \bar{x}_i)^2\right)\right]^{-1/2}.$$

Using these values for g_i, construct the $(T \times T)$ matrix $\mathbf{H}$ whose row t, column s element is given by

$$H_k\left\{(1/2)\left[g_1^2(x_{1t} - x_{1s})^2 + g_2^2(x_{2t} - x_{2s})^2 + ... + g_k^2(x_{kt} - x_{ks})^2\right]^{1/2}\right\} \tag{2.5}$$

where $H_k(.)$ is given in expression (2.2) when $k = 4$, or by zero when the argument of $H_k(.)$ exceeds unity. Next perform an OLS linear regression of y_t on $\mathbf{x}_t$, $\mathbf{z}_t$ and a constant, $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$, calculating the OLS residuals $\hat{\boldsymbol{\varepsilon}}$, regression squared standard error, $\tilde{\sigma}^2 = (T - k - p - 1)^{-1}\hat{\boldsymbol{\varepsilon}}'\hat{\boldsymbol{\varepsilon}}$, and $(T \times T)$ projection matrix $\mathbf{M} = \mathbf{I}_T - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$. Then calculate the following function of the OLS residuals:

$$\nu^2 = \frac{[\hat{\boldsymbol{\varepsilon}}'\mathbf{H}\hat{\boldsymbol{\varepsilon}} - \tilde{\sigma}^2\mathrm{tr}(\mathbf{MHM})]^2}{\tilde{\sigma}^4\left(2\mathrm{tr}\{[\mathbf{MHM} - (T - k - p - 1)^{-1}\mathbf{M}\mathrm{tr}(\mathbf{MHM})]^2\}\right)}. \tag{2.6}$$

If the OLS residuals for observation t are similar to those for other observations with similar $\mathbf{x}$'s, then ν^2 will be large and evidence against linearity is obtained. Hamilton shows that ν^2 has an asymptotic $\chi^2(1)$ distribution under the null hypothesis that the true relation is linear. Dahl's (1998) Monte Carlo evidence establishes that the test has good small-sample size and strong power against a variety of nonlinear alternatives.

3 Empirical results.

The series used for real output y_t is the quarterly growth rate of chain-weighted real GDP.[7] The oil price series o_t is 100 times the quarterly logarithmic growth rate of the nominal crude oil producer price index, seasonally unadjusted.[8] The sample used for estimation (not including the lagged initial values for conditioning) runs from $t =$ 1949:II to 2001:III, for a total of $T = 210$ usable observations.

The test statistic ν^2 of the null hypothesis of linearity has a value of 40.00, which for a $\chi^2(1)$ variable implies overwhelming rejection of the null hypothesis that the relation between oil prices and GDP growth is linear[9] . Dahl and González-Rivera (2002) proposed a number of alternative formulations of the random $\mu(.)$ formulation of nonlinearity and proposed a bootstrap procedure for approximating small-sample p-values.[10] The test statistics are reported in Table 1. Note that in these tests, the function $\mu(\mathbf{x}_t, \mathbf{z}_t)$ is treated as potentially nonlinear in all 8 variables, for which the evidence against the null hypothesis of linearity turns out to be even stronger. There seems little question that the relation between oil

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[7] Data were downloaded from the Bureau of Economic Analysis web page (http://www.bea.doc.gov/bea/dn1.htm) on November 29, 2001.

[8] The monthly WPI0561 series was converted to quarterly by using end-of-period values. Data from 1947:II to 1974:I are from Hamilton (1982). Data from 1974:II to 1999:IV are from Citibase, downloaded from http://ssdc.ucsd.edu/citibase on April 24, 2000, with the last two years from Bureau of Labor Statistics, http://stats.bls.gov/ppi/home.htm#data, downloaded on November 29, 2001.

[9] At the suggestion of a referee, we investigated the potential sensitivity of this result to outliers as follows. We dropped observation t_0 from the sample (deleting the vector $\mathbf{w}_{t_0} = (y_{t_0}, \mathbf{x}'_{t_0}, \mathbf{z}'_{t_0})'$ and retaining $\{\mathbf{w}_1, \mathbf{w}_2, ..., \mathbf{w}_{t_0-1}, \mathbf{w}_{t_0+1}, ..., \mathbf{w}_T)$ for each possible $t_0 \in \{1, 2, ..., T\}$ and calculated the resulting ν^2 statistic for the sample without observation t_0. The smallest value of ν^2 found was 23.58 for t_0 corresponding to 1950:I.

[10] I thank the authors for graciously sharing their code.

prices and GDP is nonlinear.

Bayesian posterior estimates and their standard errors[11] for the flexible nonlinear alternative are as follows:

$$\begin{aligned} y_t \;=\;& \underset{(0.15)}{0.58} - \underset{(0.0069)}{0.0020}\, o_{t-1} - \underset{(0.0066)}{0.0023}\, o_{t-2} - \underset{(0.0066)}{0.0024}\, o_{t-3} - \underset{(0.0068)}{0.0142}\, o_{t-4} \\ & + \underset{(0.07)}{0.25}\, y_{t-1} + \underset{(0.07)}{0.12}\, y_{t-2} - \underset{(0.07)}{0.07}\, y_{t-3} - \underset{(0.07)}{0.14}\, y_{t-4} \\ & + \underset{(0.05)}{0.93}\, [\underset{(0.13)}{0.33}\, m(\underset{(0.11)}{0.09}\, o_{t-1}, \underset{(0.11)}{0.09}\, o_{t-2}, \underset{(0.10)}{0.08}\, o_{t-3}, \underset{(0.09)}{0.08}\, o_{t-4}) + v_t] \end{aligned} \tag{3.1}$$

where $v_t \sim N(0,1)$ and $m(.)$ denotes an unobserved realization from a Gaussian random field with mean zero, unit variance, and correlations given by (2.2). The innovation ε_t in (2.3) is written here as $\sigma = 0.93$ times v_t, and the parameter λ in (2.2) is written as σ times the parameter ζ, whose estimate is 0.33. Each of the four lags of oil price changes exerts an overall negative effect on output growth as indicated by the linear coefficients, though only the coefficient on o_{t-4} is statistically significant. Although one would accept a hypothesis of linearity for any one of the lags of oil prices taken individually (as reflected by the insignificant t-statistics on the individual coefficients g_i), collectively the nonlinear component makes a highly significant contribution (as evidenced by the t-statistic for $\zeta = 0$ or the LM tests).

Given any particular values for the vector $\mathbf{g}$– for example, given the posterior means $\hat{\mathbf{g}} = (0.09, 0.09, 0.08, 0.08)'$– one can use (2.2) and (2.5) to calculate the value of $H_4(.)$ associated with any pair of observations on $\mathbf{x}_t$ and $\mathbf{x}_s$. For a given value of λ– for example, $\hat{\lambda} = 0.33$– one can then calculate the row t, column s element of the matrix $\mathbf{P}_0$ as $\lambda^2 H_4(.)$.

[11] Based on 20,000 draws from the importance sampling density described in Hamilton (2001).

Given values for $\boldsymbol{\alpha}$ as well, one can calculate a value for (2.4) for any $\mathbf{x}^*$ of interest, which represents the econometrician's inference as to the value of the conditional mean $\mu(\mathbf{x}^*)$ when the explanatory variables take on the value represented by $\mathbf{x}^*$ and when the parameters are known to take on these specified values. By generating values of $\mathbf{g}$ and other parameters from the posterior distribution whose mean and standard deviation are reported in (3.1), we generate a range of estimates of $\mu(\mathbf{x}^*)$, and the mean of this range then represents the econometrician's posterior inference as to the value of $\mu(\mathbf{x}^*)$.

As a first step for seeing what the nonlinear function $\mu(.)$ looks like, I fixed the values of o_{t-2}, o_{t-3}, and o_{t-4} equal to their sample means and examined the consequences of changing o_{t-1} alone, that is, I set $\mathbf{x}^* = (x_1, \overline{o}, \overline{o}, \overline{o})$ and evaluated the Bayesian posterior expectation of (2.4) for various values of x_1. Figure 3 plots the result as a function of x_1 along with 95% probability regions. The regions are narrowest for values of x_1 closest to the sample mean, for these represent the values of $\mathbf{x}^*$ for which we can have the greatest confidence about the inference. The implied function is nonlinear, suggesting that if oil prices either increase or decrease after three quarters of stability, the forecast calls for slightly slower GDP growth than if oil prices had remained stable, though increases are worse news than decreases.

Figure 4 answers the analogous question, fixing o_{t-1}, o_{t-3}, and o_{t-4} equal to their sample means and varying the value of o_{t-2}. Both it and Figure 5 (the effect of o_{t-3} in isolation) give a similar impression to that of Figure 3. Figure 6 (the effect of o_{t-4} alone) is somewhat more dramatic, suggesting that decreases in oil prices four quarters earlier have essentially no consequences for current GDP growth, whereas oil price increases significantly reduce expected GDP growth. The figure indicates that Mork's (1989) asymmetric specification (1.2) is exactly the form suggested by the data, at least as far as describing the consequences of changing o_{t-4} alone are concerned.

To get an impression about interactive effects, I calculated how the apparent consequences of o_{t-3} are affected by different values of o_{t-4}. Figure 7 compares the three functions $\hat{\mu}(\bar{o}, \bar{o}, x_3, 0)$, $\hat{\mu}(\bar{o}, \bar{o}, x_3, 5)$, and $\hat{\mu}(\bar{o}, \bar{o}, x_3, -5)$, plotted as a function of x_3. The first relation is represented by the solid line, which is essentially the same as the mean value plotted in Figure 5. The second relation shows how the effect of an x_3 percent oil price increase 3 quarters ago would be different if oil prices had also increased 5% the quarter before that. This is represented by the lower, short-dashed line in Figure 7. The line is uniformly lower than the solid line– an oil price increase 4 quarters earlier definitely causes one to lower the forecast for GDP growth, regardless of the value of o_{t-3}. Even so, if one compares the solid and short-dashed line at any given x_3, the slope of the short-dashed line is less steep than the solid line– an oil price increase 4 quarters earlier reduces the additional information content of any change, up or down, in quarter $t-3$. The top, long-dashed line plots the predicted GDP growth for quarter t when $o_{t-3} = x_3$ and $o_{t-4} = -5$. If oil prices went down 4 quarters earlier, this has little consequences for forecasting GDP if it was followed by $o_{t-3} = 0$. If a 5% decrease was followed by another change, either up or down, one should downweight the otherwise contractionary signal implied by the oil price change in period $t-3$. Overall, Figure 7 supports the view of Lee, Ni, and Ratti (1995) and Hamilton (1996) that previous turbulence in oil prices causes the marginal effect of any given oil price change to be reduced.

Another way to make this point is to look at how the three lines in Figure 7 would be predicted to appear under alternative parametric nonlinear models. The upper left panel of Figure 8 shows the values for $\tilde{\mu}(\bar{o}, \bar{o}, x_3, 0), \tilde{\mu}(\bar{o}, \bar{o}, x_3, 5)$, and $\tilde{\mu}(\bar{o}, \bar{o}, x_3, -5)$ for $\tilde{\mu}(\mathbf{x}^*) = \tilde{\alpha}_0 + \tilde{\boldsymbol{\alpha}}'\mathbf{x}^*$ the fitted values from the simple linear regression (1.6). Each plot is a straight line with slope -0.004, and changing o_{t-4} by ± 5 induces a parallel shift of the line by ∓ 0.080. The two key ways in which this figure differs from what appears in the flexible nonlinear summary of the data (Figure 7) are that, according to the flexible inference, negative values of o_{t-3} imply lower GDP growth rather than higher values as required by the linear specification, and the flexible inference suggests that negative values of o_{t-4} have a much smaller effect than do positive values of o_{t-4}.

The upper right panel of Figure 8 plots the analogous three relations for Mork's specification (1.8). The solid line plots $\mu^+(\bar{o}, \bar{o}, x_3, 0)$, which is a horizontal line for negative values of x_3 and a line with slope -0.007 for positive values of x_3. The plot of $\mu^+(\bar{o}, \bar{o}, x_3, -5)$ is exactly the same relation, since under Mork's specification, negative values for o_{t-4} are completely irrelevant. The plot of $\mu^+(\bar{o}, \bar{o}, x_3, 5)$ is a vertical downward shift of these curves by 0.11. The key difference between this panel of Figure 8 and what appears to be in the data in Figure 7 is that, contrary to Mork's specification, an oil price decrease in $t-4$ appears to mitigate somewhat the effects of an oil price increase in $t-3$.

Hamilton (1996) argued that an oil price increase of 10% that comes immediately after an oil price decrease of 20% would do little to alarm consumers or deter them from purchasing gas-guzzling vehicles. He suggested looking at the net amount by which oil prices have gone up over the past year as a better measure than the amount by which oil prices go up in any given quarter. His measure of the net oil price increase, $o_t^\dagger$, is defined as the amount by which oil prices in quarter t exceed their peak value over the previous 12 months; if they do not exceed the previous peak, then $o_t^\dagger$ is taken to be zero. OLS estimates of a relation based on this measure are as follows:

$$\begin{aligned} y_t \;=\; & \underset{(0.13)}{0.89} + \underset{(0.07)}{0.25}\, y_{t-1} + \underset{(0.07)}{0.11}\, y_{t-2} - \underset{(0.07)}{0.07}\, y_{t-3} - \underset{(0.07)}{0.14}\, y_{t-4} \\ & - \underset{(0.012)}{0.009}\, o^\dagger_{t-1} - \underset{(0.013)}{0.011}\, o^\dagger_{t-2} - \underset{(0.013)}{0.012}\, o^\dagger_{t-3} - \underset{(0.012)}{0.031}\, o^\dagger_{t-4}. \end{aligned} \tag{3,2}$$

Estimates of $\mu^\dagger(\overline{o}, \overline{o}, x_3, 0)$, $\mu^\dagger(\overline{o}, \overline{o}, x_3, -5)$, and $\mu^\dagger(\overline{o}, \overline{o}, x_3, 5)$ based on this OLS regression are plotted in the lower left panel of Figure 8 under the assumption that oil prices had been steady prior to period $t-4$. The first relation (solid line) is a horizontal line for negative values of o_{t-3} and a line with slope -0.012 for positive values of o_{t-3}. If instead $o_{t-4} = -5$ (dashed line), oil price increases only matter in $t-3$ to the extent they exceed 5%, causing the horizontal line to be extended 5% before turning down. By contrast, if $o_{t-4} = 5$ (alternate-dashed line), the original relation is everywhere shifted down by 0.015. These features are roughly consistent with what appears in the flexibly estimated nonlinear relation (Figure 7).

Lee, Ni, and Ratti (1995) pursued a related idea based on a GARCH representation of oil prices, arguing that a given change in oil prices would have a smaller effect when conditional variances are large since much of the change in oil prices would be regarded as transitory. Let o_t^R denote the real change in oil prices ($o_t^R = o_t - \Delta \ln(p_t)$ for p_t the GDP deflator for quarter t). Lee, Ni and Ratti reported the following GARCH parameter estimates[12]

$$o_t^R = -0.4965 + 0.436\ o_{t-1}^R - 0.401\ o_{t-2}^R + 0.244\ o_{t-3}^R - 0.238\ o_{t-4}^R + e_t \tag{3.3}$$

$$e_t = \sqrt{h_t} v_t \qquad \nu_t \sim N(0,1) \tag{3.4}$$

$$h_t = 1.49 + 2.208\ e_{t-1}^2 + 0.197\ h_{t-1}. \tag{3.5}$$

This highly explosive GARCH process has root 2.405 much greater than one, with oil price volatility leading to rapid increases in the variance and periods of calm bringing it quickly back down within sample. The average value for e_t^2 when calculated from (3.3) in my sample is 122, and the average value for $\sqrt{h_t}$ when generated from equation (3.5) starting from $h_0 = 100$ is 10.54. Following Lee, Ni and Ratti,[13] I defined the volatility-adjusted real oil price increase $o_t^\ddagger$ to be $o_t^R/\sqrt{h_t}$ when the latter is positive and zero otherwise. I used h_t generated from (3.3)-(3.5) to construct $o_t^\ddagger$ and obtained the following OLS estimates:

$$\begin{aligned} y_t \quad = \quad & \underset{(0.13)}{1.05} + \underset{(0.07)}{0.20}\ y_{t-1} + \underset{(0.07)}{0.12}\ y_{t-2} - \underset{(0.07)}{0.09}\ y_{t-3} - \underset{(0.07)}{0.12}\ y_{t-4} \\ & - \underset{(0.11)}{0.18}\ o_{t-1}^\ddagger - \underset{(0.11)}{0.07}\ o_{t-2}^\ddagger - \underset{(0.11)}{0.33}\ o_{t-3}^\ddagger - \underset{(0.11)}{0.46}\ o_{t-4}^\ddagger. \end{aligned} \tag{3.6}$$

The lower right panel of Figure 8 was then constructed as follows. Suppose that h_{t-4} was equal to 122 (the average value for e_t^2 in sample) and that, if o_{t-4} had equalled its average value in sample (0.4), then e_{t-4} would have been zero. Then to calculate the predicted consequences of changing o_{t-3} when o_{t-4} was not the sample average of 0.4 but instead was

[12] Figures from Table 3 in Lee, Ni, and Ratti have been converted from the annual rates used by these authors for comparability with the quarterly rates used throughout this paper.

[13] These authors used $e_t/\sqrt{h_t}$ rather than $o_t^R/\sqrt{h_t}$ as their measure. Results should be similar, and o_t^R is used here for compatability with the other results in this paper.

equal to -5, the implied value for h_{t-3} would be

$$h_{t-3} = 1.49 + (2.208)(5.4)^2 + (0.197)(122) = 89.90$$

whose square root is 9.48. Positive values for x_3 thus imply a value for $o^{\ddagger}_{t-3}$ of $x_3/9.48$ when $o_{t-4} = -5$. The plot of $\mu^{\ddagger}(\overline{o}, \overline{o}, x_3, -5)$ is thus a horizontal line for negative values of x_3 and a line with slope $-0.33/9.48$ for positive values of x_3 (the short-dashed line in the lower right panel of Figure 8).

If instead the oil price change in period $t-3$ followed a quarter of constant rather than falling oil prices, we have

$$h_{t-3} = 1.49 + (2.208)(0.4)^2 + (0.197)(122) = 25.88$$

for which $\mu^{\ddagger}(\overline{o}, \overline{o}, x_3, 0)$ is again a horizontal line for negative values of x_3 but now the solid line with the steeper slope of -0.33/5.09 for positive values. Finally, if $o_{t-4} = 5$, the relation is everywhere shifted down by $-0.46 \times 5 \div \sqrt{122} = -0.21$, but the marginal effect of o_{t-3} is now smaller owing to a higher value for h_{t-3} caused by the oil price increase in $t-4$. The flatter slope implies that the graphs of $\mu^{\ddagger}(\overline{o}, \overline{o}, x_3, 0)$ and $\mu^{\ddagger}(\overline{o}, \overline{o}, x_3, 5)$ eventually cross for sufficiently high values of x_3. One does not see such crossing in Figure 7, though the ability of the flexible inference to detect such a feature is likely to be quite weak, and the broad pattern of the bottom right panel of Figure 8 is otherwise quite consistent with that in Figure 7.

There is a more formal statistical basis for comparing the nonlinear dynamics implied by alternative specifications with what appears in the data from the flexible inference procedure used here. Note that Mork's specification (1.8), Hamilton's specification (3.2), and Lee, Ni, and Ratti's specification (3.6), although nonlinear functions of oil prices, are linear functions of the parameters, that is, they all can be described as a linear regression model of the form[14]

$$y_t = \alpha_0 + \boldsymbol{\delta}'\mathbf{z}_t + \varepsilon_t \tag{3.7}$$

for a suitable specification of $\mathbf{z}_t$. For example, equation (3.2) is a special case of (3.7) with $\mathbf{z}_t = (y_{t-1}, y_{t-2}, y_{t-3}, y_{t-4}, o^{\dagger}_{t-1}, o^{\dagger}_{t-2}, o^{\dagger}_{t-3}, o^{\dagger}_{t-4})'$. As such, one can test directly whether such a specification for $\mathbf{z}_t$ adequately captures any nonlinearity that appears in the data by comparing (3.7) with the more general model

$$y_t = \alpha_0 + \boldsymbol{\delta}'\mathbf{z}_t + \lambda m(\mathbf{x}_t) + \varepsilon_t$$

for $\mathbf{x}_t = (o_{t-1}, o_{t-2}, o_{t-3}, o_{t-4})$ and $m(.)$ a realization of the random field whose correlations are characterized by (2.2). A test of the null hypothesis $\lambda = 0$ is now a test of whether the definition of $\mathbf{z}_t$ adequately captures the nonlinear dependence of y_t on o_{t-j}. This is simply a special case of the test already described in (2.6). By changing the definition of $\mathbf{z}_t$, the test has been adapted from testing the null hypothesis of linearity to testing the null hypothesis that the nonlinearity takes on a particular known form.

The results of this specification test result in ν^2 p-values of 0.08 for Mork's formulation (1.8), 0.05 for net oil price formulation (3.2), and 0.48 for Lee, Ni and Ratti's formulation

[14] This discussion ignores the fact that $o^{\ddagger}_t$ is a generated regressor. Mitigating any concerns about this is the fact that the parameters used to construct $o^{\ddagger}_t$, although estimated, were estimated using a different sample from that used here. In any case, no such concerns apply to interpreting the statistical results for o^{+}_t and $o^{\dagger}_t$.

(3.6). It would seem on the basis of these tests that the Lee, Ni, and Ratti formulation does the best job of summarizing the nonlinearity.

The problems with the net oil price measure are most acute for the last two years of data. The oil price surge of 1999 was not followed by a noticeable economic slowing in 2000. Figure 9 plots the logarithm of nominal crude oil prices over the sample. The Asian financial crisis was associated with a drop in world oil prices of over 50% during 1997 and 1998. Although the price increases in the first half of 1999 set a new annual high, and thus qualify as a "net oil price increase" by Hamilton's (1996) measure, even by the end of 1999 they had only recovered what was lost in 1997 and 1998. If an oil price movement that simply restores prices to where they were two years earlier does not cause consumers and firms to alter their spending plans, then perhaps a net oil price increase relative to a three-year rather than a one-year horizon is the more appropriate measure. To investigate this possibility, let $o_t^{\#}$ denote the amount by which oil prices in quarter t exceed their value over the previous 12 quarters; if they do not exceed their previous peak, then $o_t^{\#}$ is taken to be zero. OLS estimation results in

$$\begin{aligned} y_t &= \underset{(0.13)}{0.98} + \underset{(0.07)}{0.22}\, y_{t-1} + \underset{(0.07)}{0.10}\, y_{t-2} - \underset{(0.07)}{0.08}\, y_{t-3} - \underset{(0.07)}{0.15}\, y_{t-4} \\ &\quad - \underset{(0.014)}{0.024}\, o_{t-1}^{\#} - \underset{(0.014)}{0.021}\, o_{t-2}^{\#} - \underset{(0.014)}{0.018}\, o_{t-3}^{\#} - \underset{(0.014)}{0.042}\, o_{t-4}^{\#}. \end{aligned} \quad (3.8)$$

The ν^2 test of the null hypothesis that (3.8) adequately captures the nonlinearity of the oil-GDP relation is accepted with a p-value of 0.21.

4 Structural stability.

Much of the interest in nonlinear functional forms comes from evidence of instability in a simple linear relation (Hooker, 1996, 1999). This section investigates this issue using the data set and the specifications considered here.

Let $\mathbf{z}_t = (1, y_{t-1}, y_{t-2}, y_{t-3}, y_{t-4})'$ denote the vector of linear explanatory variables and $\mathbf{x}_t$ a candidate vector of lagged nonlinear oil price transformations. For example, in the Mork formulation, $\mathbf{x}_t = (o^+_{t-1}, o^+_{t-2}, o^+_{t-3}, o^+_{t-4})'$. The standard chi-square test of the null hypothesis of a stable relation against the alternative that the oil coefficients changed at date t_1 is given by

$$F_{t_1} = \frac{(T-9)(RSS_0 - RSS_1)}{RSS_1} \tag{4.1}$$

where RSS_0 denotes the residual sum of squares from OLS estimation of

$$y_t = \boldsymbol{\delta}'\mathbf{z}_t + \boldsymbol{\beta}'\mathbf{x}_t + \varepsilon_t \tag{4.2}$$

whereas RSS_1 denotes the residual sum of squares of

$$y_t = \boldsymbol{\delta}'\mathbf{z}_t + \boldsymbol{\beta}_0'\mathbf{x}_t\delta_{[t\leq t_1]} + \boldsymbol{\beta}_1'\mathbf{x}_t\delta_{[t>t_1]} + \varepsilon_t$$

with both regressions based on observations $t = 1, 2, ..., T$. Under the null hypothesis of no change in the oil price coefficients, F_{t_1} would have a $\chi^2(4)$ distribution asymptotically.

We calculated the value of the statistic F_{t_1} for every possible value of t_1 between 1957:I and 1993:III, that is, for each possible mid-sample date at which the relation might have changed. The top panel of Figure 10 plots the $\chi^2(4)$ p-value from this test as a function of the break date t_1 for $\mathbf{x}_t$ corresponding to Mork's measure of positive oil price changes. The other panels of Figure 10 repeat this procedure for $\mathbf{x}_t$ corresponding to each of the other three nonlinear oil transformations discussed above. One would find consistent evidence of a structural break at any date after 1982 if one used Mork's measure and evidence of a structural break at any date after 1990 if one used the annual net oil price increase. There is no date in the sample at which one could claim to find a statistically significant break in the relation if one used either the three-year net oil price measure or the Lee, Ni, and Ratti transformation.

Of course, when one looks at a whole range of values of t_1 as here and selects the most adverse value between $T_1 = [\pi T]$ and $T_2 = [(1-\pi)T]$, the resulting statistic,

$$\sup_{t_1 \in \{T_1, T_1+1, \ldots, T_2-1, T_2\}} F_{t_1}, \tag{4.3}$$

no longer has a $\chi^2(4)$ distribution, but instead has an asymptotic distribution calculated by Andrews (1993). When one compares the statistic (4.3) with Andrews's 5% critical value, all of the four relations are found to be stable (see Table 2).

An alternative measure is to use not the most extreme value of F_{t_1} but instead its average value,

$$\text{Avg } F = (T_2 - T_1 + 1)^{-1} \sum_{t_1=T_1}^{T_2} F_{t_1},$$

as suggested by Andrews and Ploberger (1994). By this test, the Mork measure is found to exhibit statistically significant instability, though none of the other three are unstable (see again Table 2). Andrews and Ploberger also suggest the alternative statistic,

$$\text{Exp } F = \log \left[(T_2 - T_1 + 1)^{-1} \sum_{t_1 = T_1}^{T_2} \exp(F_{t_1}/2) \right].$$

As reported in Table 2, none of the four measures exhibit instability by this test.

An alternative is to test whether all of the coefficients (including the constant term and coefficients on lagged GDP) may have changed, using a $\chi^2(9)$ test in place of the $\chi^2(4)$ test in (4.1). Table 3 reports results from this test, using the asymptotic p-values proposed by Hansen (1997) and bootstrap p-values (using 1000 simulations) developed by Hansen (2000), both under an assumption of homoskedastic disturbances and heteroskedastic disturbances.[15]

None of the tests finds evidence of instability in the Lee, Ni, Ratti specification, though tests that assume homoskedastic errors invariably reject stability of the other three measures. Comparing Tables 2 and 3, it appears that any instability of relations based on the net oil price measures is primarily due to changes in the constant term or coefficients on lagged GDP rather than changes in the coefficients on oil prices.

Finally, I explore the suggestion in Hooker (1999) that the statistical significance of the oil-GDP relation is entirely due to pre-1980 data. Extending the idea in his Table 2, I estimated the fixed-coefficient regression (4.2) by OLS over $t = t_1, t_1 + 1, ...,$2001:III, using every possible starting point t_1 between 1948:II and 1989:IV. For each t_1, I calculated the p-value of the F-test of the null hypothesis that the oil-price coefficients $\boldsymbol{\beta}$ were all zero. Figure 11 plots this p-value as a function of the sample starting data t_1. The top

[15] I am grateful to Bruce Hansen for making the computer code publicly available at http://www.ssc.wisc.edu/~bhansen.

panel replicates Hooker's finding that, if one starts the sample at any date after 1960, the hypothesis that Mork's measure of oil prices has no effect on GDP would be accepted at the 5% significance level. With the annual net oil price measure, the relation is marginally significant when estimated with data beginning any time before 1975. Both the 3-year net oil increase and the Lee, Ni, and Ratti measures exhibit statistical significance as long as the sample includes both the 1990 and the 1981 oil shocks, and, with the former measure, there is some suggestion of a significant relation even if the only big oil shock in the sample is that of 1990.

To summarize, neither Mork's measure nor the 1-year net oil increase measure can do an adequate job of capturing a stable nonlinear relation between oil prices and GDP. On the other hand, both the 3-year net increase and the Lee, Ni, and Ratti measure do seem to capture the relation adequately, with the data slightly favoring the latter.

None of this addresses the evidence that Hooker (1999) reports of instability in larger vector systems. Particularly given the conflicting impressions from Tables 2 and 3, it is possible that there have been changes in monetary policy or the behavior of GDP itself. Changes in the cyclical volatility of GDP are explored in McConnell and Perez-Quiros (2000), while the role of the monetary policy reaction function in the oil-GDP relation is discussed in depth in Hamilton and Herrera (2001). Both issues deserve to be explored further in future research. But the primary question posed in this paper, namely, what is the functional form appropriate for (2.1), appears to have been adequately addressed here.

5 A Linear Instrumental Variable Interpretation.

We framed the investigation in Section 3 in the form of a pure question about forecasting, to wit, What is the correct functional form for describing the conditional expectation of GDP growth y_t conditional on lagged GDP growth and lagged oil price changes? The answer to this forecasting question could be given a causal interpretation if one were persuaded that oil price changes are exogenous.

Hamilton (1983, 1985) argued that, over the period 1948-1972, oil prices were indeed exogenous with respect to the U.S. economy, on the basis of institutional, historical, and statistical evidence. Institutionally, there was a particular reason why endogenous factors had no effect on oil prices during this period. U.S. oil producing states had commissions that actively regulated the quantity of oil that could be produced by each field, the most important of which was the Texas Railroad Commission (TRC). Whenever demand went up, the TRC would increase the amount of production it allowed, and when demand went down, the TRC would decrease the amount of production, thus preventing demand changes from causing any change in price. The only events that did change the price were exogenous disruptions to supply. Historically, one can unambiguously identify the events behind major oil price movements in this period, and they are clearly political and military developments that have little to do with the U.S. macroeconomy. In terms of statistical evidence, Granger-causality tests uncover no U.S. macroeconomic variables that could have predicted oil price changes over this period, bolstering the case for the claim of exogeneity.

None of these arguments applies to post-1973 data, however. The Texas Railroad Commission ceased to be relevant once the Middle East oil producers became the dominant factor in the world petroleum market. Today oil prices respond quite dramatically to demand conditions with constant adjustment and readjustment. Statistically, oil prices certainly are predictable from U.S. macroeconomic developments in post-1973 data (Barsky and Kilian, 2001).

If one is interested in a causal interpretation rather than a simple forecasting equation, it would be useful to isolate the component of the post-1973 oil price movements that could be attributed to strictly exogenous events. To do so, I have developed a quantitative version of the dummy-variable approach used by Dotsey and Reid (1992) and Hoover and Perez (1994). There are a number of historical episodes in which military conflicts produced dramatic and unambiguous effects on the petroleum production from particular sources. Figure 12 plots monthly levels of crude oil production over 1972 to 1992 for the three countries most affected by several of these events; these particular data are only available for the twenty-year period shown. One can see the consequences of three military conflicts quite distinctly on these graphs. Starting with the most recent, in July 1990, Iraq and Kuwait had been producing 5.3 million barrels of oil daily. After Iraq invaded Kuwait, production from these two countries stopped altogether. This shortfall amounted to 8.8% of total world petroleum production. It seems abundantly clear that this fall in production was caused by military rather than economic events.

One also sees quite clearly in the second graph the effects of the Iranian revolution. Iranian oil production fell from 6.1 million barrels a day in September 1978 to 0.7 mbd by

January 1979, representing an 8.9% drop in total world production.

Iranian production recovered somewhat, but again came to a virtual standstill as the military conflict with Iraq developed. The drop in Iraqi production caused by this conflict (top panel) is particularly abrupt and dramatic.

Substantially less apparent in these figures are the events associated in many people's minds with the first big oil shock. In October 1973, Egypt and Syria launched a military offensive against Israel, and, in support, the Organization of Arab Petroleum Exporting Countries imposed a boycott on countries perceived to be sympathetic to Israel. To the extent that the military conflict could be claimed to be the proximate cause of the production cutbacks, the nature of the causation is quite different from that for the three episodes described above. In the Iranian revolution, Iran-Iraq War, and the Persian Gulf War, the conflicts physically precluded the shipment of oil at the pre-war levels. In the Arab-Israeli War of 1973, by contrast, the decision to cut back oil production was a calculated political/military decision. Barsky and Kilian (2001) observed that, "there is considerable evidence that oil producers carefully considered the economic feasibility of the oil embargo," and argued therefore that there was a substantial component of the 1973 oil price shock that could be viewed as an endogenous response to world economic conditions.

Barsky and Kilian are surely correct in concluding that oil prices would have gone up substantially in 1973 and 1974 even had there been no Arab-Israeli conflict. Notwithstanding, the price of Saudi crude went from $3.01 a barrel on October 15 to $11.65 in January, nearly quadrupling in the space of three months. To attribute both the timing and magnitude of this increase entirely to a lagged response to a shift in the demand curve, and to dismiss any contributory role of the war that happened to immediately precede it, strains credulity. Several other details of this episode are difficult to reconcile with Barsky and Kilian's interpretation. First, while oil production from the Arab members of OPEC fell by 4.3 million barrels a day between September and November 1973, production in the rest of the world rose by 0.5 million barrels a day over these same two months. If economic factors were entirely the cause, it is difficult to see why such factors would have caused Arab oil producers to reach a different decision from non-Arab oil producers. Second, the embargo appeared to be spearheaded not by the biggest oil producers, who would be expected to have the most important economic stake, but rather by the most militant Arab nations, some of whom had no oil to sell at all. For example, the *Economist* accounted for the participation of the main oil-producing states in the production cutbacks this way: "On Tuesday, when Radio Baghdad began denouncing Saudi Arabia as a reactionary monarchy, the Gulf states had some idea of what those consequences would be. There is not much doubt that if they held back, Cairo, Damascus, and Baghdad would have launched a barrage of hostile propaganda against them and that guerilla movements in the Gulf would have been greatly strengthened. So the Gulf states opted for the stringent measures that Egypt, the spokesman for the radicals, was seeking," (October 20, 1973, page 36). Third, if economic factors were all that was involved, it is not clear why the production cutbacks were targeted at particular countries, nor why shipments were conditioned on specific diplomatic demands, as in fact they were.

Thus, while I am sympathetic to Barsky and Kilian's claim that some increase in oil prices would have occurred in 1973-74 even had there been no Arab-Israeli War, I am equally persuaded that the outbreak of hostilities caused the oil price increases to be substantially larger and more abrupt than they would have been in the absence of military conflict. As one way of separating the endogenous and exogenous components of the 1973-74 oil shock, I suggest that the drop in production by the Arab members of OPEC between September 1973 and November 1973 (representing a 7.8% fall in world production) should be attributed to military and political events rather than an endogenous response to economic developments, and propose that the component of the 1973-74 oil price increase that can be attributed to the Arab production cutbacks can be viewed as a valid measure of an exogenous oil price shock.

The final example of a clearly exogenous source of oil price movements is the Suez Crisis. In October 1956, Israeli troops invaded Egypt's Sinai Peninsula, followed by the French and British. In the ensuing crisis, oil tankers were prevented from using the Suez Canal, through which 1.2 million barrels of oil had been carried by tankers each day. The major pipeline that carried another half million barrels of oil per day from Iraq through Syria was sabotaged, and exports of Middle East oil to Britain and France were blockaded.[16]

The magnitude of the exogenous production cutbacks that arose from these five events is summarized in Table 4, which also provides further details on how the particular figures were calculated. I have dated each episode by the month in which there was the largest

[16] *Oil and Gas Journal,* November 12, 1956, pp. 122-125.

observed drop in oil production.

I then constructed a series Q_t which is defined as the magnitude of the production shortfall identified in Table 1 if an indicated episode began in quarter t and is zero otherwise, and claim that Q_t is a valid exogenous instrument for disturbances to world petroleum supplies. Note that in each case, the measure Q_t is based on how much petroleum production fell in the affected countries only. In each episode, petroleum production increased somewhere else in the world to make up in part for the lost production in the affected regions. However, it seems clear that the latter represents an endogenous response to the crisis rather than a separate exogenous event. If one wants a measure of the magnitude of the exogenous shock itself (which set off both an endogenous supply response elsewhere as well as any possible macroeconomic consequences), it is clear that Q_t is the correct measure to use in any reduced-form evaluation. Note, however, that the statistical consequences of a given shock of $Q_t = \Delta$ measure the effect of the usual historical case in which a magnitude Δ shock to petroleum production in one particular region is partly cushioned by increased production in some other part of the world, as opposed to finding the answer to the hypothetical (and counterfactual) question, What would be the effects if production were exogenously decreased by the amount Δ in some region and there was no possibility of making up this lost production elsewhere?

Although we have a clear measure of the timing and magnitude of the initial supply disruption, the endogenous response of supply increases following these shocks makes it difficult to measure how long the crisis persisted. For this reason, we simply use the size and date of the initial shock as the exogenous explanatory variable and allow unrestricted lags of this variable to summarize the cumulative economic consequences of this initial shock over time.

The suggestion is then that the fitted values of a regression of o_t on a constant and $Q_t, Q_{t-1}, ..., Q_{t-4}$ represent a component of oil price changes that can unambiguously be attributed to exogenous events. These fitted values $\hat{o}_t$ are plotted in the bottom panel of Figure 13, along with three of the nonlinear transformations of oil prices (top panels). All three transformations attenuate or eliminate most of the movements in oil prices other than those coming from these five episodes. The 3-year net oil price increase series (third panel) is particularly similar in appearance to the fitted values $\hat{o}_t$. Thus the nonlinear transformation that produced $o_t^{\#}$ from current and lagged values of o_t seem in practice to be doing something rather similar to isolating the exogenous component of oil price changes.

If one thought that the true causal relation between y_t and o_t were linear, but that much of the historical movement in oil prices was caused by endogenous factors, the correct approach would be to estimate a relation of the form of (1.6) using as instruments $Q_{t-1}, Q_{t-2}, ..., Q_{t-8}, y_{t-1}, ..., y_{t-4}$, and a constant. The result of this instrumental variable estimation is

$$\begin{aligned} y_t &= \underset{(0.17)}{0.95} + \underset{(0.09)}{0.20}\, y_{t-1} + \underset{(0.10)}{0.11}\, y_{t-2} - \underset{(0.10)}{0.04}\, y_{t-3} - \underset{(0.09)}{0.17}\, y_{t-4} \\ &\quad - \underset{(0.029)}{0.028}\, o_{t-1} - \underset{(0.027)}{0.052}\, o_{t-2} - \underset{(0.026)}{0.013}\, o_{t-3} - \underset{(0.031)}{0.064}\, o_{t-4}. \end{aligned} \tag{5.1}$$

The estimates in (5.1) are remarkably similar to those obtained by OLS for the pre-1980 data in (1.5), over which period I have argued that essentially all oil price changes were exogenous, and likewise quite similar to estimates based on the 3-year net oil price series

$o_t^{\#}$ in (3.8). Figure 14 plots the implied consequences for y_{t+j} if oil prices were to increase by 10% at date t and remain at this new level, as predicted by (5.1) (top panel) and (3.8) (bottom panel). The predicted effects are quite similar in terms of both magnitude and dynamics.

To see whether this result is unduly influenced by any single oil shock, and as a check of the robustness of having selected these five episodes, I re-estimated (5.1) dropping one oil shock. For example, to not use the Suez Crisis, I set $\tilde{Q}_t = Q_t$ for all $t \neq$ 1956:IV and $\tilde{Q}_{1956:IV} = 0$. Dropping any single oil shock reduces the precision of the estimates, but does not change the overall impact that one would attribute to an oil shock. Table 5 reports results of F-tests of the null hypothesis that all the oil coefficients are zero and t-tests of the null hypothesis that the sum of the oil coefficients is zero for instrumental variable regressions of the form of (5.1) in which one of the oil shocks has been disallowed. One would conclude that there is a statistically significant effect of oil prices on GDP from one or both of the tests on the basis of any 4 of the 5 historical oil shocks. Figure 15 plots the impulse-response functions from each of these restricted instrumental variable estimations, which illustrates again that the broad pattern of economic response is similar across all the oil shocks.

One can test formally whether the nonlinear transformations of oil prices add anything beyond that contained in the exogenous military shock component by looking at the reduced form underlying (5.1). Specifically, I regressed y_t on a constant, four lags of y_{t-j}, and eight lags of Q_{t-j}. I then added four lags of oil price increases (o_t^+) and accepted the null hypothesis that these last coefficients were all zero (p-value = 0.40). Likewise, four lags of

$o_t^\dagger$ or $o_t^\#$ add nothing to the reduced-form regression (p-value $= 0.42$ and 0.23, respectively). On the other hand, one rejects that the coefficients on the Lee, Ni and Ratti transformation ($o_t^\ddagger$) are all zero (p-value $= 0.013$). The results suggest that the predictive power of the net oil price transformations could be attributed to their ability to filter out influences on oil prices that do not come from these five particular military conflicts. The same can not be said of $o_t^\ddagger$.

6 Conclusion

There is no question that a linear regression of output on lagged oil prices exhibits instability over time. Some researchers have attributed this to the fact that the true relation is nonlinear. Others have questioned whether a specification hunt over the class of all possible nonlinear relations has simply produced a particular nonlinear relation that spuriously appears to be significant and stable.

This paper addressed this question using a framework that explicitly parameterizes the set of nonlinear relations investigated and takes into account the uncertainty about functional form in conducting hypothesis tests. The evidence appears quite strong that one should use a nonlinear function of oil price changes if the goal is to forecast GDP growth. When one looks at this nonlinear relation from a flexible, unrestricted framework, the functional form looks very much like what has been suggested in earlier parametric studies. In particular, it is quite clear from the data that oil price increases are much more important for predicting GDP than are decreases, and that oil price changes are less useful for forecasting if they follow a period of earlier volatile price changes, as suggested by earlier researchers. The transformation proposed by Lee, Ni, and Ratti (1995) seems to do the best job of the measures explored in this paper. A measure that specifies that an oil shock occurs when oil prices exceed their 3-year peak also seems to be acceptable.

The paper further suggested a linear instrumental variable interpretation of at least part of this phenomenon. One can clearly identify five military conflicts in the Middle East that have significantly disrupted world petroleum supplies. If the magnitudes of these disruptions are used as an instrument for oil price changes, the predictions of a linear IV regression are very similar to those of the nonlinear specifications. It thus appears that part of the success of the nonlinear specifications is that they filter out many of the endogenous factors that have historically contributed to changes in oil prices.

What guide does this analysis suggest for applied research? Use of oil prices themselves as an exogenous instrument or disturbance is certainly called into question. In its place, the simplest and most robust alternative might be the Dotsey and Reid (1992) or Hoover and Perez (1994) dummy variables for exogenous oil supply shocks, or the refinement suggested here of using current and lagged values of Q_t in place of oil prices themselves.

Given that the heart of the oil-price macroeconomy relation appears to be driven by these five big shocks, it remains a distinct possibility that it is events associated with the military conflicts themselves, rather than the specific changes in oil prices, that leads the economy into recession. The wars may lead to anxiety about future energy prices and availability or have other psychological effects whose consequences for consumer spending or conduct of monetary policy are as important or more important than the movements in oil prices themselves. Notwithstanding, what we can say with confidence is that historically, these events have proven highly disruptive to the U.S. economy.

Appendix A

The Bayesian priors used in this study consist of (i) a gamma prior for σ^{-2},

$$p(\sigma^{-2}) = \frac{\xi^{\nu}}{\Gamma(\nu)} \sigma^{-2(\nu-1)} \exp[-\xi\sigma^{-2}],$$

with $\nu = 0.25$ and $\xi = (\nu s_y^2/2)$ for s_y^2 the sample variance of y;.(ii) a Gaussian distribution for $\boldsymbol{\beta}$ conditional on σ^{-2},

$$p(\boldsymbol{\beta}|\sigma^{-2}) = \frac{1}{(2\pi\sigma^2)^{(p+k+1)/2}} |\mathbf{M}|^{-1/2} \exp\left[\left(\frac{-1}{2\sigma^2}\right)(\boldsymbol{\beta} - \mathbf{m})'\mathbf{M}^{-1}(\boldsymbol{\beta} - \mathbf{m})\right],$$

where the first element of $\mathbf{m}$ is the sample mean of y_t and all other elements of $\mathbf{m}$ are zero, and where $\mathbf{M} = T(\mathbf{X}'\mathbf{X})^{-1}$, so that the prior has the weight of a single observation on $(y_t, \mathbf{x}_t')$; and a lognormal prior for each element of $(\mathbf{g}',\zeta)$, where $\zeta = \lambda/\sigma$:

$$p(\mathbf{g}, \boldsymbol{\zeta}) = \frac{1}{\sqrt{2\pi}} \exp\left\{-\left[\ln(\zeta)\right]^2/2\right\} \prod_{i=1}^{k} \frac{1}{\sqrt{2\pi}\tau_i g_i} \exp\left[\frac{-[\ln(g_i) - \vartheta_i]^2}{2\tau_i^2}\right],$$

where for $i = 1, ..., k$ we set $\tau_i = 1$ and $\vartheta_i = -\ln\left(\sqrt{k s_i^2}\right)$ for $s_i^2 = T^{-1}\sum_{t=1}^{T}(x_{it} - \bar{x}_i)^2$ and $\bar{x}_i$ the sample mean of the ith explanatory variable.

Table 1

Alternative tests of the null hypothesis that $\mu(\mathbf{x}_t, \mathbf{z}_t) = \boldsymbol{\alpha}'\mathbf{x}_t + \boldsymbol{\delta}'\mathbf{z}_t$.

Test statistic	*Value*	*Asymptotic p-value*	*Bootstrap p-value*
Hamilton's ν^2	86.81	0.000	0.002
Dahl-González-Rivera λ^A	44.71	0.000	0.012
Dahl-González-Rivera λ^E	53.95	0.000	0.001
Dahl-González-Rivera g^A	17.74	0.219	0.254

Table 2

Tests for stability of coefficients on oil prices.

Oil price measure	*Sup F (date)*	*Avg F*	*Exp F*
Mork	12.11 (1991:I)	8.47*	4.77
Net increase(annual)	13.02 (1990:IV)	7.04	4.17
Net increase(3 years)	7.02 (1970:II)	3.85	2.25
Lee, Ni, Ratti	6.22 (1970:I)	3.65	2.03
Asymptotic 5% critical value	16.45	7.67	5.23

Notes to Table 2:

All tests use $\pi = 0.15$ and test $p = 4$ restrictions. Critical values taken from Andrews (1993, p. 840) and Andrews and Ploberger (1994, pages 1399 and 1401). An asterisk (*) denotes statistically significant at 5% level.

Table 3

Tests for stability of all coefficients

Oil price measure	*Test statistic*	*Asymptotic p-value*	*Homoskedastic bootstrap p-value*	*Heteroskedastic bootstrap p-value*
Mork	Sup F	0.018*	0.013*	0.130
	Avg F	0.006**	0.008**	0.077
	Exp F	0.003**	0.001**	0.014*
Net increase (annual)	Sup F	0.019*	0.029*	0.119
	Avg F	0.006**	0.015*	0.074
	Exp F	0.004**	0.008**	0.016*
Net increase (3 years)	Sup F	0.036*	0.045*	0.139
	Avg F	0.012*	0.018*	0.077
	Exp F	0.048*	0.035*	0.049*
Lee, Ni, Ratti	Sup F	0.400	0.399	0.592
	Avg F	0.289	0.316	0.495
	Exp F	0.325	0.361	0.389

Notes to Table 3:

All tests use $\pi = 0.15$ and test $p = 9$ restrictions. Asymptotic p-values calculated as in Hansen (1997), bootstrap p-values as in Hansen (2000). An asterisk (*) denotes statistically significant at 5% level, double asterisk (**) denotes significant at 1% level.

Table 4

Exogenous disruptions in world petroleum supply.

Date	*Event*	*Drop in world production*
Nov. 1956	Suez Crisis	10.1%
Nov. 1973	Arab-Israel War	7.8%
Nov. 1978	Iranian Revolution	8.9%
Oct. 1980	Iran-Iraq War	7.2%
Aug. 1990	Persian Gulf War	8.8%

Notes to Table 4:

1956. Middle East production fell by 1.7 million barrels per day (1.7 mbd) between October and November of 1956, or 10.1% of total world crude production of 16.8 mbd.(*Oil and Gas Journal,* April 1, 1957, p. 96.)

1973. Production of oil from the Arab members of OPEC fell from 19.865 mbd in September 1973 to 15.528 mbd in November, or a loss of 7.8% of 1973 world production of 55.679 mbd. (Data are from *Monthly Energy Review,* available from ftp://ftp.eia.doe.gov/pub/energy.overview/monthly.energy/historic.mer/tab10-1a.txt.

1978. Iranian production from 6.093 mbd in September 1978 to 0.729 mbd by January 1979, or 8.9% of 1978 world production of 60.158 mbd.

1980. Iraqi production fell from 3.240 mbd in July 1980 to 0.143 mbd by October 1980, while Iranian production fell from 1.699 mbd in July to 0.510 in October. The combined drop represents 7.2% of 1980 world oil production of 59.599 mbd.

1990. Kuwaiti production had been 1.858 mbd in July 1990 while Iraq had been producing 3.454 mbd, representing 8.8% of 1990 world production of 60.471 mbd.

Table 5

Statistical significance of oil shocks in IV regression that disallows one oil shock (p-values).

Oil shock left out	*F-test of* H_0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$	*t-test of* H_0: $\beta_1 + \beta_2 + \beta_3 + \beta_4 = 0$
Suez Crisis	0.06	0.01
Arab-Israel War	0.13	0.03
Iranian Revolution	0.01	0.04
Iran-Iraq War	0.20	0.01
Persian Gulf War	0.05	0.09

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Figure Captions

Figure 1. Simulated data when oil price changes are all increases. True relation (dashed line): $y_t = 2 - 0.1o_t + u_t$ where y_t is GDP growth, $o_t \sim N(0, 10^2)$ is the oil price change, and $u_t \sim N(0, 1.5^2)$. Estimated relation (solid line): equation (1.3).

Figure 2. Simulated data when oil prices can go up or down. True relation (dashed line): $y_t = 2 + u_t$ if $o_t \leq 0$ and $y_t = 2 - 0.1o_t + u_t$ if $o_t > 0$. Estimated relation (solid line): equation (1.4).

Figure 3. Effect of oil prices on GDP growth one quarter later. Solid line plots the posterior expectation of the function $\alpha_0 + \boldsymbol{\alpha}'\mathbf{x}_t + \boldsymbol{\delta}'\mathbf{z}_t + \lambda m(\mathbf{x}_t)$ evaluated at $\mathbf{x}_t = (x_1, \overline{o}_{-2}, \overline{o}_{-3}, \overline{o}_{-4})'$ and $\mathbf{z}_t = (\overline{y}_{-1}, \overline{y}_{-2}, \overline{y}_{-3}, \overline{y}_{-4})'$ as a function of x_1 where $\overline{z}_{-j} = T^{-1} \sum_{t=1}^{T} z_{t-j}$ and where the expectation is with respect to the posterior distribution of $\alpha_0, \boldsymbol{\alpha}, \boldsymbol{\delta}, \lambda$, and $m(\mathbf{x}_t)$ conditional on observation of $\{y_t, \mathbf{x}_t, \mathbf{z}_t\}_{t=1}^{T}$, with this posterior distribution estimated by Monte Carlo importance sampling with 20,000 simulations. Dashed lines give 95% probability regions.

Figure 4. Effect of oil prices on GDP growth two quarters later. Solid line plots the posterior expectation of the function $\alpha_0 + \boldsymbol{\alpha}'\mathbf{x}_t + \boldsymbol{\delta}'\mathbf{z}_t + \lambda m(\mathbf{x}_t)$ evaluated at $\mathbf{x}_t = (\overline{o}_{-1}, x_2, \overline{o}_{-3}, \overline{o}_{-4})'$ and $\mathbf{z}_t = (\overline{y}_{-1}, \overline{y}_{-2}, \overline{y}_{-3}, \overline{y}_{-4})'$ as a function of x_2.

Figure 5. Effect of oil prices on GDP growth three quarters later. Solid line plots the posterior expectation of the function $\alpha_0 + \boldsymbol{\alpha}'\mathbf{x}_t + \boldsymbol{\delta}'\mathbf{z}_t + \lambda m(\mathbf{x}_t)$ evaluated at $\mathbf{x}_t = (\overline{o}_{-1}, \overline{o}_{-2}, x_3, \overline{o}_{-4})'$ and $\mathbf{z}_t = (\overline{y}_{-1}, \overline{y}_{-2}, \overline{y}_{-3}, \overline{y}_{-4})'$ as a function of x_3.

Figure 6. Effect of oil prices on GDP growth four quarters later. Solid line plots the posterior expectation of the function $\alpha_0 + \boldsymbol{\alpha}'\mathbf{x}_t + \boldsymbol{\delta}'\mathbf{z}_t + \lambda m(\mathbf{x}_t)$ evaluated at $\mathbf{x}_t =$

$(\overline{o}_{-1}, \overline{o}_{-2}, \overline{o}_{-3}, x_4)'$ and $\mathbf{z}_t = (\overline{y}_{-1}, \overline{y}_{-2}, \overline{y}_{-3}, \overline{y}_{-4})'$ as a function of x_4.

Figure 7. Effect of oil prices on GDP growth three quarters later for different possible values of o_{t-4}. Each line plots the posterior expectation of the function $\alpha_0 + \boldsymbol{\alpha}'\mathbf{x}_t + \boldsymbol{\delta}'\mathbf{z}_t + \lambda m(\mathbf{x}_t)$ evaluated at $\mathbf{x}_t = (\overline{o}_{-1}, \overline{o}_{-2}, x_3, x_4)'$ and $\mathbf{z}_t = (\overline{y}_{-1}, \overline{y}_{-2}, \overline{y}_{-3}, \overline{y}_{-4})'$ as a function of x_3. For the solid line, $x_4 = 0$, for the long-dashed line, $x_4 = -5$, and for the short-dashed line, $x_4 = 5$.

Figure 8. Effects predicted by four different models. In each panel, the solid line plots (as a function of x_3) the function $E(y_t|y_{t-1} = \overline{y}_{-1}, y_{t-2} = \overline{y}_{-2}, y_{t-3} = \overline{y}_{-3}, y_{t-4} = \overline{y}_{-4}, o_{t-1} = \overline{o}_{-1}, o_{t-2} = \overline{o}_{-2}, o_{t-3} = x_3, o_{t-4} = x_4)$. For the solid line, $x_4 = 0$, for the dashed line, $x_4 = -5$, and for the alternate-dashed line, $x_4 = 5$. In the upper left panel, the conditional expectation is based on the linear regression (1.6). The other panels (reading clockwise) are based on (1.8), (3.6), and (3.2), respectively.

Figure 9. Logarithm of nominal crude oil price index, 1947:II-2001:III (1947:I = 1.00).

Figure 10. Evidence of structural change in various relations. Each figure plots the p-value for a test of the null hypothesis that regression coefficients were stable against alternative that coefficients on oil price measure changed at indicated date. Dashed lines denote $p = 0.05$.

Figure 11. Evidence of Granger causality. Each figure plots the p-value for a test of the null hypothesis that coefficients on the oil price measure are zero in a regression of GDP growth on a constant, four of its own lags, and four lags of the oil price measure, where the first date used in the regression is the value plotted on the horizontal axis. Dashed lines

denote $p = 0.05$.

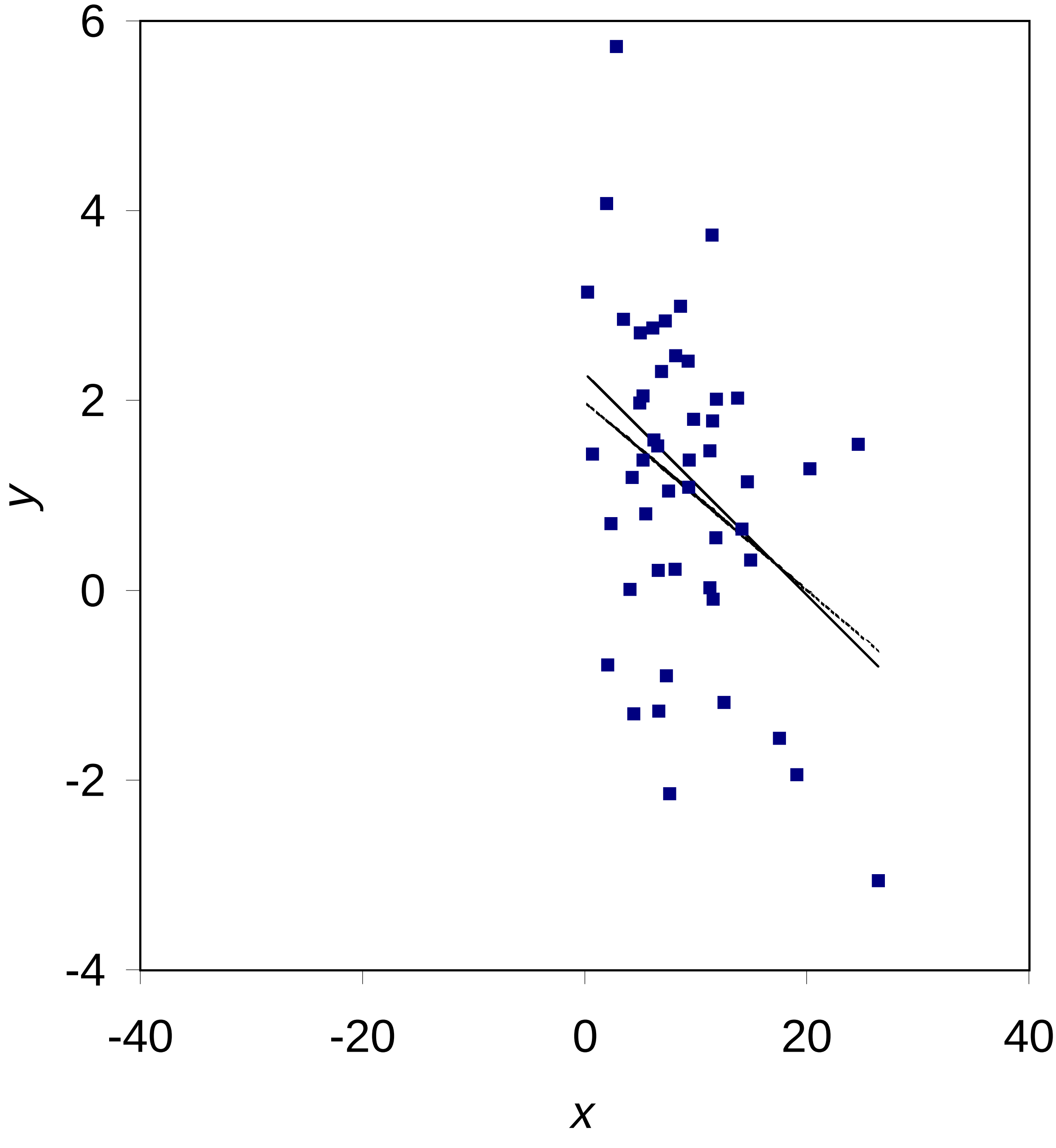
Figure 12. Monthly crude oil production for Iraq, Iran, and Kuwait, 1973:1-1992:12. Source: *Monthly Energy Review,* available from ftp://ftp.eia.doe.gov/pub/energy.overview/monthly.energy/historic.mer/tab10-1a.txt.

Figure 13. Alternative measures of oil price shocks. Top panel: oil price increase divided by conditional standard deviation, zero otherwise ($o_t^{\ddagger}$). Second panel: amount by which oil price exceeds the maximum over the previous year, zero otherwise ($o_t^{\dagger}$). Third panel: amount by which oil price exceeds its 3-year maximum; zero otherwise ($o_t^{\#}$). Bottom panel: fitted values from a regression of o_t on a constant and $Q_t, Q_{t-1}, ..., Q_{t-4}$ ($\hat{o}_t$).

Figure 14. Dynamic effects of a 10% oil price increase. Both panels plot $10\times$ $\partial E(y_{t+j}|y_t, y_{t-1}, y_{t-2}, y_{t-3}, o_{t+j} = 0, o_{t+j-1} = 0, ..., o_{t+1} = 0, o_t, o_{t-1}, o_{t-2}, o_{t-3})/\partial o_t$ as a function of j. For the top model, the conditional expectation is based on (5.1). For the bottom panel, it is based on (3.8).

Figure 15. Effects with one oil shock left out of the estimation. Each panel plots $10 \times \partial E(y_{t+j}|y_t, y_{t-1}, y_{t-2}, y_{t-3}, o_{t+j} = 0, o_{t+j-1} = 0, ..., o_{t+1} = 0, o_t, o_{t-1}, o_{t-2}, o_{t-3})/\partial o_t$ as a function of j. In each panel, Q_t has been reset to zero for the t associated with the indicated episode.

Figure 1



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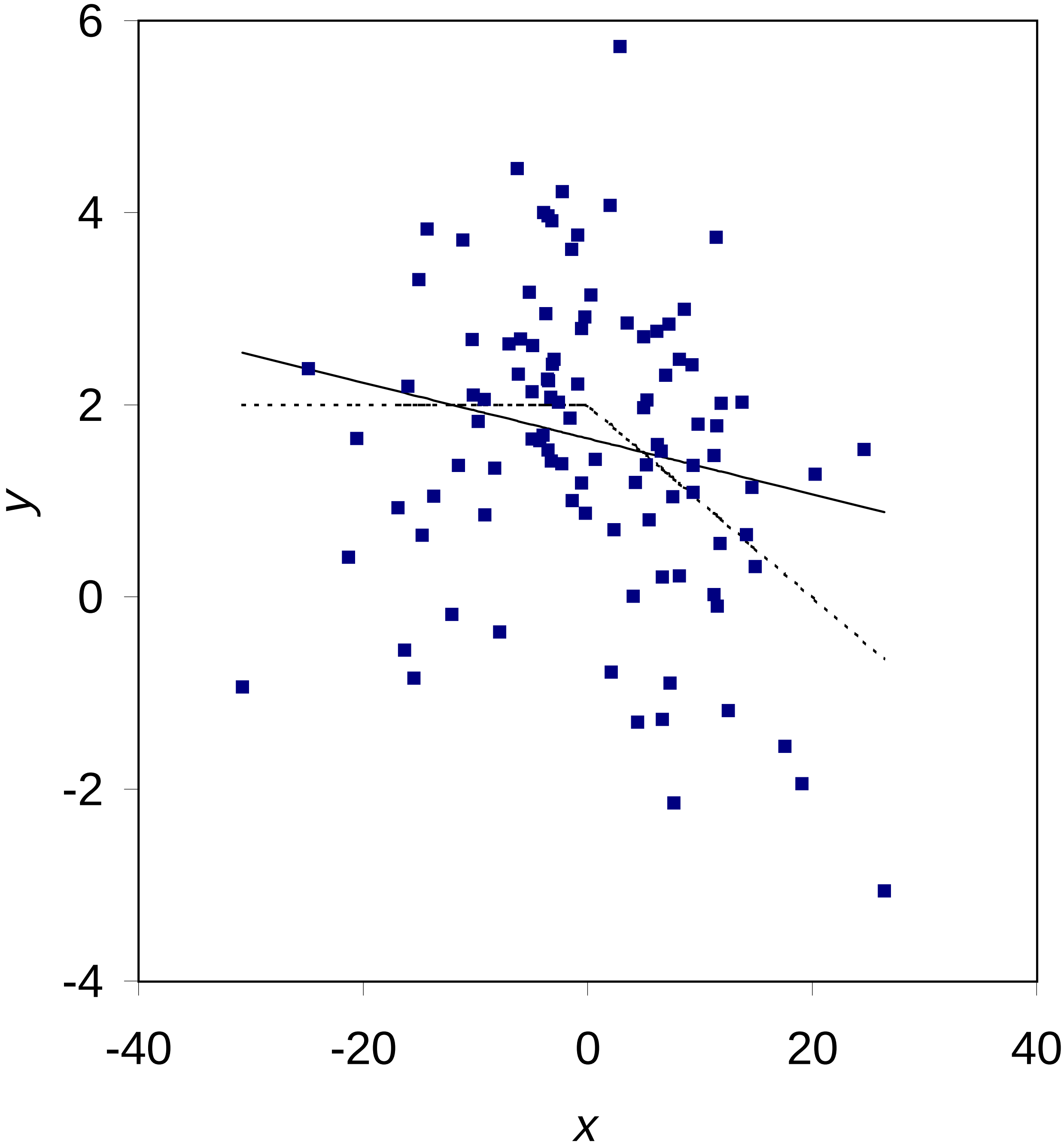

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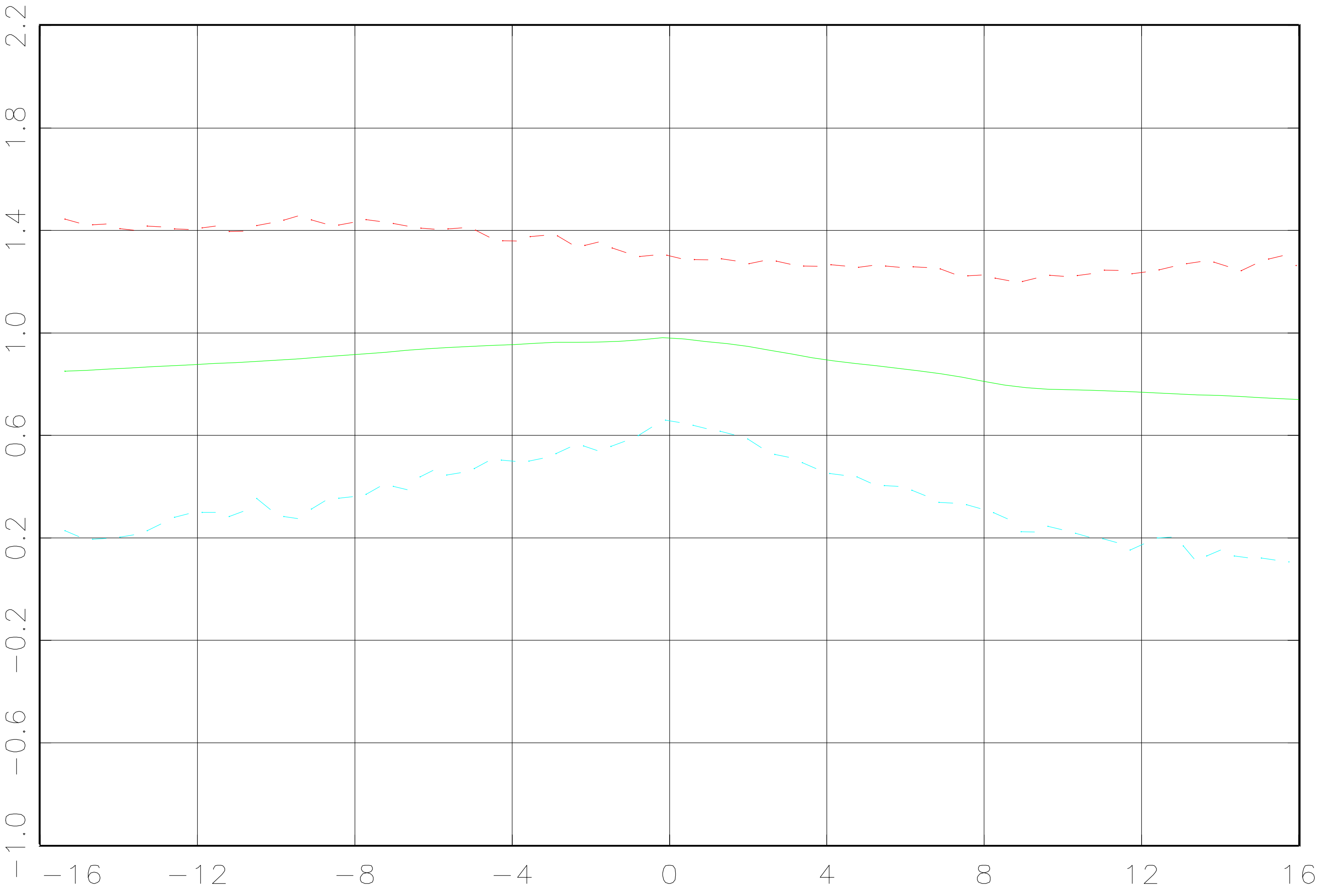

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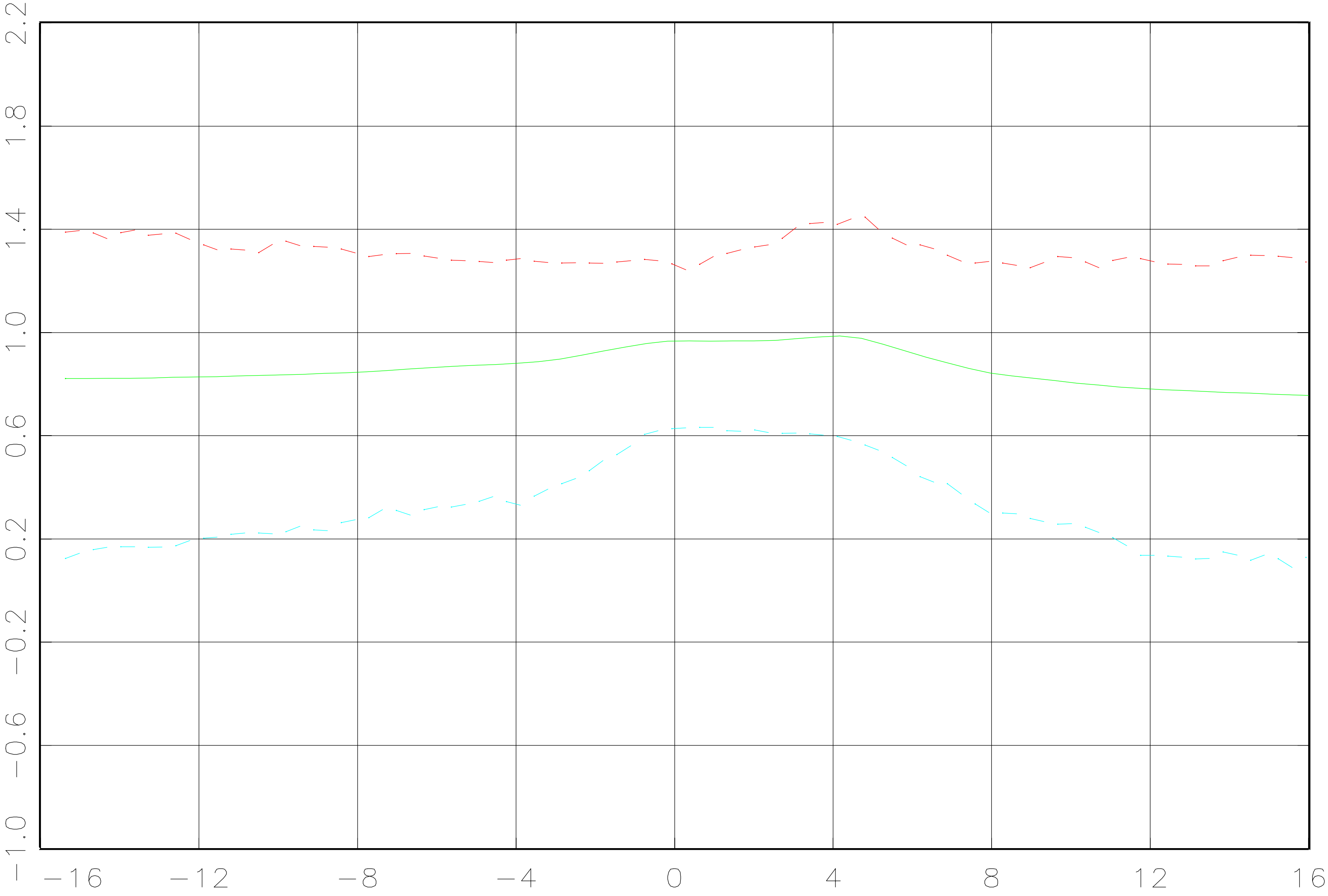

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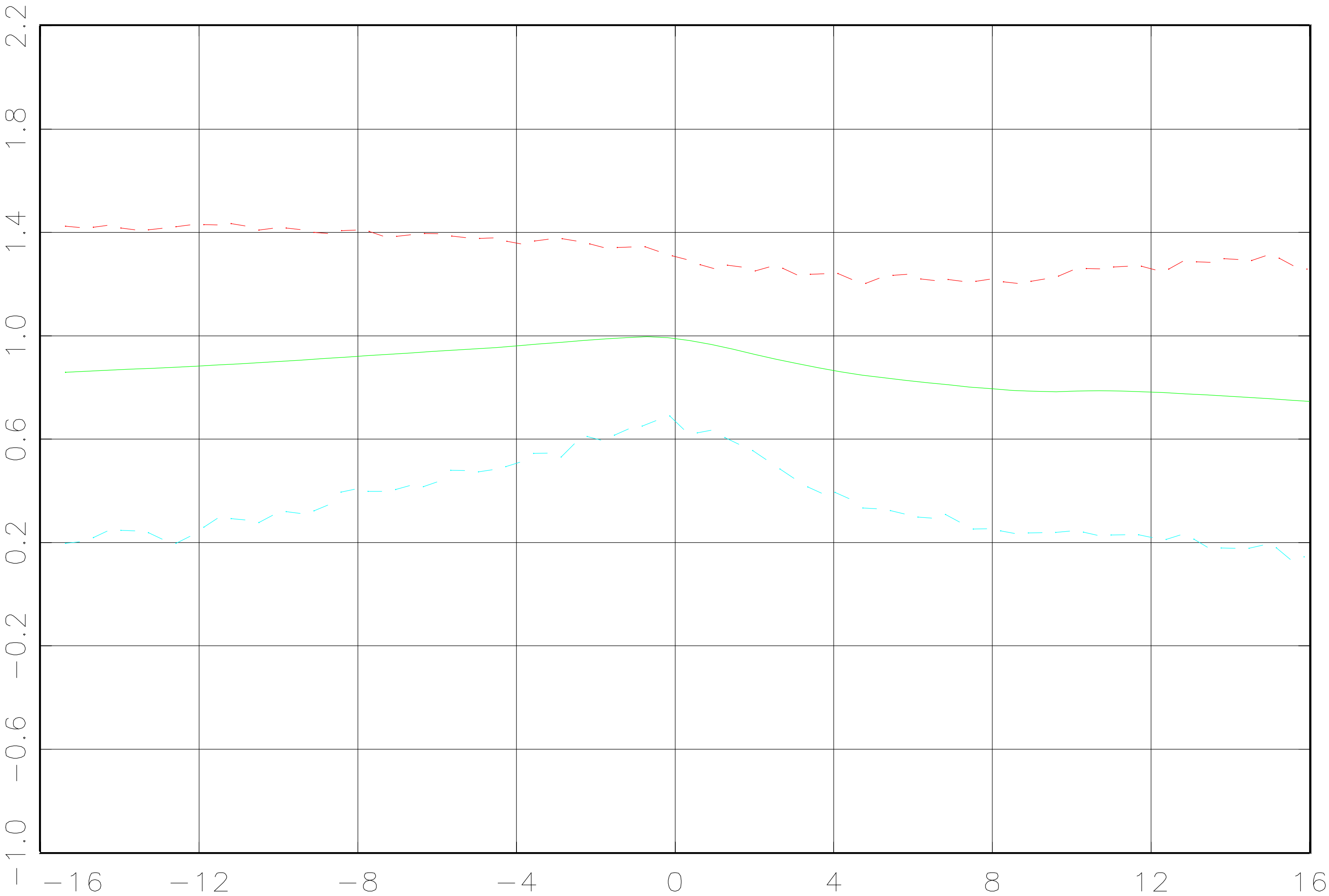

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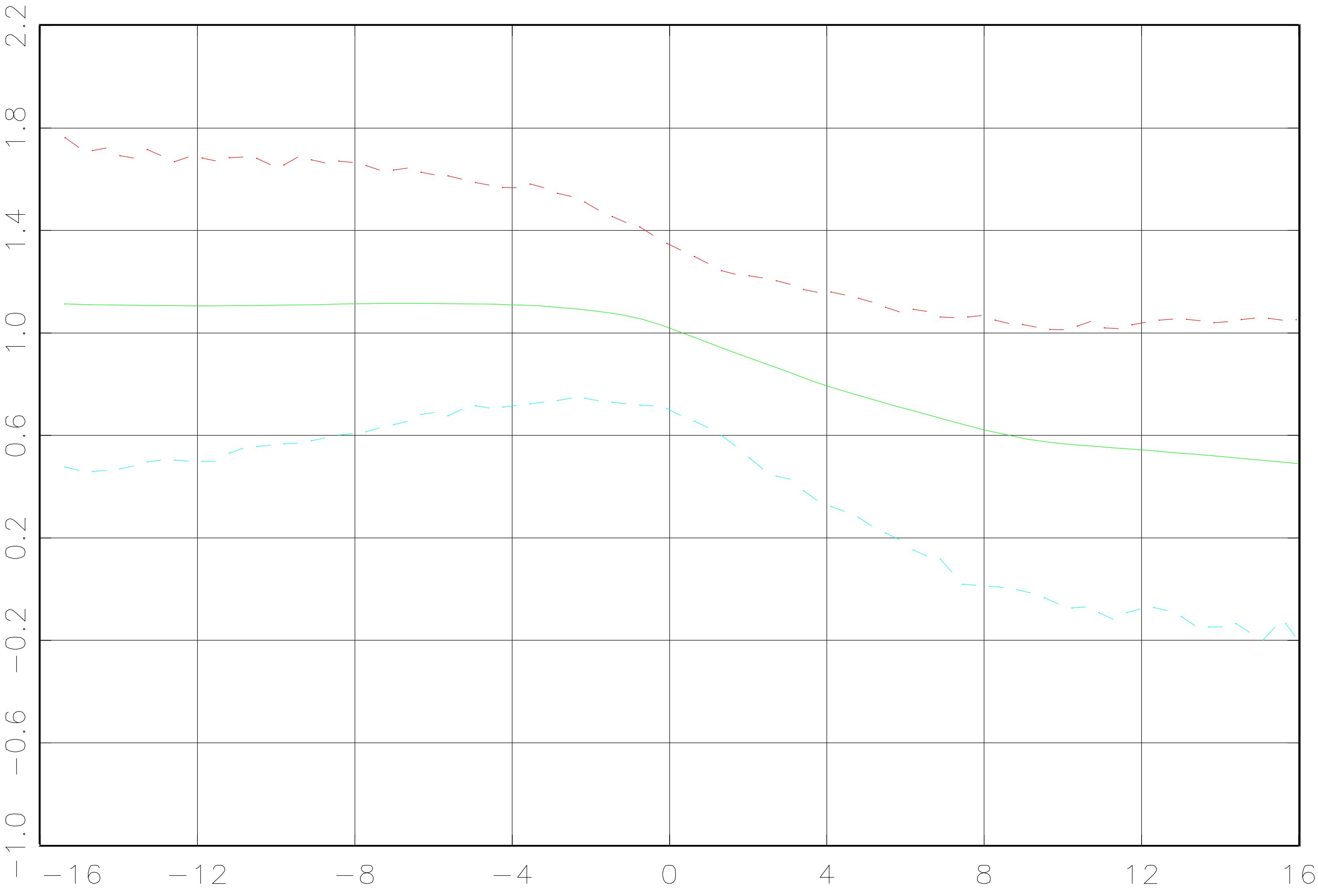

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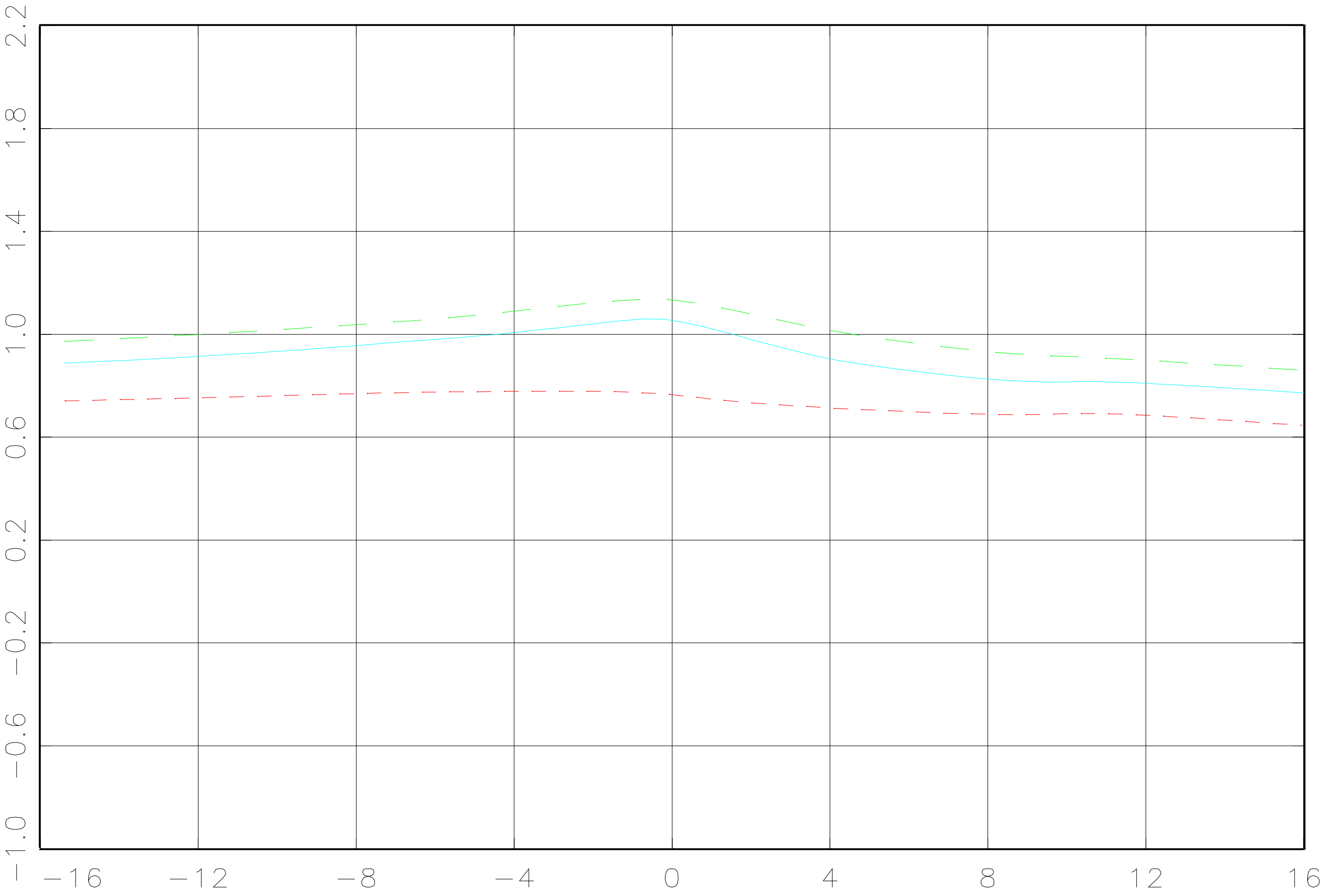

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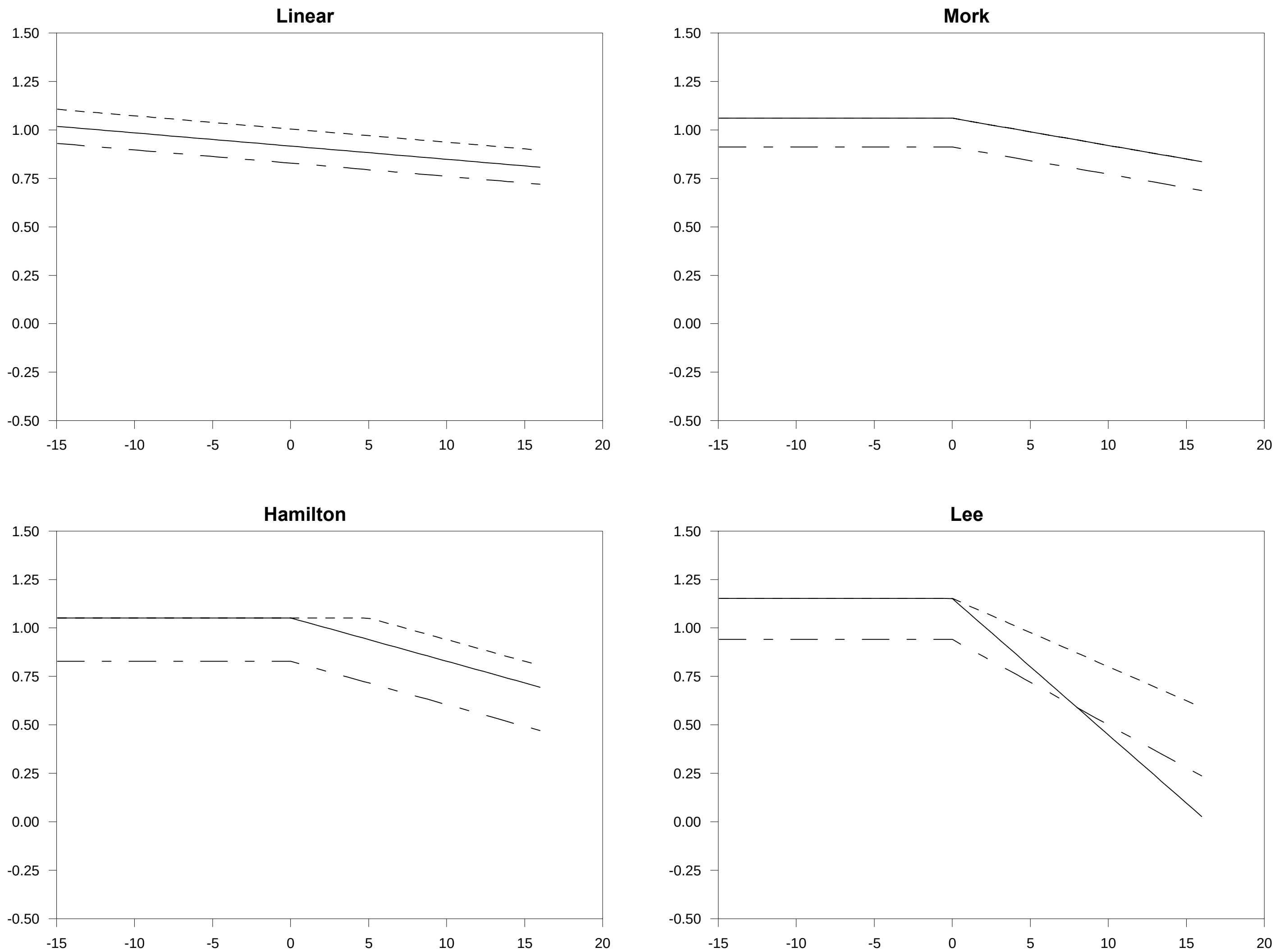


Linear
Mork
Hamilton
Lee
1.50
1.25
1.00
0.75
0.50
0.25
0.00
-0.25
-0.50
-15
-10
-5
0
5
10
15
20

Figure 9

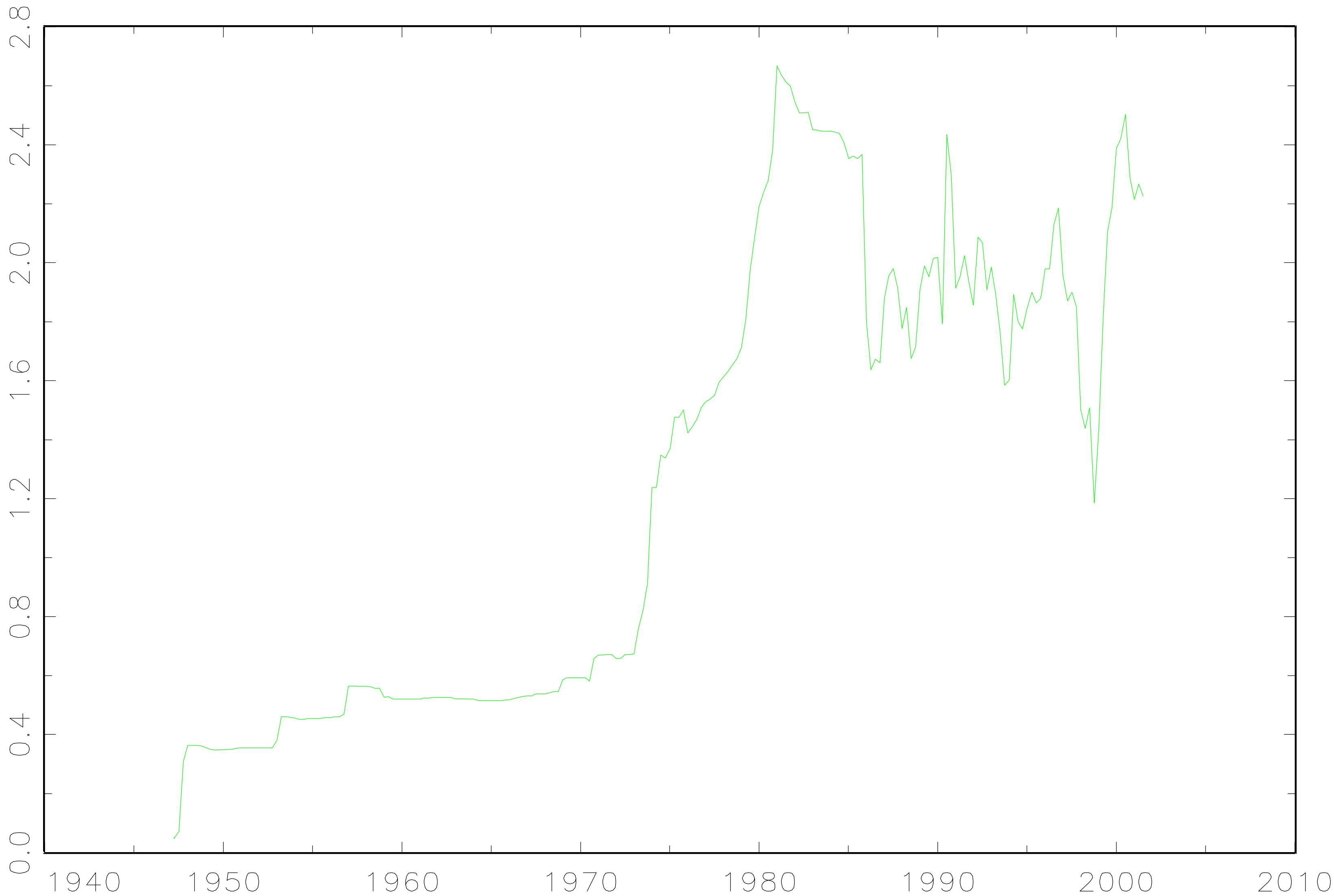


Figure 10

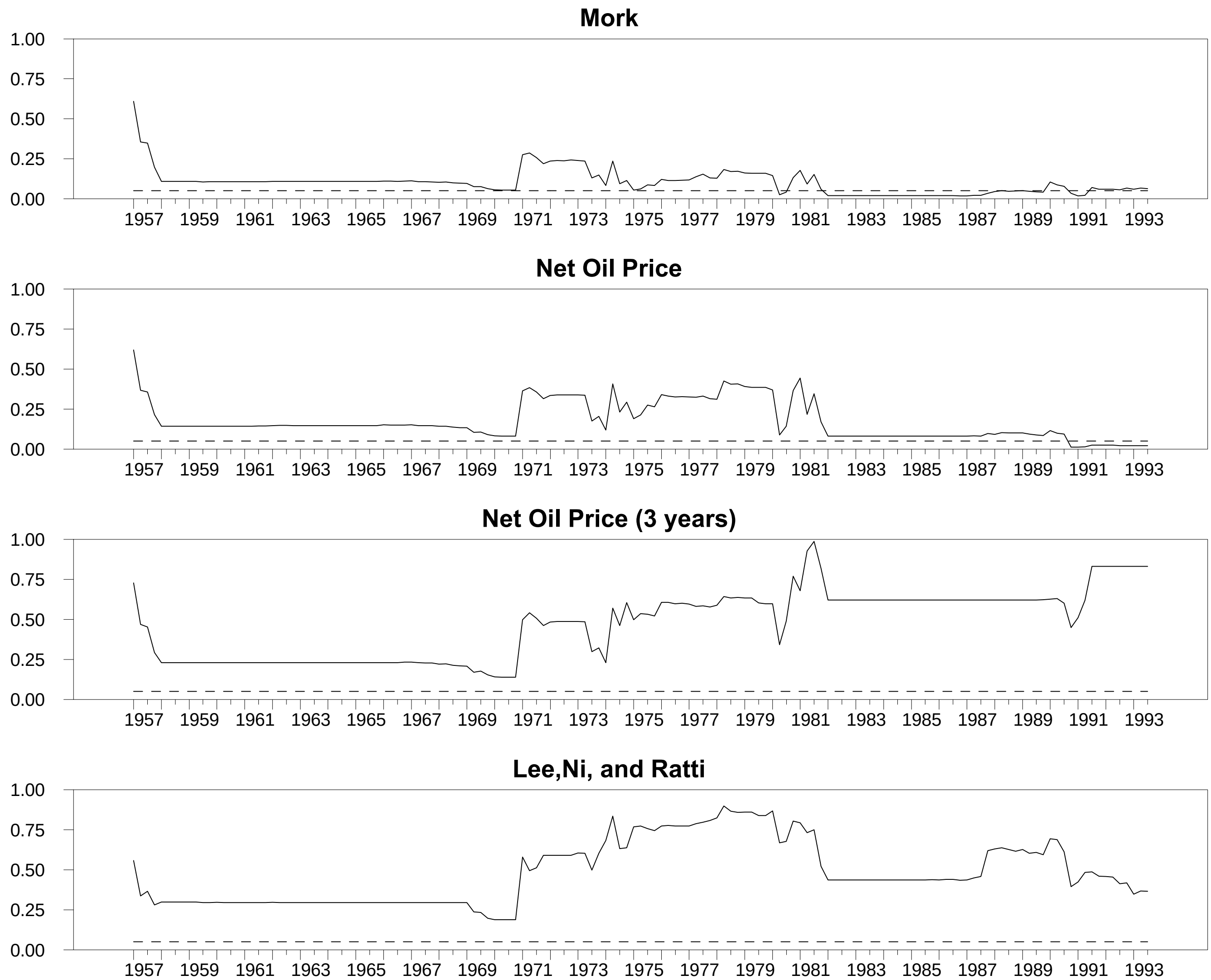

Mork
Net Oil Price
Net Oil Price (3 years)
Lee,Ni, and Ratti
1.00
0.75
0.50
0.25
0.00
1957 1959 1961 1963 1965 1967 1969 1971 1973 1975 1977 1979 1981 1983 1985 1987 1989 1991 1993

Figure 11

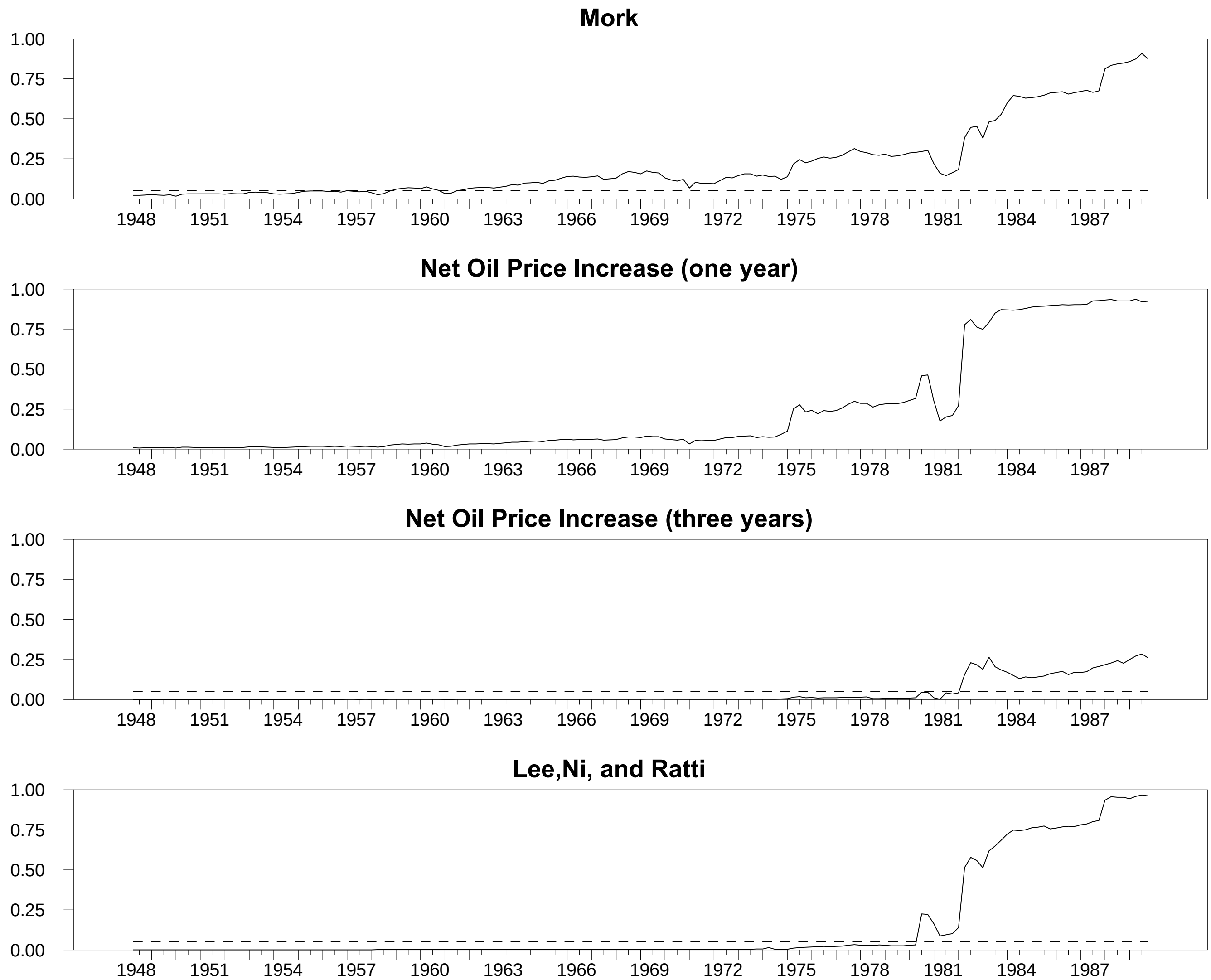

Mork
Net Oil Price Increase (one year)
Net Oil Price Increase (three years)
Lee,Ni, and Ratti
1.00
0.75
0.50
0.25
0.00
1948
1951
1954
1957
1960
1963
1966
1969
1972
1975
1978
1981
1984
1987

Figure 12

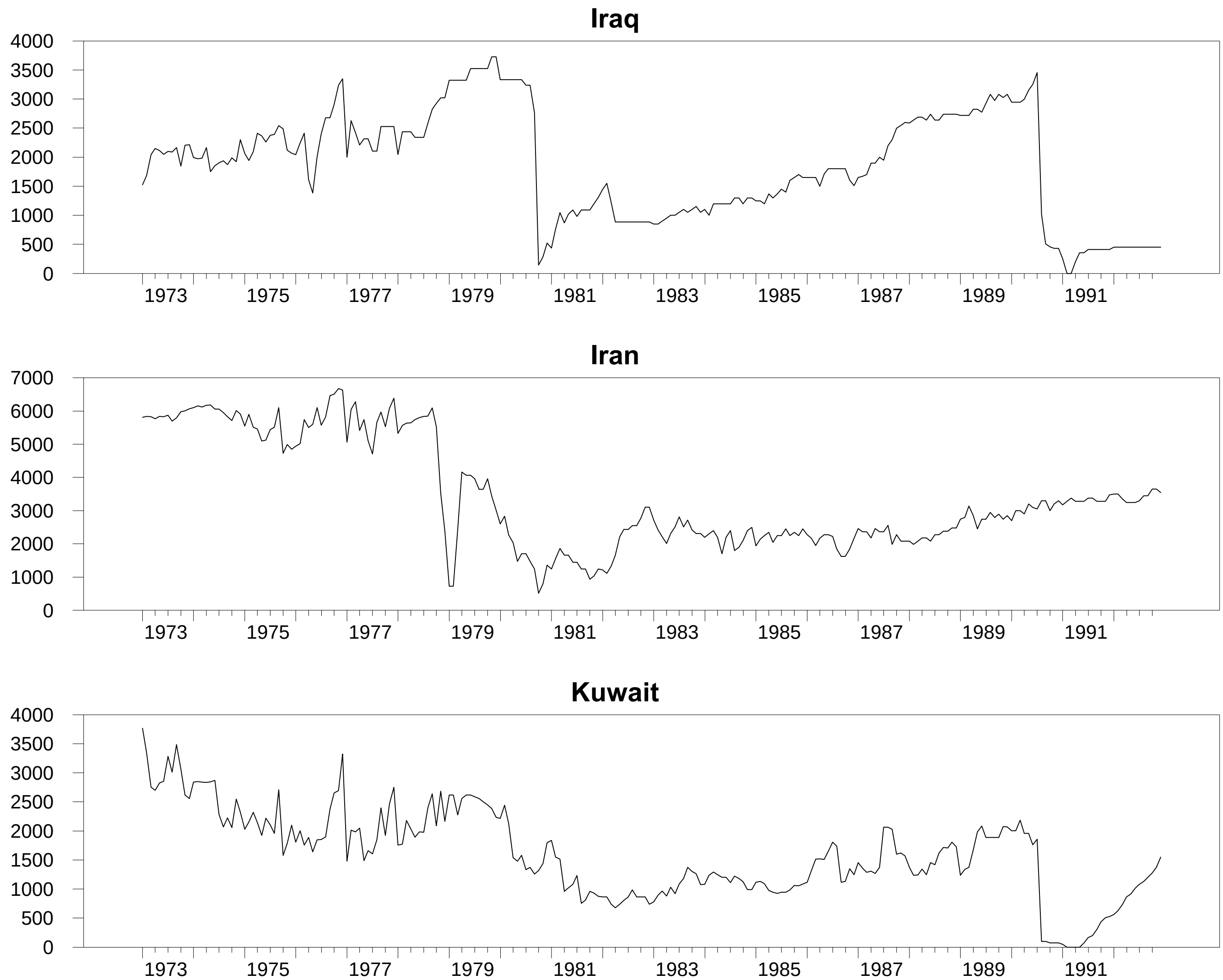

Iraq
4000
3500
3000
2500
2000
1500
1000
500
0
1973
1975
1977
1979
1981
1983
1985
1987
1989
1991
Iran
7000
6000
5000
4000
3000
2000
1000
0
1973
1975
1977
1979
1981
1983
1985
1987
1989
1991
Kuwait
4000
3500
3000
2500
2000
1500
1000
500
0
1973
1975
1977
1979
1981
1983
1985
1987
1989
1991

Figure 13

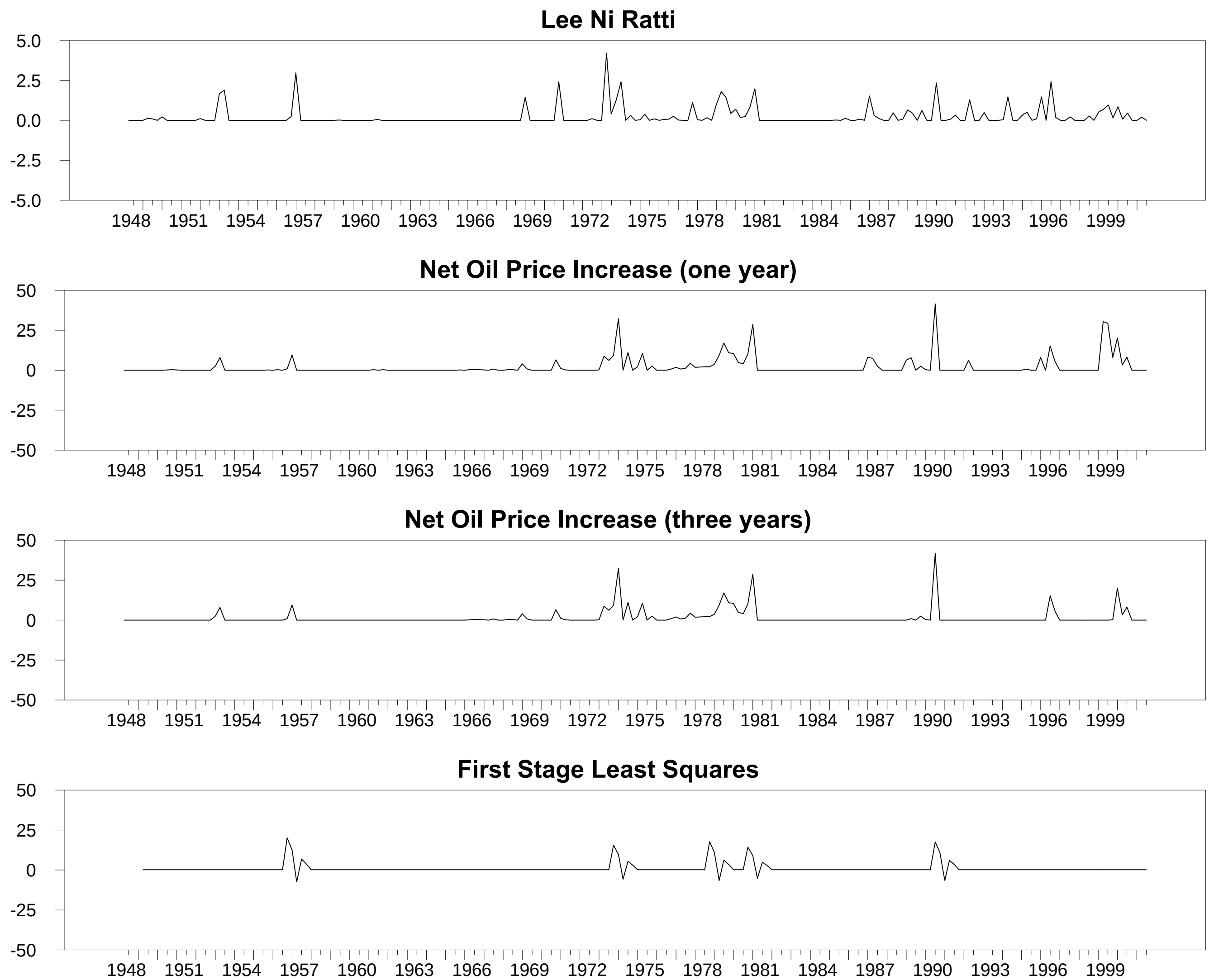
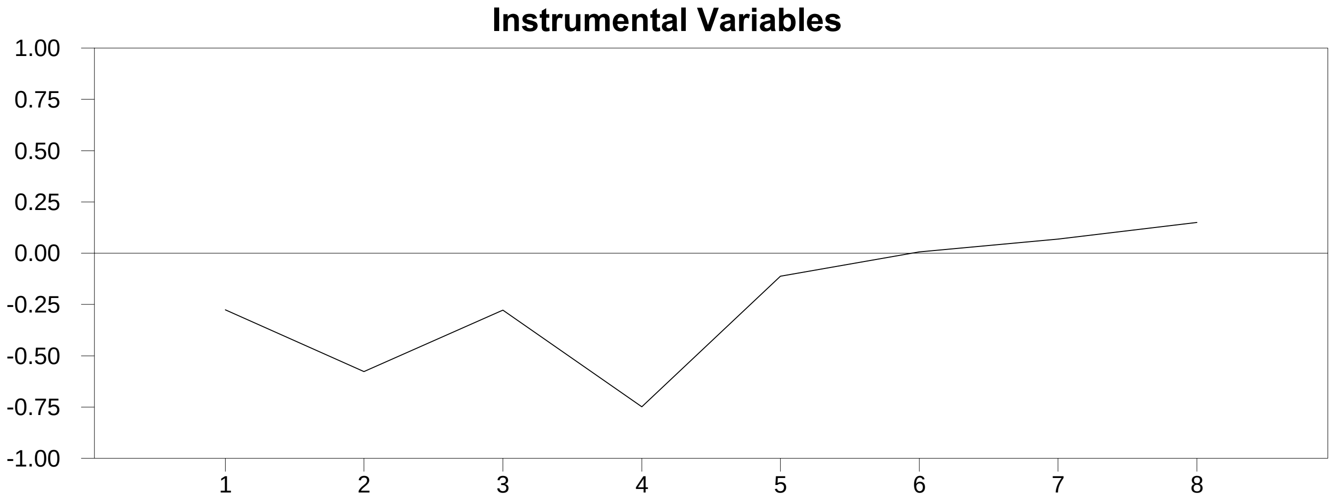

Lee Ni Ratti
5.0
2.5
0.0
-2.5
-5.0
Net Oil Price Increase (one year)
Net Oil Price Increase (three years)
First Stage Least Squares
50
25
0
-25
-50
1948
1951
1954
1957
1960
1963
1966
1969
1972
1975
1978
1981
1984
1987
1990
1993
1996
1999

Figure 14


Instrumental Variables
1.00
0.75
0.50
0.25
0.00
-0.25
-0.50
-0.75
-1.00
1
2
3
4
5
6
7
8

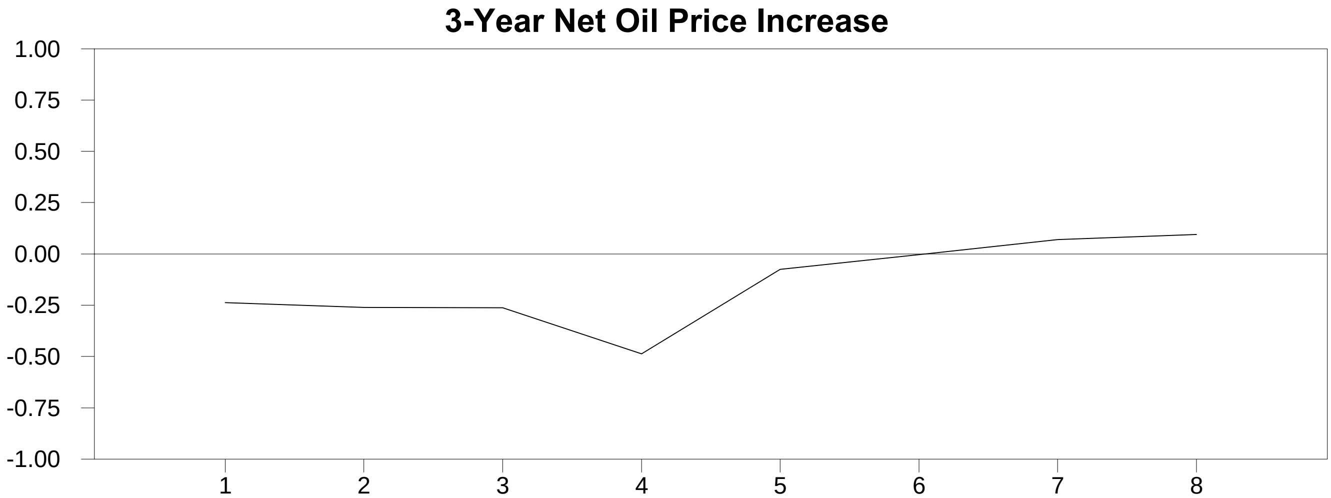
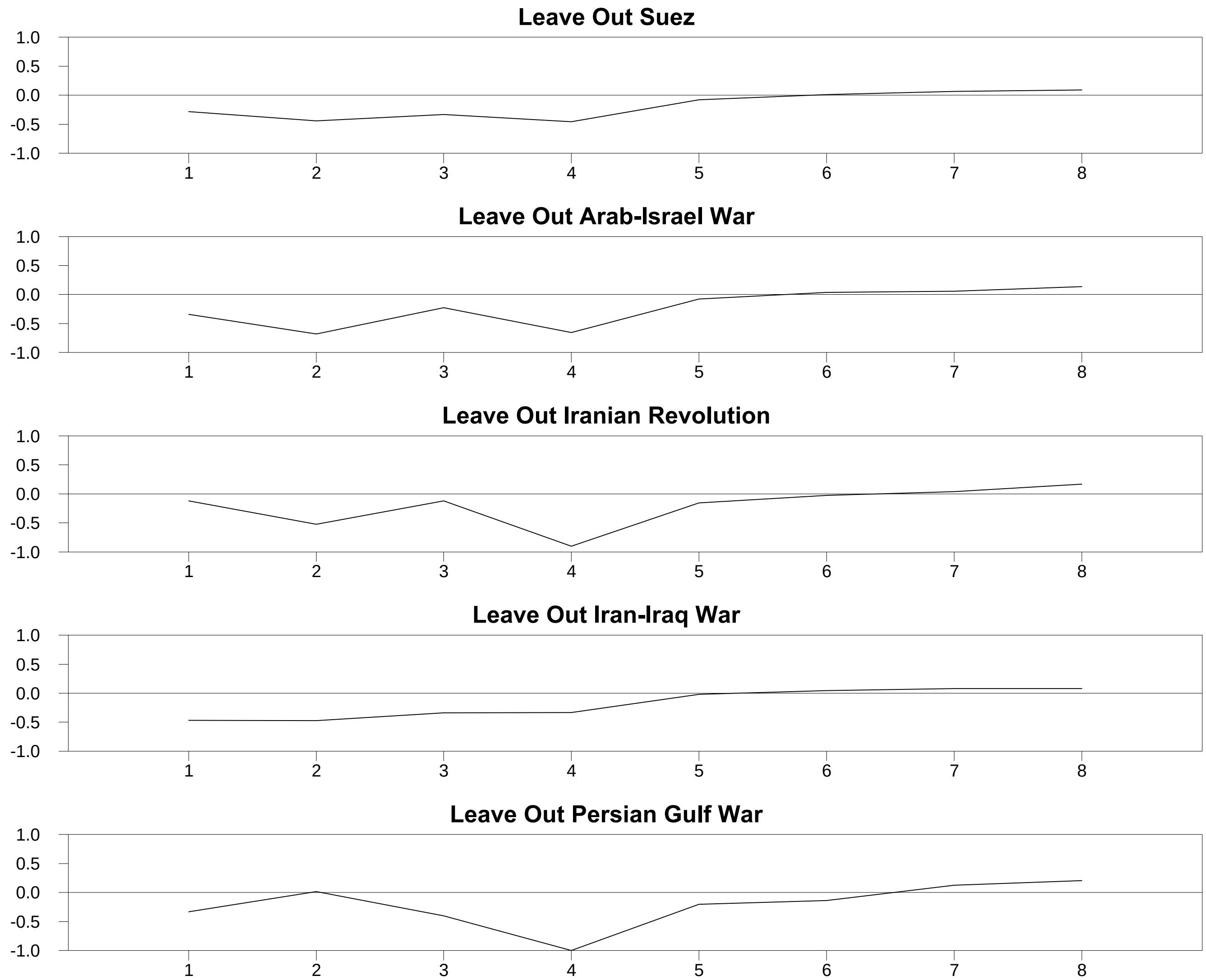

3-Year Net Oil Price Increase
1.00
0.75
0.50
0.25
0.00
-0.25
-0.50
-0.75
-1.00
1
2
3
4
5
6
7
8

Figure 15


Leave Out Suez
1.0
0.5
0.0
-0.5
-1.0
1 2 3 4 5 6 7 8
Leave Out Arab-Israel War
1.0
0.5
0.0
-0.5
-1.0
1 2 3 4 5 6 7 8
Leave Out Iranian Revolution
1.0
0.5
0.0
-0.5
-1.0
1 2 3 4 5 6 7 8
Leave Out Iran-Iraq War
1.0
0.5
0.0
-0.5
-1.0
1 2 3 4 5 6 7 8
Leave Out Persian Gulf War
1.0
0.5
0.0
-0.5
-1.0
1 2 3 4 5 6 7 8