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Energy Shocks and Financial Markets: Nonlinear Linkages

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Abstract. *This paper examines the dynamic linkages between oil prices and the stock market. Prior work argues that daily oil futures price changes and the S&P 500 stock index movements are not related. This conclusion could be due to the fact that only linear linkages have been examined. Relying on nonlinear causality tests, this study provides evidence that oil shocks affect stock index returns, which is consistent with the documented influence of oil on economic output. Moreover, the study finds that the linkage between oil prices and the stock market was stronger in the 1990s.*

Keywords. oil prices, nonlinear causality, equity markets

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1 Introduction

The negative relationship between oil price shocks and the U.S. economic output has been documented in many studies. In an influential paper, Hamilton (1983) argues that oil price shocks are responsible, at least partly, for every U.S. recession in the post–World War II period. Several other studies, such as Loungani (1986), Burbridge and Harrison (1984), Mork (1989), and Lee, Ni, and Ratti (1995), report similar conclusions, using different data and statistical approaches. Mork, Olsen, and Mysen (1994) extend these findings to six other industrialized countries: Japan, Germany, Canada, France, the United Kingdom, and Norway. They show that oil price shocks affect the GDP in all of these countries, although the effects are stronger for the United States, Japan, and Norway.

Relatively few papers, however, investigate linkages between oil prices and equity markets. If oil affects real output, increases in oil price depress aggregate stock prices by lowering expected earnings, or vice versa. This suggests that oil prices should be associated with stock returns. In notable studies, Kaul and Jones (1996) and Sadorsky (1999) find that oil price movements do indeed affect U.S. stock returns. These studies, however, use quarterly and monthly data, respectively, and have a macroeconomic focus.

Huang, Masulis, and Stoll (1996, hereafter HMS) investigate the impact of oil price shocks on the U.S. equity market from a financial markets perspective. Within the framework of a vector autoregression (VAR) model, they examine dynamic interactions between daily oil futures returns and stock returns. Although they find evidence for significant Granger causality from oil futures to stocks of individual oil companies, they detect no impact on a broad-based index like the S&P 500. Based on this result, they conclude that the much-touted influence of oil price shocks on the aggregate economy is more of a myth than reality.

This conclusion could be due to the fact that the tests that HMS rely on are not powerful enough to detect nonlinear linkages. This is important since a number of authors, such as Mork (1989), Hamilton (1996, 2000), Balke, Brown, and Yucel (1999), and Mork, Olsen, and Mysen (1994), argue that there is a nonlinear relationship between oil and the economy. Specifically, these studies show that oil price increases are much more influential than oil price decreases, creating an asymmetric relationship between oil prices and the economic output. This suggests that nonlinear linkages between oil prices and the stock market could be uncovered.[1]

This paper extends the understanding of the relationship between oil prices and the stock market by testing for nonlinear linkages, in addition to linear linkages. The modified Baek and Brock test, fully developed in Hiemstra and Jones (1994), is used to examine nonlinear linkages. Using the same data set as the HMS article, the study finds significant nonlinear Granger causality from crude oil futures returns to S&P 500 index returns. Furthermore, there is evidence that stock index returns also affect crude oil futures, suggesting a feedback relation. No causality is found, however, between heating oil futures returns and stock index returns, in either direction.

The study conducts a similar analysis for the 1990s to examine whether these findings are sample specific. The results from this period provide even stronger support for a nonlinear relationship between oil prices and the stock market. Specifically, although there is still no linear Granger causality, significant bidirectional nonlinear Granger causality exists between oil futures returns (both crude and heating oil) and stock index returns. It is notable that Sadorsky (1999), using a different data set and statistical approach, also finds that the impact of oil prices on stock returns is significantly stronger after 1986, when turbulence in the oil market has increased.

The rest of the paper is organized as follows: the next section discusses the econometric method. The third section presents the data set, and the empirical findings of the study are reported in the fourth section. The fifth section contains a discussion of the findings, and the final section offers the concluding remarks of the study.

2 Econometric Approach

2.1 Testing for linear Granger causality

Granger causality testing investigates whether the past of one time series improves the predictability of the present and future of another time series. Testing for linear Granger causality can be conducted within the context of a VAR model. The benefit of VAR models is that they account for linear intertemporal dynamics between variables without imposing a priori the restrictions of a particular theoretical model. Hence, they are ideally suited to detect stylized facts in data. A VAR model for oil futures returns and S&P 500 index returns can be expressed as

$$R_{o,t} = a_o + \sum_{i=1}^{l} b_{o,i} R_{o,t-i} + \sum_{i=1}^{l} c_{o,i} R_{s,t-i} + u_{o,t} \tag{2.1}$$

$$R_{s,t} = a_s + \sum_{i=1}^{l} b_{s,i} R_{o,t-i} + \sum_{i=1}^{l} c_{s,i} R_{s,t-i} + u_{s,t} \tag{2.2}$$

[1] Several recent theoretical and empirical studies further motivate an analysis of nonlinear dependencies. For example, Bansal and Viswanathan (1993) and Bansal, Hsieh, and Viswanathan (1993) demonstrate the economic significance of nonlinearities in asset pricing. Also, Hiemstra and Kramer (1997) argue that linear asset-pricing models omit potentially useful aspects of the relationship between macroeconomic variables and stock returns. They find significant linear and nonlinear feedback between U.S. stock returns and commonly used macroeconomic variables.

where $R_{o,t}$ and $R_{s,t}$ represent daily oil futures returns and the S&P 500 index returns, respectively, and $u_{o,t}$ and $u_{s,t}$ are error terms.[2] Within the context of this VAR model, linear Granger causality restrictions can be defined as follows: if the null hypothesis that all c_os jointly equal zero is rejected, it is argued that stock index returns Granger-cause oil futures returns. Similarly, if the null hypothesis that all b_ss jointly equal zero is rejected, it is argued that oil futures returns Granger-cause stock index returns. If both of the null hypotheses are rejected, bidirectional Granger causality, or a feedback relation, is asserted to exist between the variables.[3]

Different test statistics have been proposed to test for linear Granger causality restrictions. This study, like the HMS study, relies on the conventional chi-square test for joint exclusion restrictions. Evidence reported in the literature suggests that this simplest form of linear causality test has the most power (see, for example, Geweke, Meese, and Dent, 1983).

2.2 Testing for nonlinear Granger causality

In addition to linear dependencies, economic variables may exhibit nonlinear dependencies. However, the chi-square test discussed above does not have the power to detect nonlinear linkages.[4] This could be particularly important for the problem at hand, since several studies argue that the relationship between oil and the economic output is nonlinear, as mentioned in the introduction.

This study uses the modified Baek and Brock (1992) test to examine nonlinear causality relations. Baek and Brock offer a nonparametric statistical method to detect nonlinear causal relations that, by construction, cannot be uncovered by linear causality tests. Hiemstra and Jones (1994) modify Baek and Brock's test to allow the variables to which the test is applied to exhibit short-term temporal dependence, rather than the Baek and Brock assumption that the variables are mutually independent and identically distributed.

The Baek and Brock (1992) approach begins with a testable implication of the definition of strict Granger noncausality. Consider two strictly stationary and weakly dependent time series $\{X_t\}$ and $\{Y_t\}$, $t = 1, 2, \ldots$. Denote the m-length lead vector of X_t by $\mathbf{X}_t^m$ and the Lx-length and Ly-length lag vectors of X_t and Y_t, respectively. For given values of m, Lx, and $Ly \geq 1$ and for $e > 0$, Y does not strictly Granger-cause X if

$$\begin{aligned} &\Pr(\|\mathbf{X}_t^m - \mathbf{X}_s^m\| < e \mid \|\mathbf{X}_{t-Lx}^{Lx} - \mathbf{X}_{s-Lx}^{Lx}\| < e,\ \|\mathbf{Y}_{t-ly}^{Ly} - \mathbf{Y}_{s-Ly}^{Ly}\| \ < e \\ &\quad = \Pr(\|\mathbf{X}_t^m - \mathbf{X}_x^m\| \ < e \mid \|\mathbf{X}_{t-Lx}^{Lx} - \mathbf{X}_{s-Lx}^{Lx}\| \ < e) \end{aligned} \tag{2.3}$$

where $\Pr(\cdot)$ denotes probability and $\| \ \|$ denotes the maximum norm. The probability on the left side of Equation (2.3) is the conditional probability that two arbitrary m-length lead vectors of $\{X_t\}$ are within a distance, e, of each other, given that the corresponding Lx-length lag vectors of $\{X_t\}$ and Ly-length lag vectors of $\{Y_t\}$ are within e of each other. The strict Granger noncausality condition in Equation (2.3) can then be expressed as

$$\frac{C1(m + Lx, Ly, e)}{C2(Lx, Ly, e)} = \frac{C3(m + Lx, e)}{C4(Lx, e)} \tag{2.4}$$

[2]Returns are calculated as log price changes. It is noteworthy that, in a strict sense, there is no return in futures markets, since there is no investment.

[3]HMS estimate a similar VAR model to test for linear Granger causality between oil futures returns and stock index returns. In their model, the US interest rate is also included to account for possible interactions via the interest rate. The interest rate variable is not included in the VAR model in this study, because the modified Baek and Brock test is applicable to residuals from a bivariate VAR model. However, this should not factor in the conclusions since HMS also report that their findings are not affected whether or not the interest rate is included as the third variable.

[4]To illustrate this point, consider the following simple bivariate nonlinear model, adopted from Hiemstra and Jones (1994):

$$X_t = \beta Y_{t-l} \cdot X_{t-m} + \varepsilon_t$$

where Y_t and ε_t are orthogonal to each other and are individually i.i.d. time series, β is a parameter, l and m represent lag lengths. Y_t Granger-causes X_t, since past values of Y improve the forecast of the present of X. However, linear Granger causality tests will not detect this relation between X_t and Y_t, since all autocorrelations and cross-correlations are zero.

for given values of m, Lx, and $Ly \geq 1$ and $e > 0$, where C1,...,C4 are the correlation-integral estimates of the joint probabilities. Hiemstra and Jones (1994) discuss how to derive the joint probabilities and their corresponding correlation-integral estimators. Assuming that X_t and Y_t are strictly stationary, weakly dependent, and satisfy the mixing conditions of Denker and Keller (1983), if Y_t does not Granger-cause X_t, then,

$$\sqrt{n}\left(\frac{C1(m+Lx, Ly, e, n)}{C2(Lx, Ly, e, n)} = \frac{C3(m+Lx, e, n)}{C4(Lx, e, n)}\right) \sim N(0, \sigma^2(m, Lx, Ly, e)) \tag{2.5}$$

Hiemstra and Jones (1994) show that a consistent estimator of the variance is $\sigma^2(m, Lx, Ly, e) = \delta(n) \cdot \sum(n) \cdot \delta(n)'$.[5] To test for nonlinear causality between oil futures returns and stock index returns, the test in Equation (2.5) is applied to residual series obtained from the VAR models. Since the VAR model accounts for any linear dependencies, any remaining predictive power of one residual series with respect to another can be considered nonlinear predictive power.

3 Data

The data consist of daily closing prices of oil futures contracts traded on the New York Mercantile Exchange (NYMEX) and the S&P 500 stock index. The first part of the empirical analysis uses the HMS data. This data set contains heating oil futures prices starting on October 9, 1979, and crude oil futures prices starting on April 11, 1983, both through March 16, 1990, along with daily S&P 500 stock index prices. The futures prices are from nearby futures contracts.[6]

The second part of the study extends the analysis to the 1990s. The data set used for this part of the empirical analysis contains nearby settlement prices of crude oil and heating oil futures prices starting on March 20, 1990, through March 2, 2000, for both of the contracts, along with daily S&P 500 stock index prices. The futures price data for this part of the analysis are provided by the NYMEX, and the stock index data are again obtained from Commodity Systems Inc.

Oil futures have been active on the NYMEX since October 1974, when the NYMEX introduced the heating oil futures contract. The crude oil futures contract, introduced in March 1983, is currently the most actively traded energy futures contract. Several papers examine the relationship between oil futures and spot prices. Studies by Gurcan (1998) and Crowder and Hamed (1993) conclude that NYMEX crude oil futures are unbiased predictors of future spot prices.

4 Empirical Findings

4.1 Linear Granger causality

The analysis begins by estimating the bivariate VAR models in (2.1) and (2.2), using the HMS data set, to examine linear linkages. The lag lengths for the VAR systems are determined by the Akaike information criterion (AIC) and dummy variables are used to account for the day-of-the-week and the month-of-the-year effects in stock returns. Also, four crash dummies for the days October 16, 19, 20, and 21 in 1987 are included to capture the influence of the stock market crash.[7]

The equations are estimated by ordinary least squares, and White's (1980) heteroskedasticity-consistent standard errors are calculated. The results of linear Granger causality tests, which are reported in Table 1, are

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[5]A significantly positive value for the test statistic in (2.5) indicates that past values of Y help to forecast X, whereas a significantly negative value indicates that past values of Y confound the forecast of X. Therefore, Hiemstra and Jones (1994) argue that the test statistic should be evaluated with right-tailed critical values when testing for Granger causality.

[6]Roger Huang generously provided the oil futures prices for this data set, and the stock index data are obtained from Commodity Systems Inc.

[7]The regressions are also estimated with a dummy for the October 1989 minicrash. The results are robust to the inclusion of this dummy.

Table 1
Linear Granger causality analysis: The 1980s

Panel A: Testing for linear Granger causality				
	χ^2 value			
$R_{co} \rightarrow R_s$	4.78			
	(.44)			
$R_s \rightarrow R_{co}$	3.41			
	(.63)			
$R_{ho} \rightarrow R_s$	10.07			
	(.75)			
$R_s \rightarrow R_{ho}$	20.00			
	(.13)			
Panel B: Residual diagnostics				
	Q(6)	Q(12)	$Q^2(6)$	$Q^2(12)$
u_{co}	.20	13.96	712.35	1345.94
	(.99)	(.30)	(.00)	(.00)
$u_{s,co}$	3.80	14.69	366.70	381.45
	(.70)	(.25)	(.00)	(.00)
u_{ho}	.11	.24	1331.71	1853.96
	(.99)	(.99)	(.00)	(.00)
$u_{s,ho}$	1.81	2.93	504.17	512.78
	(.99)	(.99)	(.00)	(.00)

Note: This table provides the results of testing for linear Granger causality between oil futures returns and stock index returns, as well as diagnostics for error terms. The arrows point out the direction of causality. R_{co} and R_{ho} denote crude oil and heating oil futures returns, respectively, and R_s denotes stock index returns. The VAR model for R_{ho} and R_s is estimated with 14 lags, and the model for R_{co} and R_s is estimated with 5 lags. The Q-test is the Ljung-Box test and the Q^2-test is the McLeod-Li test, at 6 and 12 lags. The results are robust to other lag lengths. *p*-values for statistical significance are given in parentheses.

consistent with HMS. The test statistics are insignificant, indicating no linear Granger causality between oil futures and stock returns.

Two sets of tests are conducted as residual diagnostics. The Ljung-Box Q-test is used to examine linear dependencies in the residuals, and McLeod and Li's (1983) Q^2-test is used to examine nonlinear dependencies. The null hypothesis of the Q-test is no serial correlation in residuals, and the null hypothesis of the Q^2-test is no serial correlation in squared residuals. Both tests have chi-square asymptotic distributions. The test statistics, which are also reported in Table 1, suggest that the VAR models successfully eliminate serial correlation in residuals; significant nonlinear dependencies remain, however.

Linear Granger causality analysis is extended to the 1990s by constructing similar bivariate VAR models. Dummy variables are again included to account for the seasonalities in stock returns. An important event in oil markets in the 1990s is the Iraqi invasion of Kuwait on August 2, 1990, and the subsequent Gulf War. Oil prices fluctuated dramatically during this period, and a dummy variable is included for the period between August 2, 1990, and February 27, 1991, the end of the Gulf War.[8] The lag lengths are again determined by the AIC.

The chi-square test statistics, reported in Table 2, are insignificant, suggesting no linear Granger causality between oil and stock returns. Results of residual diagnostics are also similar to the results from the previous period. The residuals do not exhibit linear dependencies, but there is evidence for significant nonlinear dependencies. Thus, the linear Granger causality analysis for the 1990s would also lead to the conclusion that the significance of oil price for the aggregate economy is greatly exaggerated.

[8]The analysis is also conducted without this war dummy. The results are qualitatively the same.

Table 2
Linear Granger causality analysis: The 1990s

Panel A: Testing for linear Granger causality

	χ^2 test
$R_{co} \rightarrow R_s$	5.49
	(.60)
$R_s \rightarrow R_{co}$	2.51
	(.92)
$R_{ho} \rightarrow R_s$	25.93
	(.20)
$R_s \rightarrow R_{ho}$	30.30
	(.09)

Panel B: Residual diagnostics

	Q(6)	Q(12)	$Q^2(6)$	$Q^2(12)$
u_{co}	.13	9.90	108.71	130.66
	(.99)	(.62)	(.00)	(.00)
$u_{s,co}$	.03	8.82	285.96	394.52
	(.99)	(.71)	(.00)	(.00)
u_{ho}	.09	.18	127.13	151.44
	(.99)	(.99)	(.00)	(.00)
$u_{s,ho}$	.05	.13	250.22	337.20
	(.99)	(.99)	(.00)	(.00)

Note: This table provides the results of testing for linear Granger causality between oil futures returns and stock index returns, as well as diagnostics for error terms. The arrows point out the direction of causality. R_{co} and R_{ho} denote crude oil and heating oil futures returns, respectively, and R_s denotes stock index returns. The VAR model for R_{ho} and R_s is estimated with 21 lags, and the model for R_{co} and R_s is estimated with 7 lags. The Q-test is the Ljung-Box test and the Q^2-test is the McLeod-Li test, at 6 and 12 lags. The results are robust to other lag lengths. *p*-values for statistical significance are given in parentheses.

4.2 Nonlinear Granger causality

As mentioned in the introduction, several studies suggest a nonlinear relation between oil and the economy. The Q^2-tests, indicating nonlinear dependency in error terms, also suggest that nonlinear linkages could be uncovered. The modified Baek and Brock test is applied to residuals from the VAR models to investigate nonlinear Granger causality dynamics. To implement the modified Baek and Brock test, values for the lead length, m, the lag lengths, Lx and Ly, and the scale parameter, e, have to be selected. Unlike in testing for linear causality, no methods have been developed in the literature to select the optimal values for these variables. This study, following Hiemstra and Jones (1994) and Fujihara and Mougoue (1997), relies on the Monte Carlo evidence in Hiemstra and Jones (1993) and sets the lead lag length at $m = 1$ and $Lx = Ly$ for all cases. Also, common lag lengths of one to eight lags and a common scale parameter of $e = 1.0\sigma$ are used, where $\sigma = 1$ denotes the standard deviation of the standardized series.

Table 3 presents the results of nonlinear Granger causality tests for the HMS data. They show that there is indeed some evidence of nonlinear Granger causality from crude oil futures returns to stock index returns. There is no nonlinear Granger causality, however, from heating oil futures to stock index returns. The test statistics are not significant at any lag.[9] An interesting observation is the significance of the modified Baek and Brock test for nonlinear Granger causality from stock index returns to crude oil futures returns at several lags. This suggests evidence for a feedback relation between oil prices and the stock markets, which is further examined below.

[9]The data set for the heating oil futures start in 1979, while crude oil futures data start in 1983. It is examined whether this is the cause why the results are different for crude oil futures and heating oil futures. The analysis is reconducted with heating oil futures data starting in 1983. However, the results are qualitatively the same.

Table 3
Nonlinear Granger causality analysis: The 1980s

Panel A: The case of crude oil futures					
$R_{co} \to R_s$			$R_s \to R_{co}$		
$Lx = Ly$	CS	TVAL	$Lx = Ly$	CS	TVAL
1	−.000	−.160	1	.004	1.132
2	−.000	−.068	2	.014	2.530
3	.003	.444	3	.014	2.149
4	.017	1.917	4	.018	3.438
5	.016	1.601	5	.014	1.789
6	.024	2.189	6	.009	1.004
7	.019	1.566	7	.002	.184
8	.024	1.836	8	.001	.141
Panel B: The case of heating oil futures					
$R_{ho} \to R_s$			$R_s \to R_{ho}$		
$Lx = Ly$	CS	TVAL	$Lx = Ly$	CS	TVAL
1	−.000	−.206	1	.000	.082
2	−.002	−.589	2	−.002	−.605
3	.000	.087	3	−.002	−.335
4	.004	.630	4	.006	.837
5	.002	.311	5	−.002	−.256
6	.004	.392	6	−.007	−.711
7	.005	.450	7	−.011	−.978
8	.005	.366	8	.008	−.644

Note: This table provides the results the modified Baek and Brock test statistics applied to the residuals from the bivariate VAR models for the 1980s. R_{co} and R_{ho} denote crude oil and heating oil futures returns, respectively, and R_s denotes stock index returns. CS and TVAL are the difference between the two conditional probabilities in Equation (2.4) and the standardized test statistic in Equation (2.5), respectively. The null hypothesis of the test statistic is no nonlinear Granger causality, and it is asymptotically distributed $N(0, 1)$. The critical value at 5% significance level is 1.64.

The study proceeds to test for nonlinear dependencies in the 1990s. The modified Baek and Brock test is similarly applied to residuals extracted from the VAR models. The findings, which are reported in Table 4, suggest even more pronounced nonlinear causality dynamics in this period. Test statistics are significant at almost all lags, and the values are greater. Thus, the results indicate bidirectional nonlinear Granger causality between oil futures returns (both crude oil and heating oil) and stock index returns.

5 Discussion

Overall, the analysis points to two main findings. First, there is a nonlinear feedback relation between oil and the stock market. This is, in general, consistent with studies giving a special place for oil in the economy and also with Kaul and Jones (1996) and Sadorsky (1999), which argue that oil shocks affect stock returns using different data and estimation methods.[10] Although these studies do not report a feedback relation, the findings of the present paper are consistent with Barsky and Kilian (1998) and Hamilton (2000), which argue that oil prices are predictable from U.S. macro variables in the post-1973 data.

A recent treatment of asset-pricing models in finance by Cochrane (2001) offers an explanation for the linkage between these markets.[11] The analysis in Cochrane suggests that returns on oil futures and the stock market are linked via a stochastic discount factor that is common to all assets. If the link between oil and the

[10] A caveat should be mentioned about the interpretation of the findings. The standard valuation model (see, for example, Campbell, 1991) suggests a negative relation between oil price shocks and stock returns. It is not possible, however, to determine whether the nonlinear causality detected by the modified Baek and Brock test is evidence for negative or positive causality.

[11] The author thanks an anonymous reviewer for suggesting this interpretation.

Table 4
Nonlinear Granger causality analysis: The 1900s

Panel A: The case of crude oil futures

$R_{co} \rightarrow R_s$			$R_s \rightarrow R_{co}$		
$Lx = Ly$	CS	TVAL	$Lx = Ly$	CS	TVAL
1	.011	3.558	1	.017	4.801
2	.019	4.080	2	.027	4.926
3	.030	4.611	3	.035	5.986
4	.036	4.487	4	.042	5.066
5	.035	3.867	5	.040	4.146
6	.028	2.662	6	.039	3.586
7	.014	1.125	7	.044	4.053
8	.018	1.328	8	.035	2.881

Panel B: The case of heating oil futures

$R_{ho} \rightarrow R_s$			$R_s \rightarrow R_{ho}$		
$Lx = Ly$	CS	TVAL	$Lx = Ly$	CS	TVAL
1	.012	3.629	1	.012	3.581
2	.014	3.076	2	.018	3.576
3	.016	2.622	3	.020	3.392
4	.017	2.357	4	.024	3.291
5	.018	2.157	5	.023	2.559
6	.006	.615	6	.027	2.423
7	.001	.122	7	.038	2.961
8	.001	.113	8	.025	1.600

Note: This table provides the results the modified Baek and Brock test statistics applied to the residuals from the bivariate VAR models for the 1990s. R_{co} and R_{ho} denote crude oil and heating oil futures returns, respectively, and R_s denotes stock index returns. CS and TVAL are the difference between the two conditional probabilities in Equation (2.4) and the standardized test statistic in Equation (2.5), respectively. The null hypothesis of the test statistic is no nonlinear Granger causality, and it is asymptotically distributed $N(0, 1)$. The critical value at 5% significance level is 1.64.

stock market depends on the properties of the discount factor, it is arguable that the inflation rate plays a significant role in the transmission process. The well-known Fisher hypothesis states that the risk-free component of the discount factor is composed of expected inflation and a real rate of return.[12] Hence, shocks to the inflation rate are likely to affect both oil and stock returns, creating a link.[13]

The second main finding of the study is that the linkage between oil prices and the stock index movements is stronger in the 1990s. Although Sadorsky (1999) reaches the same conclusion from an investigation of impulse responses between oil price shocks and stock returns, this finding contradicts Hooker (1996). Hooker examines linear Granger causality between oil prices and U.S. macro variables and finds that the influence of oil prices on the U.S. economy disappears after 1986.

Hamilton (1996), however, suggests that most of the oil price increases since 1986 should be viewed as corrections to earlier declines and that oil prices should be compared to their values in the previous year, rather than during the previous quarter alone, to determine the impact of oil price changes. He shows that oil

[12]The discount factor also includes asset-specific risk factors. A single discount factor for each asset incorporates asset-specific risk adjustments, however, because they are generated by the correlation between random components of the common discount factor and the asset-specific payoffs. See Cochrane (2001) for further discussion.

[13]A reviewer raised the issue that the observed nonlinear feedback could be due to omitted information effects, in particular to autoregressive conditional heteroskedasticity (ARCH) effects. If oil and stock prices are synchronously influenced by a latent common factor, representing daily information flow to the market, the test statistics may indeed capture lagged volatility persistence. Engle and Kozicki's (1993) cofeature test is used to examine whether oil and stock markets have a common volatility structure as a response to a latent common factor. The test statistics, however, strongly reject this. For example, the Engle-Kozicki test for the null hypothesis of common ARCH effects between crude oil futures and stock returns for the 1990s is 129.84, and the chi-square critical value at 11 degrees of freedom is 19.7. Full details of the tests are available upon request.

prices continue to influence U.S. macro variables when net change in oil prices over a year is used in causality tests. Furthermore, Hamilton (2000) argues that if the true relation between oil and the economy is nonlinear, a linear approximation may seem unstable over time even if the underlying relation is stable. He formally tests for a linear relation against an alternative of nonlinear specifications and provides overwhelming evidence for a nonlinear relation between oil and the economy. The present study's findings are consistent with Hamilton's results.

6 Summary and Conclusion

This paper extends the understanding of linkages between oil prices and the U.S. equity market. In an important contribution, HMS detect no relationship between oil price shocks and the movements of the S&P 500 index, which is against the conclusions of prior research that suggest a significant relationship between oil prices and the economy. This study argues that this conclusion is due to the fact that HMS focus solely on linear dependencies.

Linear and nonlinear causality tests are conducted between oil futures returns and stock index returns for the 1980s, using the HMS data, and also for the 1990s. Highlighting the importance of testing for nonlinear linkages in addition to linear linkages, the results of the empirical analysis suggest that oil price shocks indeed affect the stock index returns in a nonlinear fashion. The study also finds that stock index returns affect oil futures markets, suggesting a feedback relation, especially in the 1990s. The overall statistical analysis in this paper hence clearly supports a nonlinear modeling of the relationship between oil and the economy and, along these lines, it can be viewed as complementary to Hamilton (2000).

The findings of the study offer at least two avenues for future research. First, evidence from international equity markets should be produced to examine the robustness of the findings. Second, the feedback relation between oil futures and the stock markets implies predictability in both markets. The economic significance of this predictability should be examined for conclusions on market efficiency.

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