Lead Lag Relationships Between Resource Prices and Corresponding Resource Company Share Prices

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The objective of this study is to analyze the lead-lag relationship between resource prices and corresponding share prices. Investment fund managers holding resource stocks often follow the stock's underlying commodity price as a source of leading information, in hopes that this price information can be used for analyzing future stock price movements. For example, investment managers would expect to find a relationship between crude oil price and an oil producing company such as Exxon. This study will attempt to provide further information on these types of relationships by analyzing the lead-lag relationships between commodity prices and stock prices.

Lead lag relationships in markets refer to the tendency of prices to be determined in one market, and with information then passed on during a lag period to a corresponding market. Considerable information exists on lead lag analysis from a number of studies Coleman (1996), Copeland (1998), Fung (1999), Joukivolle (1995), and Koutmos (1996). Leuthold points out that often traders are interested identifying which market registers the new information the most quickly (Leuthold et al. 1992). Lead lag relationships are determined based on the origin of important news when comparing two markets (Franses et al. 1997). Lead lag analysis also attempts to determine the dominant market. Dominant markets are those markets that are closest to important economic activities and have the ability to assimilate information quickly, and then pass the information on to other related markets, and they are considered pre-eminent in the price discovery process (Leuthold et al. 1992).

The nature of the new information may affect the different markets in different ways. The leading behavior of the futures market often strengthens significantly around the time of

macroeconomic news releases (Frino et al. 2000). As well, evidence shows that feedback from the equities market to the futures market strengthens around stock-specific information releases and that the lead of the futures market weakens during this time (Frino et al. 2000). Little research has been done on the lead-lag relationships between a firm's stock value and the value of the underlying commodity's futures price. However, research shows that the futures market does have a causality relationship with the spot market or vice versa. For example, a number of researchers have found that that hog futures market play an important role in the spot price discovery process for hogs (Leuthold et al. 1992). Lead lag relationships have also been found between the currency options market and spot markets (Pan et al. 1996).

Some research has been undertaken on the lead lag relationship between equity index futures values and equity index spot values. Results show that on high volatility days the futures market is the dominant market for price discovery when comparing the S&P 500 futures index and spot index (Albert et al. 1993). As well, others have found feedback between the S&P 500 futures and the S&P 500 spot index (Kawaller et al. 1993).

Lags may occur due to factors such as imperfect information, information arriving in large doses, and market imperfections, and several possible outcomes exist regarding the lead-lag relationships between corresponding commodity futures prices and stock prices. First, there could be no causality, and so one market would not affect the other. Second, the equity market could cause movements in the commodity futures market . This could be due to the ability of one or several firms together being able to influence the supply of the commodity, or simply that market information arrives first in the commodity futures market. Third, the commodity futures market could cause movements in the stock market. For example, an increase in gold price would be expected to increase profits and share price for a gold mining firm.

Data

Daily data is used for the 15 year period from January 1, 1984 to December 31, 1998. Stock prices are included for 42 resource firms based in Canada and the USA. The data is converted to US dollars as required using exchange rates, and stocks are adjusted for splits. Commodity futures prices are from the USA exchanges. Commodity futures values from seven commodities are included from the agricultural, interest rate, lumber, metals and petroleum sectors.

Procedure

The procedure used is similar to that of Boyd and Brorsen (1985, 1986). Percentage price changes of the data are taken to remove any linear time trends Next, a series of bivariate autoregressive (AR) models are constructed. These are used in the causality tests which follow. The number of lags included is selected using Akaike's Information Criterion (AIC) (Akaike, 1976). The AIC tends to overestimate the true number of lags, thus lessening the probability of selecting too small an order in a small sample (Shibata, 1976).

The bivariate model can be written as

$$P_t = \sum_{i=1}^{p} AP_{t-i} + e_{t,}$$

where

$$P_t = \begin{bmatrix} P_{1t} \\ P_{2t} \end{bmatrix}, \quad A = \begin{bmatrix} a_{11}(i) & a_{12}(i) \\ a_{21}(i) & a_{22}(i) \end{bmatrix}, \quad and\ e_t = \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \qquad (1)$$

and P_{1t} and P_{2t} are the futures price and the stock price, the e_t's are residuals, and the a's are coefficients to be estimated. Residuals of the bivariate autoregressive models are checked for white noise and if the true AR model is selected and the residuals are white noise, then

consistent and asymptotically efficient estimates of the parameters and standard errors are obtained by least squares techniques.

The concept of Granger (1969) causality is used to determine the direction of dynamic price adjustments. Pierce and Haugh (1977) define causality in terms of predictability. A variable X does not cause variable Y if Y cannot be predicted better by using past values of X than if past values of X are not used. If X causes Y and Y does not cause X, then X is said to unidirectionally cause Y. Bivariate causality occurs when X causes Y and Y causes X. This is called a feedback
relationship. Unidirectional causality has implications for price discovery. For example, if gold futures prices cause Barrick Gold stock prices, then it would imply that prices are first discovered in the gold futures market.

The test for causality running from X to Y is performed by testing the significance of the coefficients as a group rather than individually. This test is conducted with the Wald F statistic (Wald, *1943).* This test procedure is a variant of Granger's test which Monte Carlo studies have shown to be more powerful than the causality tests of either Sims *(1972, 1977)* or Haugh (Nelson and Schwert, *1982;* Geweke et al., *1983).*

Instantaneous causality tests have been used frequently in past research (e.g. Uri and Rifkin, *1985),* even though some have questioned their validity (Price, *1979;* Layton, *1984).* The test is usually accomplished by adding the current period's price to the model. In this paper, we are primarily concerned with instantaneous relationships when no lagged relationship is present. For a zero lag model, the test of instantaneous causality can be accomplished by testing the significance of the contemporaneous correlation coefficient. Unfortunately, the direction of
causality cannot be determined for an instantaneous relationship.

Two equations are used for the following bivariate model that has a two period lag in this example:

$$Stock\ Price = f(Stock\ Price_{t-1}, Stock\ Price_{t-2}, Futures\ Price_{t-1}, Futures\ Price_{t-2}) \quad (2)$$

$$Futures\ Price = f(Stock\ Price_{t-1}, Stock\ Price_{t-2}, Futures\ Price_{t-1}, Futures\ Price_{t-2}) \quad (3)$$

If adding the past commodity futures prices adds significant explanatory power to stock price in equation (2), as measured by the use of the F-test, then the commodity futures market "causes" or leads the corresponding stock price. Likewise, if the past stock prices add significant explanatory power to commodity futures prices in equation (3), as measured by the use of the F-test, then the stock price "causes" or leads the corresponding commodity futures price.

Results

The causality *F*-statistics and equation R^2 values are shown in Table 1. Forty-five of the eighty-four equations have significant *F* statistics at the 5% level, indicating significant explanatory power. None of the equations have an R^2 value over 0.05. This is expected, as the equations were constructed from daily data, which is in percentage changes rather than levels and therefore high R^2 values would not be expected, compared to annual data in levels, for example. Lags ranged from one to ten days. The petroleum sector generally had the longest lags.

Nineteen out of forty-two firms showed that the underlying commodity futures price led the equity price, indicating that the commodity futures markets were a lead source of information for the corresponding markets of the stocks. This would generally be expected to

be the case that the futures market leads the stock market. Only three of forty-two firms showed that the stock price led the underlying commodity futures price, indicating that the stock market was the primary source of information in these cases. These firms were Georgia-Pacific in the lumber sector, and Barrick Gold and Placer Dome in the mining sector.

Eleven firms showed feedback between the stock market and the underlying commodity futures market. This indicates each market passes information back to the other in relatively simultaneous fashion. Only eight of the forty-two firms did not show a significant led in either market.

Table 1 shows that in the agricultural sector, one of the two companys' stock price lagged its corresponding underlying commodity futures price by two days. The was no significant feedback between the markets, nor did the stock price lead the underlying commodity futures market.

In the utility sector, the U.S. 3-month T-Bills futures lead the stock price for two of five firms, while there was significant feedback between the markets for two other firms. There was no significant feedback between lumber futures and the stock price in the forest products sector. One lumber firm's results showed that lumber futures price leads the stock price, while another firm's results indicated that stock price leads the lumber futures price.

In the mining sector, both firms showed significant feedback between the markets for copper production. Of the seven firms in gold mining, three showed significant feedback between the markets, and the stock prices led gold futures for two firms, while gold futures led the stock price for one firm.

In the petroleum sector, all ten integrated petroleum firms’ equity prices were led by the crude oil price. Two of four firms showed significant feedback between the markets for petroleum producers, while crude oil futures price led the stock price for the other two firms.

The crude oil futures price led the stock price for three of six firms in oilfield services. For two other firms in oilfield services there was significant feedback between the markets.

Conclusion

There appears to be some useful information available to investment fund managers as evidenced by the lead lag relationships found in this study. Significant lead-lag relationships between markets were found in thirty-four of the forty-two firms studied.

In terms of sectors, the petroleum sector was the most prominent in terms of number of lead lag relationships, with only one of twenty firms not having a significant lead-lag relationship between oil price and stock price. For fifteen of the firms the crude oil futures price led the equity price while four firms had feedback relationships between the markets. The utility and metal sectors had the highest number of feedback relationships, with two of the five firms in utilities and five of nine firms in the metal sector.

By studying these relationships further, investment managers may be able to improve their stock price transaction decisions, especially for oil stocks. Oil futures prices appear to quite consistently lead stock prices, and so they may serve as a useful predictor of stock price.

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Table 1. Daily Lead-Lag and Causality Price Relationships for the Underlying Commodity Futures Price and Corresponding Stock Price.

Sector	Stock/Commodity			Wald F-statistic	R^2
Agriculture	Deere & Co	3	Soybeans	1.05	0.00
	Soybeans	3	Deere & Co	0.39	0.02
	Monsanto	2	Soybeans	1.04	0.00
	Soybeans	2[a]	Monsanto	5.43*	0.01
Utility	Bell Atlantic	7[b]	U.S. 3 Month T-Bills	2.80*	0.01
	U.S. 3 Month T-Bills	7	Bell Atlantic	2.75*	0.01
	B.C. Telus	2	U.S. 3 Month T-Bills	0.02	0.00
	U.S. 3 Month T-Bills	2	B.C. Telus	9.38*	0.01
	Con Edison	4	U.S. 3 Month T-Bills	3.82*	0.01
	U.S. 3 Month T-Bills	4	Con Edison	5.00*	0.01
	GTE Corp	5	U.S. 3 Month T-Bills	1.29	0.00
	U.S. 3 Month T-Bills	5	GTE Corp	4.02*	0.02
	Transalta	2	U.S. 3 Month T-Bills	1.89	0.00
	U.S. 3 Month T-Bills	2	Transalta	2.52	0.01
Lumber	Abitibi Consolidated	3	Lumber	0.11	0.01
	Lumber	3	Abitibi Consolidated	0.68	0.01
	Champion Int.	1	Lumber	0.19	0.01
	Lumber	1	Champion Int.	0.89	0.00
	Domtar Inc	2	Lumber	0.97	0.01
	Lumber	2	Domtar Inc	1.72	0.00
	Georgia-Pacific Corp	4	Lumber	2.67*	0.01
	Lumber	4	Georgia-Pacific Corp	1.23	0.02
	MacMillan Bloedel	2	Lumber	0.94	0.01
	Lumber	2	MacMillan Bloedel	3.37*	0.01
	Weyerhauser	2	Lumber	0.25	0.01
	Lumber	2	Weyerhauser	1.11	0.00
Copper	Noranda	4	Copper	2.80*	0.01
	Copper	4	Noranda	11.93*	0.02
	Phelps Dodge	3	Copper	10.58*	0.01
	Copper	3	Phelps Dodge	6.54*	0.03
Gold	Barrick	1	Gold	3.97*	0.00
	Gold	1	Barrick	0.26	0.00
	Coeur d'Alene Mines	6	Gold	1.47	0.01
	Gold	6	Coeur d'Alene Mines	2.62*	0.01
	Echo Bay Mines	2	Gold	1.33	0.01
	Gold	2	Echo Bay Mines	0.65	0.00
	Homestake Mining Co.	4	Gold	5.80*	0.01
	Gold	4	Homestake Mining Co.	2.53*	0.01
	Newmont Mining Corp	6	Gold	2.28*	0.01
	Gold	6	Newmont Mining Corp	2.30*	0.01
	Placer Dome	2	Gold	3.76*	0.01
	Gold	2	Placer Dome	1.75	0.01

Table 1 (cont.)

	Teck Corp	2	Gold	4.30*	0.01
	Gold	2	Teck Corp	12.27*	0.01
Petroleum Integrated					
	Arco	8	Crude Oil	1.06	0.02
	Crude Oil	8	Arco	6.68*	0.02
	Cdn. Occidental	8	Crude Oil	1.23	0.02
	Crude Oil	8	Cdn. Occidental	6.30*	0.03
	Chevron	8	Crude Oil	0.64	0.02
	Crude Oil	8	Chevron	3.86*	0.02
	Exxon	8	Crude Oil	0.42	0.02
	Crude Oil	8	Exxon	2.60*	0.05
	Imperial Oil	8	Crude Oil	0.62	0.02
	Crude Oil	8	Imperial Oil	5.36*	0.03
	Mobil Corp	8	Crude Oil	0.81	0.02
	Crude Oil	8	Mobil Corp	5.21*	0.03
	Occidental	5	Crude Oil	0.65	0.01
	Crude Oil	5	Occidental	5.65*	0.02
	Royal Dutch Petroleum	9	Crude Oil	1.20	0.02
	Crude Oil	9	Royal Dutch Petroleum	4.71*	0.02
	Shell Canada	8	Crude Oil	1.18	0.02
	Crude Oil	8	Shell Canada	3.94*	0.01
	Texaco	8	Crude Oil	1.51	0.02
	Crude Oil	8	Texaco	4.26*	0.02
Producers	Alberta Energy Co	9	Crude Oil	14291.31*	0.02
	Crude Oil	9	Alberta Energy Co	6.96*	0.03
	Apache Corp	9	Crude Oil	1.22	0.02
	Crude Oil	9	Apache Corp	9.18*	0.03
	Pan Canadian Petroleum	5	Crude Oil	1.15	0.01
	Crude Oil	5	Pan Canadian Petroleum	6.89*	0.01
	Ranger Oil	8	Crude Oil	2.17*	0.02
	Crude Oil	8	Ranger Oil	8.07*	0.03
Services	Computalog Ltd.	7	Crude Oil	1.05	0.01
	Crude Oil	7	Computalog Ltd.	7.43*	0.03
	Global Marine Inc	8	Crude Oil	0.90	0.02
	Crude Oil	8	Global Marine Inc	1.25	0.01
	Halliburton Co	8	Crude Oil	0.78	0.02
	Crude Oil	8	Halliburton Co	5.18*	0.02
	Schumberger Ltd.	8	Crude Oil	0.56	0.02
	Crude Oil	8	Schumberger Ltd.	4.64*	0.02
	Smith International	10	Crude Oil	1.88*	0.02
	Crude Oil	10	Smith International	4.54*	0.03
	Tesco Corp	10	Crude Oil	2.60*	0.02
	Crude Oil	10	Tesco Corp	2.30*	0.04

* Denotes significance at the 5% level.

[a] For example, Soybean futures price leads or 'causes' Monsanto stock price by 2 days, as evidenced by the significant causality *F*-statistic.

[b] Shows evidence of feedback relationships given the two significant causality *F*-statistics. For example Bell Atlantic stock price leads or 'causes' U. S. 3 Month T-Bills futures price by 7 days, while U. S. 3 Month T-Bills futures price leads or 'causes' Bell Atlantic stock price by 7 days.