COMMODITY PRICES AS PREDICTORS OF AGGREGATE PRICE CHANGE*

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Many analysts have advocated using commodity prices as a guide for monetary policy.[1] The basic reasoning can be simply put: "Money creation is intended to promote price stability and is best guided by an index of prices set in real markets." [*Wall Street Journal,* 1988] The rationale for stabilizing commodity prices can also be expressed in three propositions. First, inflation is a monetary phenomenon that should be eliminated. Second, commodity prices are determined in auction markets; they will therefore change quickly in response to monetary policy actions. Third, changes in commodity prices are good predictors of future aggregate price change. If all three propositions are accepted, then commodity prices might well be a useful guide for monetary policy, possibly serving as an intermediate target or at least as an important indicator variable.

This paper examines the third proposition: commodity prices are good predictors of aggregate price change. Other economists have reported varying results. Alan Garner [1988, p. 12], for example, found "broad commodity price indexes are always useful in predicting consumer price inflation." Joseph Whitt [1988] found that commodity price indexes had substantial predictive value in the volatile post-1975 period, and Philip Klein [1985] found a commodity price index to be a useful leading indicator. Aguais et al. (1988, p. 14], however, found "there is no evidence that [commodity price indexes] provide any information [for predicting movements in the general price index] beyond what is already contained in wages and supply conditions." Bennett McCallum [1988] also found that two commodity indexes had little predictive value. Most of the authors used Granger causality tests to reach their conclusions.

This paper also examines the relation of commodity and aggregate prices by using Granger causality tests. Those tests, however, are implemented somewhat differently than in other studies in order to avoid several potential pitfalls. In addition, this study is broadened to include a multivariate forecasting procedure, to examine multistep forecasting, and to investigate forecasting performance around turning points. It therefore goes beyond related work in examining the proposition that commodity price indexes are useful predictors of aggregate price measures.

Indexes Examined

Many indexes are used to measure aggregate and commodity prices. The most useful measures for analysis should have relatively long track records, so that statistical results are not dominated by the peculiarities that exist in short intervals. In addition, the indexes should be well understood by economists so that the results can be evaluated with respect to the known strengths and weaknesses of particular indexes.

The Consumer Price Index for all urban consumers (CPI) is used below as the measure of the aggregate price level. It is available monthly, is seasonally adjusted by the Bureau of Labor Statistics, has been calculated for 70 years, and has been subjected to substantial professional examination and comment.[2] One commodity price index that has attracted much attention is the *Journal of Commerce* Materials Index (JOCI), designed by Geoffrey H. Moore and his associates at the Center for International Business Cycle Research. They have constructed monthly values as far back as 1948. It includes 18 industrial commodities and was specifically designed to help

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[1] For example, Irving Fisher [1920] presented a detailed strategy for stabilizing an index of 75 commodity prices. More recent proposals that have attracted considerable attention have been made by Wayne Angell [1987], James Baker [1987], and Manuel Johnson [1988].

[2] For further information, the U.S. Bureau of Labor Statistics publishes numerous references, including [1978].

predict changes in aggregate price measures.[3] Another widely used index is the Spot Price Index (SPI) published by Knight-Ridder's Commodity Research Bureau. It includes 10 foodstuffs and 13 raw industrial commodities, and is also available monthly from 1948. Before 1981 it was compiled by the Bureau of Labor Statistics[4].

Charts 1 and 2 show twelve-month changes in both commodity price indexes and the CPI. Both indexes have been much more volatile than the CPI throughout the postwar period. Casual interpretation of commodity price movements is therefore difficult and potentially misleading. Commodity price volatility should also be kept in mind when interpreting the more formal statistical results below.

[3]For further information, see *Journal of Commerce* [1986].

[4]John Rosine [1987] provides a useful discussion of the construction of commodity price indexes.

Testing for Granger Causality

To test for Granger causality, one can examine whether lagged values of one series add statistically significant predictive power to another series' own lagged values for one-step ahead forecasts. If so, the first series is said to Granger-cause the second. Consider the equation

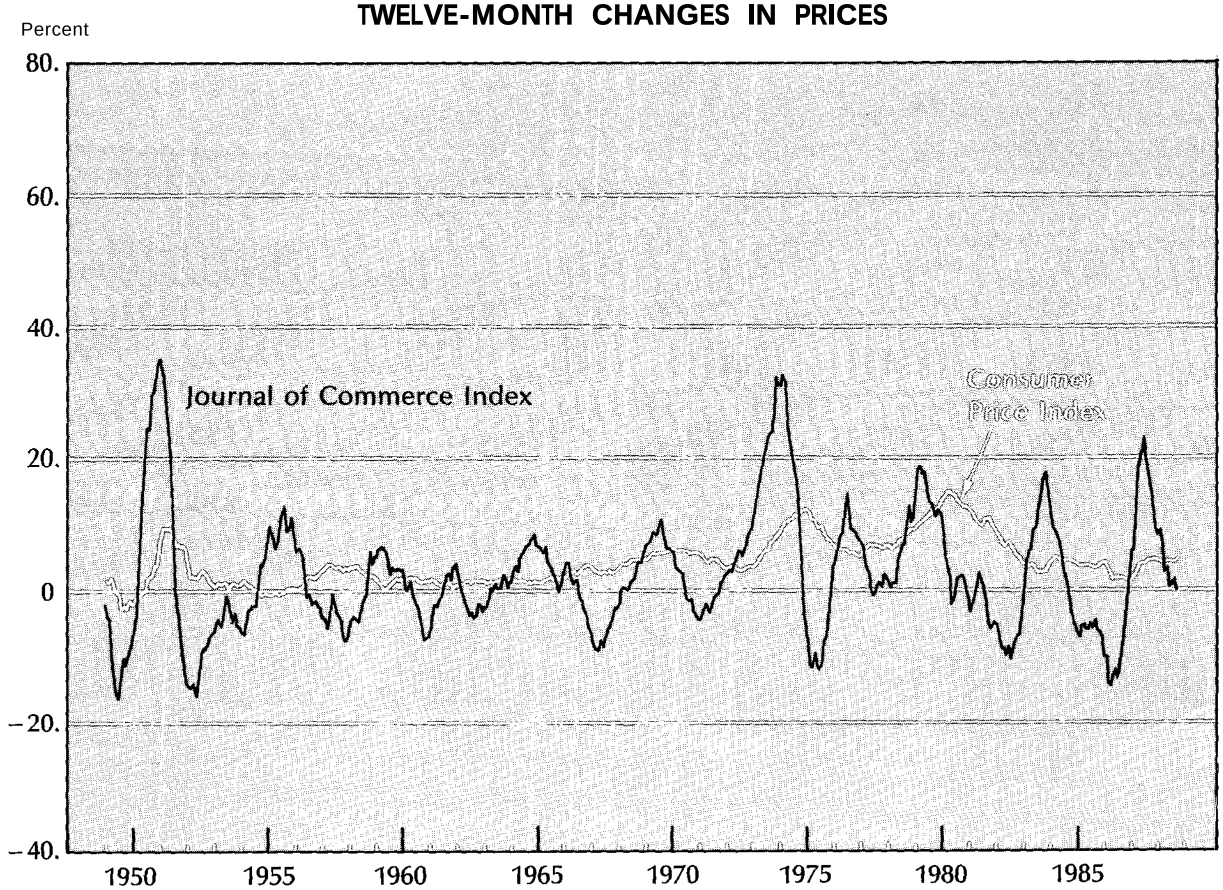
$$P_t = \alpha + \sum_{i=1}^{l} \beta_i P_{t-i} + \sum_{i=1}^{l} \gamma_i Q_{t-i} + \epsilon_t \qquad (1)$$

where P and Q are series of macroeconomic variables, α, the β_is and the γ_is are regression coefficients, ϵ_t is a white noise error term, and l is an integer representing the lag length. If an F test finds the estimated γ_is to be statistically significant, then the series Q Granger-causes P.

Several decisions are necessary in order to implement a Granger causality test using equation (1). What lag lengths should be used? Should the series

Chart 1

TWELVE-MONTH CHANGES IN PRICES



Note: *Each series contains the percentage change in the monthly value of the price index from the monthly value twelve months earlier. The chart extends from January 1949 through October 1988.*

be differenced? What diagnostic test should be used to determine whether the residuals are serially correlated? Are the results sensitive to the starting and ending dates? The answers to each question are important since each choice can affect the final result.

First, consider the choice of the lag length. Nelson and Schwert [1982] found that heavily paramaterized forms of equation (1)-that is, unnecessarily large values of the lag length *l*- can result in a serious loss of power in causality tests. To guard against overly profligate parameterization, a model selection statistic, the Schwarz Criterion, is used below to set the lag length. Choosing the lag length for which the Schwarz Criterion is minimized leads to a relatively parsimonious specification in most cases below.[5]

The next choice, whether the series should be differenced, can be made by using tests designed to examine series for unit roots. Yash Mehra [1988] noted that the presence of a unit root in time series can cause F statistics to have nonstandard distributions. In equation (1), therefore, if either series had a unit root the typical F test might not be meaningful.

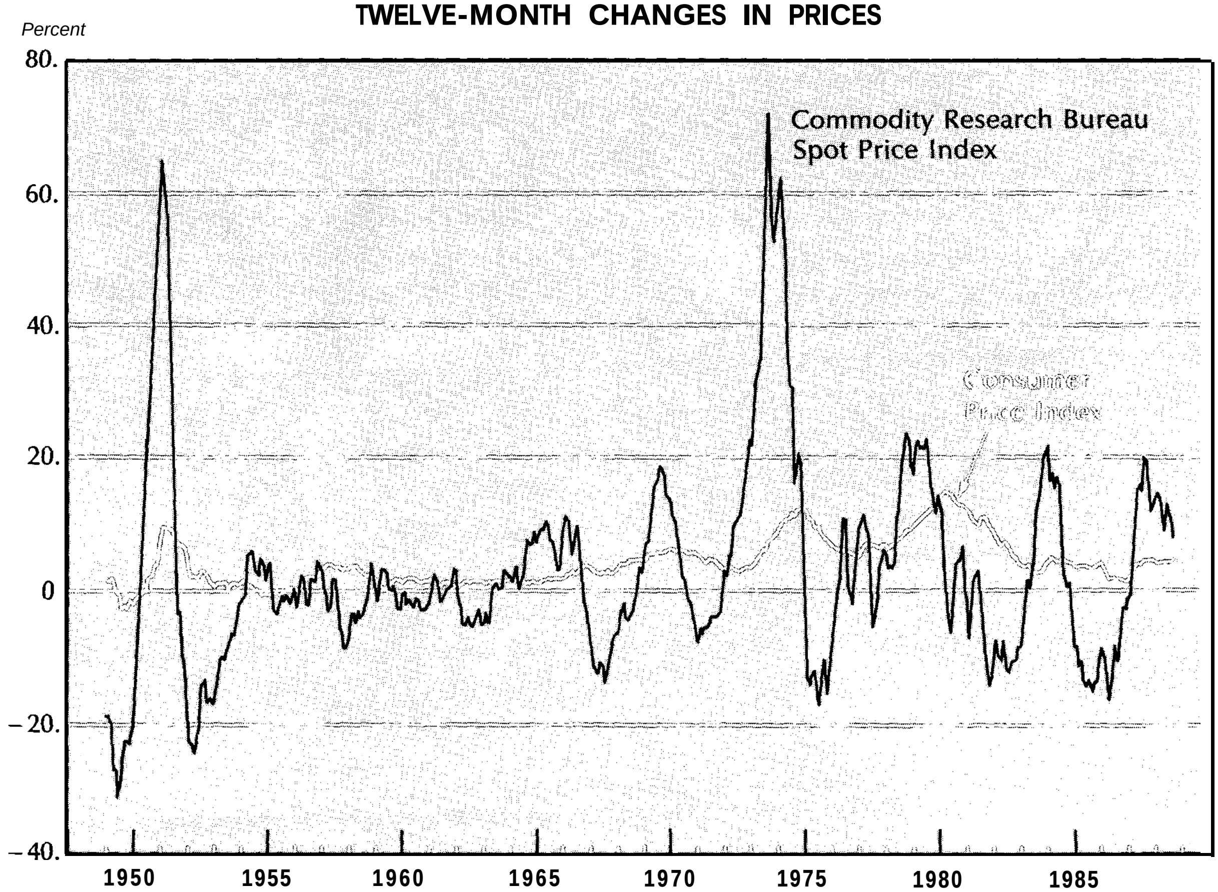
Unit Root Test To guard against that problem, (logs of) the CPI, JOCI, and SPI series were first tested for unit roots. The test, as proposed by Dickey

[5] Priestly [1981] discusses the relative merits of several model selection statistics. The Schwarz Criterion (SC) is given by $S = n \log \hat{\sigma}^2 + q \log n$ where n is the number of degrees of freedom, q is the number of parameters estimated, and $\hat{\sigma}^2$ is the residual variance. It can be seen that although adding an additional coefficient to an equation can lower the first term of the SC by lowering the residual variance, the additional coefficient also raises the second term.

In practice, the SC usually reaches a well-defined global minimum with a fairly parsimonious parameterization. Yi and Judge [1988] compare SC with two popular alternatives, finding that both alternatives asymptotically overestimate the true size of a model with a positive probability, whereas the SC's asymptotic probability of overestimating the true size is zero.

Chart 2

TWELVE-MONTH CHANGES IN PRICES



Note: Each series contains the percentage change in the monthly value of the price index from the month/y value twelve months earlier. The chart extends from January 1949 through October 1988.

and Fuller [1979], involves estimating the coefficients in the following equation:

$$\Delta X_t = \alpha_0 + \alpha_1 T + \beta X_{t-1} + \sum_{i=1}^{l} \gamma_i \Delta X_{t-i} + \epsilon_t \qquad (2)$$

where X is the series being tested for a unit root, A is the first difference operator, T is a time trend, and e_t is a white noise error term. Under the null hypothesis that there is a unit root in the series X, the coefficient ß should be zero. The standard t statistic is used for testing whether ß is significantly different from zero; critical values, however, are not standard but are given by Fuller [1976].

The results of unit root tests are given in Table I. In each case the lag length was set at the value that minimized the Schwarz Criterion. The first three equations can be used to test whether the series in log-level form is appropriate. In all cases the null hypothesis-the existence of a unit root-is not rejected by examining the t statistic for the estimated coefficient ß.

It is possible that there are multiple unit roots, and consequently differences of the series are not stationary. The last three equations can be used to test for a unit root when the series in first difference form-that is, the series X in equation (2) is ΔCPI, ΔJOCI, or ΔSPI. In each case the null hypothesis is rejected; it therefore appears that there is no unit root in first differences of the series.

Since both commodity price indexes are not seasonally adjusted, autocorrelations of the differenced series were examined. In neighborhoods of the 12th and 24th lags the autocorrelations were close to zero. The series therefore do not appear to suffer from seasonal autocorrelation.

Granger Causality Test Results The tests for unit roots support testing for Granger casuality with each series in first differences (of logs). In equation (1), let the series P be the first difference of the CPI and the series Q be the first difference of either the JOCI or the SPI. Table II contains the results of those tests. For the SPI an F test rejected the null hypothesis that the coefficients on the lagged values of commodity prices are zero. In other words, over the sample period the SPI Granger-caused the CPI. Since the F test is derived by assuming white noise residuals, a Lagrange multiplier test proposed by Godfrey [1978] was used to look for either autoregressive or moving average errors. The null hypothesis, the absence of AR or MA errors, was not rejected at conventional levels using a Chi-squared test.

For the JOCI an F test also rejected the null hypothesis that coefficients on lagged commodity prices are zero. The Lagrange multiplier test did, however, reject the null hypothesis and thus indicated that the residuals were consistent with either an AR or MA process. After experimentation equation (1)

Table I

UNIT ROOT TEST STATISTICS

Time bounds: January 1954 to July 1988

Equation: $\Delta CPI_t = \alpha_0 + \alpha_1 T + \beta CPI_{t-1} + \sum_{i=1}^{l} \gamma_i \Delta CPI_{t-i} + \epsilon_t$

Lag length l: 2 $\bar{R}^2 = .52$ Schwarz Criterion: −4920

Test statistic for $\hat{\beta}=0$: −2.16

Equation: $\Delta JOCI_t = \alpha_0 + \alpha_1 T + \beta JOCI_{t-1} + \sum_{i=1}^{l} \gamma_i \Delta JOCI_{t-i} + \epsilon_t$

Lag length l: 1 $\bar{R}^2 = .22$ Schwarz Criterion: −3698

Test statistic for $\hat{\beta}=0$: −1.86

Equation: $\Delta SPI_t = \alpha_0 + \alpha_1 T + \beta SPI_{t-1} + \sum_{i=1}^{l} \gamma_i \Delta SPI_{t-i} + \epsilon_t$

Lag length l: 1 $\bar{R}^2 = .31$ Schwarz Criterion: −3202

Test statistic for $\hat{\beta}=0$: −1.98

Equation: $\Delta^2 CPI_t = \alpha_0 + \alpha_1 T + \beta \Delta CPI_{t-1} + \sum_{i=1}^{l} \gamma_i \Delta^2 CPI_{t-i} + \epsilon_t$

Lag length l: 1 $\bar{R}^2 = .37$ Schwarz Criterion: −4934

Test statistic for $\hat{\beta}=0$: −6.22

Equation: $\Delta^2 JOCI_t = \alpha_0 + \alpha_1 T + \beta \Delta JOCI_{t-1} + \sum_{i=1}^{l} \gamma_i \Delta^2 JOCI_{t-i} + \epsilon_t$

Lag length l: 1 $\bar{R}^2 = .26$ Schwarz Criterion: −3695

Test statistic for $\hat{\beta}=0$: −10.01

Equation: $\Delta^2 SPI_t = \alpha_0 + \alpha_1 T + \beta \Delta SPI_{t-1} + \sum_{i=1}^{l} \gamma_i \Delta^2 SPI_{t-i} + \epsilon_t$

Lag length l: 1 $\bar{R}^2 = .31$ Schwarz Criterion: −3200

Test statistic for $\hat{\beta}=0$: −11.99

Note: For the tests above the 5 percent and 1 percent critical values are -3.42 and - 3.98, respectively.

Table II

GRANGER CAUSALITY TEST STATISTICS

Time bounds: January 1954 to July 1988

Equation: $$\Delta CPI_t = \alpha + \sum_{i=1}^{l} \beta_i \Delta CPI_{t-i} + \sum_{i=1}^{l} \gamma_i \Delta SPI_{t-i} + \epsilon_t$$

Lag length l: 9	$\bar{R}^2 = .59$	Schwarz Criterion: -4733
Test statistic for $\Sigma\hat{\gamma}_i = 0$: 5.36		Significance level: 10^{-7}
LM test statistic: 2.40		Significance level: .12

Equation: $$\Delta CPI_t = \alpha + \sum_{i=1}^{l} \beta_i \Delta CPI_{t-i} + \sum_{i=1}^{l} \gamma_i \Delta JOCI_{t-i} + \epsilon_t$$

Lag length l: 2	$\bar{R}^2 = .52$	Schwarz Criterion: -4919
Test statistic for $\Sigma\hat{\gamma}_i = 0$: 5.67		Significance level: .0038
LM test statistic: 6.66		Significance level: .0099

Equation: $$\Delta CPI_t = \alpha + \sum_{i=1}^{l} \beta_i \Delta CPI_{t-i} + \sum_{i=1}^{l} \gamma_i \Delta JOCI_{t-i} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2}$$

Lag length l: 2	$\bar{R}^2 = .57$	Schwarz Criterion: -4927
Test statistic for $\Sigma\hat{\gamma}_i = 0$: 16.7		Significance level: 10^{-8}
LM test statistic: 4.84		Significance level: .089

Note: The test for zero coefficients is a conventional F test. The LM test for first order AR or MA residuals is $X^2(1)$.

was estimated assuming that residuals followed a second order moving average process. Again an F test rejected the null hypothesis, thereby indicating that the JOCI Granger-caused the CPI. The Lagrange multiplier test did not indicate significant remaining residual correlation at the 5 percent level.

A note of caution is in order: several results mentioned above are sensitive to the lag lengths employed. For example, with a lag length of twelve in the unit root test for ΔCPI, the t statistic for $\hat{\beta}$ is -2.37; the null hypothesis in that instance is not rejected for first differences of the CPI. And in the Granger causality test for the JOCI with a lag length of eight, the F statistic is 1.24, thereby failing to reject the hypothesis that coefficients on the lagged values of the JOCI are zero. Although the results of Nelson and Schwert strongly support the relatively parsimonious specifications reported in Tables I and II, the sensitivity of the results to the lag length does cause one to question the amount of information conveyed by these tests.

In addition, although both commodity price indexes add statistically significant explanatory power to lagged values of the CPI, the actual reduction in the standard error of estimated residuals (SEE) was quite small. Comparing the final regression equation reported in Table II with one omitting the lagged JOCI, the annualized SEE was increased from 2.72 to 2.82 by omitting lagged JOCI terms. Similarly, with nine lagged values, the SEE was increased from 2.61 including the SPI to 2.77 without it. In short, the incremental predictive value of both indexes was small over the sample period.

Perhaps the incremental predictive value has increased over time; the results over the whole sample would thus understate the current effect. In particular, it is possible that the incremental predictive value increased after the United States abandoned the gold standard[6]. To test that possibility the sample was split at 1971 Q3 and equation 1 was estimated for the early and late subperiods as well as the entire sample. An F test was then used to test the hypothesis that regression coefficients were equal in both subperiods. For the SPI the F value was 1.50; the null hypothesis was therefore not rejected at the 5 percent level. But for the JOCI an F value of 2.90 indicates that the null hypothesis was rejected at the 1 percent level.

As anticipated, the JOCI did not Granger-cause the CPI in the early period, but did Granger-cause the CPI in the late period. The incremental predictive value of the JOCI remained small, however. Omitting the JOCI from the late period equation only increased the SEE to 3.13 from 2.95. Focusing only on the later observations, therefore, does not alter the conclusion that commodity prices add little for predicting the CPI one step ahead.

A Broader Framework

That commodity prices Granger-cause aggregate price change is not sufficient to establish their total value in prediction. Granger causality traditionally

[6] The author is indebted to Robert Keleher for this suggestion.

measures *one-step ahead* prediction in a *bivariate* environment. As policy indicators, multistep predictions would be much more valuable than one-month forecasts. Also, it may be that other macroeconomic variables add substantial predictive value; including those other variables could alter the incremental predictive value of commodity prices.

Model Description A vector autoregressive (VAR) model provides a convenient framework for examining both properties. Small VAR models have been found to provide forecasts of macroeconomic variables that are often competitive with forecasts from much larger models.[7] Containing no exogenous variables, VAR models can be used to produce forecasts as many periods ahead as desired.

Three VAR models will be used in this section. The first, VAR1, will include the CPI and JOCI plus the 90-day Treasury bill rate (RTB), the capacity utilization rate in manufacturing (CU), the foreign exchange value of the dollar (EVD), and the monetary base (MB).[8] The CPI, JOCI, and MB are logged and differenced to provide stationary series. The second model, VAR2, substitutes the logged and differenced SPI for the JOCI. The third model omits any measure of commodity prices. Forecasts from each model can then be compared to examine any differences.

Just as overly paramaterized equations can reduce the power of statistical tests, overly parameterized VAR models can reduce the accuracy of forecasts. Consider first the equation for the CPI from the unrestricted form of the VARl model:

$$CPI_t = \alpha + \sum_{i=1}^{l} \beta_{1,i} CPI_{t-i} + \sum_{i=1}^{l} \beta_{2,i} JOCI_{t-i} + \ldots + \sum_{i=1}^{l} \beta_{6,i} MB_{t-i} + \epsilon_t \qquad (3)$$

where α is a constant term, l is the common lag length, i represents the coefficient for variable v at lag i, and ϵ_t is a white noise disturbance term. The model contains six equations, each with the same independent variables: with l= 6 for example, there are six lagged values for each of six variables plus a constant, resulting in 37 estimated coefficients per equation.

In order to improve forecasting performance the number of estimated coefficients is reduced by using a simplified version of a strategy proposed in Webb [1985]. Instead of using a common lag length as in equation (3), lag lengths are set as in the equation below:

$$CPI_t = \alpha + \sum_{i=1}^{l_1} \beta_{1,i} CPI_{t-i} + \sum_{i=1}^{l_2} \beta_{2,i} JOCI_{t-i} + \ldots + \sum_{i=1}^{l_6} \beta_{6,i} MB_{t-i} + \epsilon_t \qquad (4)$$

where l_v is the lag length for variable v in the CPI equation. The lag lengths are set in each equation to minimize the Schwarz Criterion, yielding a substantial reduction in the number of parameters estimated.[9] VAR1 and VAR2 thus consist of six equations of the form of equation (4); lag lengths are presented in Table III below. VAR3 is VAR1 minus the equation for commodity prices and all lagged commodity price terms in other **equations.**

Forecasting Results Each model was estimated using data through June 1975; forecasts were computed for each month through June 1976. The forecasts for July 1975 were compared with actual data and the resulting one-step ahead errors were recorded; forecasts for August were used for two-step ahead errors; and similarly, forecast errors up to twelve steps ahead were calculated. Then the process was updated one month, with the model estimated through July 1975 and forecasts made through July 1976. The process of estimation and forecasting was repeated each month through May 1988. The resulting forecast errors were tabulated and summary statistics are displayed in Table IV,

[7] For examples using traditional measures of forecast accuracy, see Lupoletti and Webb [1986] or McNees [1986].

[8] MB is from the Federal Reserve Bank of St. Louis. EVD is the Federal Reserve Board's nominal trade-weighted index from 1967, extrapolated before 1967 using movements in dollar exchange rates with the Canadian dollar, British pound, and German mark. RTB and CU are both published by the Federal Reserve Board.

Why were these particular variables chosen? MB, EVD, RTB, and CU are part of a larger quarterly VAR model used by the author to forecast GNP and its components on a regular basis. It was suspected that each would help predict the CPI. The only experimentation with the model's composition was the addition of the change in outstanding federal debt, which can be thought of as a rough measure of fiscal actions. Adding that variable to VAR3 did not improve forecasts of the CPI; model statistics are therefore not included.

[9] The exact strategy for selecting the lag lengths in an equation is as follows. (1) Iterate over a large number of possibilities and choose a pair of integers I and J that minimizes the Schwarz Criterion, where I is the lag length for the dependent variable and J is a common lag length for the independent variables. (2) If there is at least one independent variable for which all lagged values are not significantly different from zero at the 10 percent level, drop the least significant independent variable from the equation. (3) Repeat step (2) until all variables are significantly different from zero or the Schwarz Criterion increases.

Table III

LAG LENGTHS IN 2 VAR MODELS

VAR 1

Dependent Variable	Independent Variable CPI	JOCI	RTB	CU	EVD	MB
CPI	2	1	1	1	1	1
JOCI	-	6	3	-	3	-
RTB	-	1	3	-	1	1
CU	-	1	1	2	-	-
EVD	-	-	1	-	2	-
MB	-	-	-	1	1	3

VAR 2

Dependent Variable	Independent Variable CPI	SPI	RTB	CU	EVD	MB
CPI	2	1	1	1	1	1
SPI	6	6	6	6	6	6
RTB	-	1	2	-	-	1
CU	-	1	1	2	-	-
EVD	-	-	1	-	2	-
MB	-	-	-	1	1	3

including the traditional mean absolute error statistic (expressed in percentage points, annualized). As expected, those errors increase over the forecast horizon.

Also included are Theil U statistics, which are equal to the ratio of root mean squared error of the model forecasts to the root mean squared error from a no change forecast. Values less than unity indicate that the model forecast outperformed a naive no change forecast. One can meaningfully compare forecast errors for a stationary series with the no change forecast; however, for nonstationary series it is trivial to achieve a low U value. As shown in Table IV, both models do better than simple extrapolation of current conditions for all variables. In some cases the relative accuracy increases with the forecast horizon. Most importantly, the forecast statistics indicate little difference between the accuracy of CPI forecasts from the three models. At each forecast horizon, including those not shown in the table, the difference in mean absolute error between VAR3 and each of the larger models is less than 0.10[10]. The value of including a measure of commodity prices in this forecasting environment is therefore quite small.[11]

[10] It is of course possible that this result is due to some feature of the model used. In particular, some analysts prefer to use VAR models in level form, even if some series appear to have unit roots. To see whether this particular model might perform better in level form, lag lengths in VAR3 were reset with the CPI and monetary base in log levels. The forecasting experiment described in Table IV was then repeated. The accuracy of forecasts of the percentage change in the CPI deteriorated: one-month ahead forecasts had a mean absolute error of 2.23 (versus 2.15 in VAR3); six-months ahead, 2.83 (versus 2.71); and twelve-months ahead, 3.11 (versus 2.95).

[11] Furlong [1988] found similar results. He first found that the JOCI added statistically significant explanatory power in a regression equation for the CPI. In his VAR model (substantially different from the models examined in this paper) the JOCI improved forecast accuracy by only a rather small increment. Finally, he found that the SPI was inferior to the JOCI in multiperiod forecasts.

Table IV

FORECAST RESULTS FROM 3 VAR MODELS

VAR1 ERROR STATISTICS

Variable	1 Step Mae	1 Step Theil U	6 Step Mae	6 Step Theil U	12 Step Mae	12 Step Theil U
CPI	2.14	.87	2.67	.82	2.86	.81
RTB	0.44	.81	1.44	.93	1.86	.89
CU	0.44	.85	1.73	.81	2.63	.75
EVD	1.61	.92	6.25	.95	11.02	.99
MB	2.91	.69	3.06	.75	3.07	.76
JOCI	9.94	.79	12.54	.78	13.09	.70

VAR2 ERROR STATISTICS

Variable	1 Step Mae	1 Step Theil U	6 Step Mae	6 Step Theil U	12 Step Mae	12 Step Theil U
CPI	2.15	.87	2.77	.85	2.88	.83
RTB	0.46	.84	1.32	.94	1.70	.89
CU	0.45	.85	1.72	.79	2.76	.76
EVD	1.61	.92	6.25	.95	10.95	1.00
MB	2.91	.69	3.06	.75	3.07	.76
SPI	17.70	.75	22.91	.75	21.76	.72

VAR3 ERROR STATISTICS

Variable	1 Step Mae	1 Step Theil U	6 Step Mae	6 Step Theil U	12 Step Mae	12 Step Theil U
CPI	2.15	.88	2.71	.83	2.95	.83
RTB	0.43	.82	1.45	.94	1.93	.91
CU	0.46	.87	1.78	.83	2.95	.80
EVD	1.61	.92	6.27	.95	11.09	1.00
MB	2.91	.69	3.06	.75	3.08	.76

Note: Each model was estimated from January 1967 to June 1975, and forecasts generated for each month up to 12 months ahead. Each model was then reestimated through July 1975 and a new set of forecasts was produced. The procedure was repeated through May 1988. The resulting forecasts were compared with the actual data, and the resulting error statistics are displayed in this table.

Accuracy Near Turning Points Traditional statistics such as those presented in Table IV may not completely reveal the value of observing commodity prices. Proponents of commodity price indexes often stress their value in predicting major changes in the rate of inflation. With only a few major changes of inflation trends in the sample period studied above, however, it is possible that a substantial positive effect at a few critical periods was obscured by the noise from many other periods.

Analysts at the Center for International Business Cycle Research have identified a set of turning points for major changes in the rate of growth of aggregate prices. The idea is similar to the traditional use of peaks and troughs for separating expansions and recessions in business cycle analysis. The resulting set of inflationary turning points defines broad phases of advancing and declining inflation rates. Unfortunately (for the analyst, that is) there are few turning points in the entire sample period. With VAR1 (which predicted the CPI more accurately than VAR2) estimated through June 1975, the post-sample forecasts can be evaluated over a period including three turning points: troughs in June 1976 and April 1986, and a peak in March 1980.

Table V contains forecast results for the CPI from the VAR1 and VAR3 models when forecasts were made near inflationary turning points. While one-month **ahead forecasts made near turning points were** less accurate than those made over the entire sample, the results are mildly surprising at longer horizons. In both models, six-month ahead forecasts were roughly as accurate near turning points as at other times, and twelve-month ahead forecasts were actually more accurate near turning points.

Table V

FORECAST ACCURACY NEAR TURNING POINTS

Mean Absolute Errors

Turning Point	VAR1			VAR3		
	1 step	6 step	12 step	1 step	6 step	12 step
June 1976	1.59	1.24	1.49	1.59	1.39	1.58
March 1980	2.45	3.92	3.87	2.48	4.02	4.41
April 1986	3.06	2.69	1.61	3.00	3.01	1.72
Average	2.37	2.61	2.32	2.36	2.71	2.57

Note: Forecast errors were collected for forecasts made in the month of a turning point, in the 6 previous months, and in the 6 following months, for a total of 13 forecasts around each turning point.

Comparing the VAR1 and VAR3 models, for one-month forecasts the model without the JOCI was very slightly more accurate. For six-month forecasts, the model containing the JOCI was slightly more accurate. But for twelve-month forecasts, the model containing the JOCI was more accurate by 0.25 percent. This is the largest gain from using the JOCI found in this article; it is still rather small.

Conclusion

This article examined the ability of the *Journal of Commerce* Materials Index and the Commodity Research Bureau Spot Price Index to improve forecasts of inflation, which was measured by changes in the Consumer Price Index. Although Granger causality tests indicated statistically significant effects, the magnitude of improvement was very small and the test result for the JOCI was sensitive to the lag length employed.

Each commodity price index was next included in a small VAR model designed to predict the CPI. Again, while adding the JOCI to the model improved forecasts of the CPI at each horizon, the: magnitude of improvement was small. Adding the SPI to the model had mixed results, only improving forecasts by a small amount for twelve-month forecasts. Examining errors made **by** forecasts **dated near** inflationary turning points again revealed only a small improvement in forecast accuracy when including the JOCI.

Since only one aggregate price index and two commodity price indexes were examined, these results are only suggestive. It would certainly be useful to study other indexes, other time periods, and data from other countries. With that important qualification in mind, it is difficult to see a major role for commodity prices in the conduct of monetary policy. That commodity prices added a *small* amount of predictive power suggests that a *small* improvement in anti-inflation policy could be achieved by using them as an indicator variable. None of the results presented in this paper, however, suggest that slightly more accurate inflation forecasts by themselves would have allowed policymakers to avoid the sixfold increase in the CPI in the post-World War II period.

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