THE EXCESS CO-MOVEMENT OF COMMODITY PRICES

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1. Introduction.

This paper tests and confirms the existence of a puzzling phenomenon- the prices of raw commodities have a persistent tendency to move together. We find that this co-movement of prices applies to a broad set of commodities that are largely unrelated, i.e., for which the cross-price elasticities of demand and supply are close to zero. Furthermore, the co-movement is well in excess of anything that can be explained by the common effects of inflation, or changes in aggregate demand, interest rates, and exchange rates.

Our test for excess co-movement is also a test of the standard competitive model of commodity price formation with storage. An innovative aspect of our test, and one that distinguishes it from, say, Eichenbaum's (1983, 1984) tests of finished goods inventory behavior under rational expectations, is that we do not need data on inventory stocks. Our test relies instead on the joint behavior of prices across a range of commodities, and the fact that those prices should only move together in response to common macroeconomic shocks.

In finding excess co-movement, we reject the standard competitive commodity price model. A possible explanation for our finding is that commodity price movements are to at least some extent the result of "herd" behavior in financial markets. (By "herd" behavior we mean that traders are alternatively bullish or bearish on all commodities for no plausible economic reason.) Indeed, our finding would be of little surprise to brokers, traders, and others who deal regularly in the futures and cash markets, many of whom have held the common belief that commodity prices tend to move together. Analyses of futures and commodity markets issued by brokerage firms, or that appear on the financial pages of newspapers and magazines, refer to copper or oil or coffee prices going up because commodity prices in general are rising, as though increases in those prices are caused by or have the same causes as increases in wheat, cotton, and gold prices.[1]

To conclude that prices exhibit excess co-movement, we must account for the effects of any common macroeconomic shocks. Current and expected future values of macroeconomic variables such as inflation, industrial production, etc., should have common effects on current and expected future demands (and possibly supplies) of commodities, and hence on current prices. For example, a rise in interest rates should lead to a fall in commodity prices overall because higher interest rates can depress future aggregate demand (and hence commodity demands), and because it raises commodity carrying costs. At issue is whether the prices of unrelated commodities tend to move together after accounting for these macroeconomic effects. We find that they do.

The next section discusses the set of commodities that we choose to examine, the data, and the nature of the price correlations. As we will see, price changes are highly correlated. In Section 3 we try to explain these correlations using a simple regression model. We find that after allowing for the common effects of current and past values of economic variables, there is still a great deal of correlation that remains. One possible explanation is that commodity demands and supplies are affected by unobserved forecasts of the economic variables. In Sections 4 and 5 we show how a latent variable model can be used to test this possibility. We find that latent variables representing unobserved forecasts of inflation and

[1]Price movements for individual commodities are often linked to aggregate indices such as the futures price index of the Commodities Research Bureau, or the Commodity Price Index of the Economist magazine.

industrial production are indeed significant explanators of commodity prices. However, even after accounting for these latent variables, there is still excess co-movement left over. Section 6 concludes, and discusses possible extensions of our model to the behavior of stock prices.

2. The Correlation of Commodity Prices.

We study the monthly price movements of seven commodities: wheat, cotton, copper, gold, crude oil, lumber, and cocoa. This is a set of commodities that are as unrelated as possible, but that also cover as broad a spectrum as possible. For example, all of the agricultural products we have chosen are grown in different climates and serve different uses. None of the included commodities are substitutes or complements, none are co-produced, and none is used as an input for the production of another. Barring price movements due to common macroeconomic factors, we would expect these prices to be uncorrelated.

Our price data represent average monthly cash prices in the United States for the years 1960 through 1985. Ideally, the data should correspond to a current price quotation for immediate delivery of a homogeneous good. However, all commodities are at least somewhat heterogenous, and delivery dates can vary. We have tried to obtain price data that reflect as closely as possible what sellers are charging at the time for current delivery of a well-specified commodity. Specific price series and data sources are listed in the Appendix.

Table 1 shows a correlation matrix for the monthly changes in the logarithms of these prices. Note that 10 out of the 21 correlations are greater than .1. Gold, for example, shows strong correlations with copper, crude oil, lumber, and cocoa; cotton is also correlated with copper, lumber, and wheat; and lumber is correlated with copper and cocoa.

Are these correlations as a group statistically significant? To answer this we can perform a likelihood ratio test of the hypothesis that the correlation matrix is equal to the identity matrix. It is worth discussing this test briefly because it is closely related to the tests we carry out in later sections of the paper. Consider m jointly normal random variables whose theoretical covariance matrix is given by Σ. The matrix Σ incorporates whatever restrictions are implied by the theory that is being tested, e.g., Σ would be a diagonal matrix when the variables are uncorrelated. Denote by $\hat{\Sigma}$ the maximum likelihood estimate of Σ, and let Ω be the actual covariance matrix of the variables. Then the likelihood of the data under the theoretical restrictions is given by:

$$L = |\hat{\Sigma}|^{-N/2} e^{-(N/2)\mathrm{tr}(\Sigma^{-1}\Omega)} \tag{1}$$

where N is the number of observations. In the special case in which Σ is diagonal, the elements of $\hat{\Sigma}$ are the inverses of the corresponding elements of Ω, so that $\mathrm{tr}(\hat{\Sigma}^{-1}\Omega)$ is simply equal to m. The likelihood of the data absent any restrictions is given by (1), but with Ω substituted for $\hat{\Sigma}$.

In the case of a diagonal covariance matrix, the likelihood ratio is $|\Omega|^{N/2}$ divided by the product of the variances, also to the N/2 power. As shown in Morrison (1967), this implies that the ratio of the restricted and unrestricted likelihood functions is $\lambda = |R|^{N/2}$, where $|R|$ is the determinant of the correlation matrix. Our test statistic is therefore $-2\log\lambda$, which is distributed as χ^2 with (1/2)p(p-1) degrees of freedom, where p is the number of commodities. For the seven commodities in our sample, this statistic is 114.6. With 21 degrees of freedom, this is highly significant, so we can easily reject the hypothesis that these commodity prices are uncorrelated.

Of course these correlations might be due to common macroeconomic factors, such as changes in current or expected future inflation or aggregate demand growth. We explore this possibility below.

3. The Explanatory Power of Current and Past Macroeconomic Variables.

Commodity prices may have common movements because of changes in macroeconomic variables that affect demands and/or supplies for broad sets of commodities. These changes can affect prices in two ways. First, macroeconomic variables may directly effect commodity demands and supplies. For example, an increase in the rate of industrial production will raise the demands for industrial commodities such as copper, lumber, or crude oil because these commodities are used as inputs to production, and will raise the demands for non-industrial commodities such as cocoa or wheat through the resulting increases in income.

Second, changing macroeconomic variables can affect commodity prices by affecting expectations about future supplies and demands, either directly, or indirectly by affecting expectations about future macroeconomic conditions. These effects occur because commodities are storable, so that changing expectations about future market conditions and prices affect the demand for storage and hence current prices. For example, a change in interest rates might affect expected rates of capital investment in the industries for a number of commodities, which would affect expected future supplies, and hence current prices. In addition, a change in interest rates might affect expectations about future aggregate economic activity, which would affect expected future commodity demands, and again, current prices.

We can formalize these arguments with the following simple model.[2] Write the net supply of commodity i at time t as:

$$Q_{i,t} = a_{i,t} + b_i P_{i,t} \tag{2}$$

where $a_{i,t} = a_{i,t}(x_t)$ is a determinant of both supply and demand, and is a function of current and lagged values of x_t, a vector of macroeconomic variables such as the index of industrial production, interest rates, inflation, etc. (For example, for most commodities an increase in the rate of industrial production would increase demand, so that $a_{i,t}$ would fall.) Inventory evolution is given by the following accounting identity:

$$I_{i,t} = I_{i,t-1} + Q_{i,t} \tag{3}$$

Finally, under the assumption that risk-neutral inventory holders maximize expected profits, the evolution of the price of commodity i is given by:

$$\delta E_t P_{i,t+1} = P_{i,t} + C_{i,t} \tag{4}$$

where $\delta = 1/(1+r)$ is the discount factor, E_t is the expectation conditional on all information available at time t, and $C_{i,t}$ is the one-period holding cost of the commodity, less its marginal convenience yield.

Note that the convenience yield is the flow of benefits that one obtains from holding stocks, e.g., the resulting assurance of supply as needed, ease of scheduling, etc. On the margin, this depends on the total quantity of inventory held. (The larger is $I_{i,t}$, the smaller is the benefit from holding an extra unit of inventory.) The convenience yield is also likely to depend on macroeconomic variables.[3] (For example, an increase in the rate of industrial production implies an increase in the rate of

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[2] This model is similar in structure to the finished goods inventory model of Eichenbaum (1983). It is also similar to the commodity price models of Stein (1986) and Turnovsky (1983), but more general in that they assume i.i.d. shocks, and we allow for a more general error structure.

[3] For an explicit model of convenience yield that illustrates some of these general dependencies, see Williams (1987).

consumption of industrial commodities, and therefore an increase in desired stocks.) We model $C_{i,t}$ as a linear function of $I_{i,t}$:

$$C_{i,t} = c_{i,t} - \gamma_i I_{i,t} \tag{5}$$

where $c_{i,t}$ is a function of current and past values of x_t, the vector of macroeconomic variables.

In principle the discount rate δ depends on the interest rate r which varies over time. As an approximation, we will assume instead that any variations in r and hence δ can be subsumed in $c_{i,t}$, so that δ is constant in eq. (4).[4] The model is completed with the transversality condition:

$$\lim_{T\to\infty} \delta^{(T-t)} E_t I_{i,T} = 0 \tag{6}$$

Combining (2) - (5) gives the following difference equation for $I_{i,t}$:

$$E_t I_{i,t+1} - \frac{(1+\delta+b_i\gamma_i)}{\delta} I_{i,t} + \frac{1}{\delta} I_{i,t-1} = a_{i,t+1} - \frac{1}{\delta} a_{i,t} - \frac{1}{\delta} b_i c_{i,t} \tag{7}$$

By factoring eqn. (7), one can show that its non-explosive solution is:[5]

$$I_{i,t} = k_i I_{i,t-1} + d_i E_t \sum_{j=0}^{\infty} d_i^j (a_{i,t+j} - \delta a_{i,t+j+1} + b_i c_{i,t+j} \tag{8}$$

where k_i and d_i are commodity-specific constants which lie between 0 and 1 and depend on b_i, γ_i, and δ. Eqn. (8) describes the change in inventories in terms of current and expected future values of $a_{i,t}$ and $c_{i,t}$. To see that price is also a function of current and expected future values of $a_{i,t}$ and $c_{i,t}$, just combine eqns. (2), (3) and (8):

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[4]Suppose δ_t and $P_{i,t}$ are mean-reverting stochastic processes, with means δ^* and P_i^* respectively. Then (4) can be rewritten as:

$$\delta^* E_t P_{i,t+1} = P_{i,t} + C_{i,t} - (\delta_t - \delta^*) P_i^* - (\delta_t - \delta^*)(E_t P_{i,t+1} - P_i^*) \tag{i}$$

The third term on the RHS of (i) can be included as part of $C_{i,t}$. We ignore the last term which is of second order so that we can obtain a solution to the model. This approximation is analogous to that used by Abel and Blanchard (1986).

[5]Methods for solving linear stochastic difference equations are reviewed in Sargent (1979).

$$P_{i,t} = \frac{1}{b_i}\left[(k_i-1)I_{i,t-1} + d_i E_t \sum_{j=0}^{\infty} d_i^j (a_{i,t+j} - \delta a_{i,t+j+1} + b_i c_{i,t+j}) - a_{i,t}\right] \quad (9)$$

Recall that $a_{i,t}$ and $c_{i,t}$ both depend on current and lagged values of x_t. Therefore, $P_{i,t}$ depends on expected future values of x_t, so that an equation is needed to forecast x_t. We will assume that forecasts of x_t are based on current and past values of x_t, and also on current and past values of a vector z_t of exogenous economic variables that do not directly affect commodity prices (e.g., the money supply and the stock market):

$$E_t x_{t+j} = \theta_j(L)x_t + \phi_j(L)z_t \quad (10)$$

Together with eqn. (9), this implies the following equation for the price of commodity i:

$$P_{i,t} = \sum_{k=0}^{K} \alpha_{ik} x_{t-k} + \sum_{k=0}^{K} \beta_{ik} z_{t-k} + u_{i,t} \quad (11)$$

The error term $u_{i,t}$ includes all commodity-specific factors, including the inventory level $I_{i,t-1}$, i.e., it includes all factors <u>not</u> explained by the macroeconomic variables x_t. For example, in the case of copper, $u_{i,t}$ might include current and past reserve levels, shocks accounting for strikes, etc. Thus under our null hypothesis, the $u_{i,t}$'s are uncorrelated across commodities.

We will also assume that the $u_{i,t}$'s follow a random walk. In this case $E_t(u_{i,t+j}) = u_{i,t}$ for $j > 0$, and changes in $u_{i,t}$ are serially uncorrelated. We then have the following estimating equation:

$$\Delta P_{i,t} = \sum_{k=0}^{K} \alpha_{ik} \Delta x_{t-k} + \sum_{k=0}^{K} \beta_{ik} \Delta z_{t-k} + \epsilon_{i,t} \quad (12)$$

where $\epsilon_{i,t}$ is serially uncorrelated, and under our null hypothesis, $E(\epsilon_{i,t}\epsilon_{j,t}) = 0$ for all $i \neq j$.

<u>Estimation</u>.

We estimate eqn. (12) for each of our seven commodities using OLS. The vector x_t includes the index of industrial production (Y), the consumer price index (π), the exchange value of the dollar against (equally weighted) the British pound, German mark, and Japanese yen (E), and the nominal interest rate on 3-month Treasury bills (R).[6] The vector z_t includes the money supply, M1 (M), and the S&P Common Stock Index (S). The model is first estimated with each of these variables included unlagged and lagged one month, and then is re-estimated with each of the variables included unlagged and lagged one through six months.

Table 2 shows estimation results for equations that include x_t and z_t unlagged and lagged one month. Note that except for gold, crude oil, and lumber, the R^2's are low; most of the variance of price changes is unexplained. Increases in inflation and the money supply are both associated with increases in the prices of all of the commodities, and the interest rate with decreases in prices. The effects of the other variables, however, are mixed, for some commodities associated with increases in prices and for others decreases.

Table 3 shows likelihood ratio tests for group exclusions of explanatory variables from all seven commodity price equations. Column (1) applies to equations with explanatory variables unlagged and lagged one month, and column (2) to equations with explanatory variables unlagged and lagged one through six months. Each statistic is twice the difference of the log likelihood functions for the unrestricted and restricted models, and is distributed as χ^2 with degrees of freedom equal to the number of restrictions (14 and 49 respectively). Note that all of the variables are

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[6] When estimating eqn. (12), the interest rate is in level rather than first-differenced form. This is a somewhat more general model since it is not inconsistent with having the first difference of the interes rate affect the rate of change of commodity prices. We include its level because the level of interest rates may well be a good predictor of future inflation and because equation (4) suggests that levels of interst rates may help predict individual commodity price changes.

significant explanators of commodity prices as a group. With the exception of the stock market variable in column (1) and the Index of Industrial Production in column (2), all of the statistics are significant at the 1 percent level.

Denote by $\hat{\epsilon}_t$ the vector of residuals $(\hat{\epsilon}_{1,t}, \ldots, \hat{\epsilon}_{7,t})'$, and let Ω be the covariance matrix of $\hat{\epsilon}$. If our model is complete, Ω should be diagonal. We tested whether this covariance matrix is indeed diagonal using the technique decribed in Section 2, and the results of the tests are included in Table 3. Note that the test statistic is significant at the 1 percent level for both versions of the model. Also, the data reject a diagonal covariance matrix more strongly when we include six lags of all the variables than when we include only one lag. Perhaps this is to be expected in small samples where the addition of even irrelevant explanatory variables automatically reduces the variance of the $\hat{\epsilon}_i$'s without necessarily reducing the covariances by a commensurate amount. One could argue that our x vector may be incomplete; we might not have included all the macroeconomic determinants of commodity supplies and demands. However, the finding that adding more lags makes the correlation more significant suggests that adding more macroeconomic variables will not change our result.

We also reestimated the model including a lagged dependent variable on the RHS of eqn. (12) because the OLS regressions shown in Table 2 exhibit signs of serial correlation In some sense this exercise is different from the other tests we carry out, since it includes a commodity-specific explanatory variable. Note that the inclusion of many such commodity-specific explanators would reduce the residual variance of the equation explaining that commodity's price without having any commensurate effect on the covariances across commodities, and thus would increase the significance of residual correlations.

To test for excessive co-movement when there is a lagged dependent variable, we must estimate the model both with and without the constraints imposed. The likelihood ratio test for a diagonal residual correlation matrix is then 71.5, which while slightly lower than for the regressions shown in Table 2, is still highly significant.

After accounting for commodity price movements that are due to common macroeconomic factors, price changes remain correlated across commodities. We make a further attempt to account for these co-movements in the next two sections.

4. A Latent Variable Model.

In the previous section we considered the possibility that the correlations among commodity prices are due to the correlation of each commodity price with variables which are related to future conditions in commodity markets. In other words, we tried to attribute the correlation between commodity prices to correlations of commodity prices with past and present observable macroeconomic variables. Recall that when prices are set according to (8), they depend on the expectation of future x's conditional on all information available at t.

This approach is subject to an important limitation: Individuals have more information about future x's than can be obtained from <u>any set</u> of current and past x's and z's which are directly observable. This means that equation (10) is too restrictive. In particular, some of the news about future macroeconomic variables is of a qualitative nature which is difficult to include in regressions such as those analyzed previously. This qualitative information about future macroeconomic variables could in principle affects all commodity prices and could thus be a source of correlation among commodity prices.

A natural way of capturing such information about the future is by incorporating a set of latent variables into our model. These latent variables represent the market's forecasts of the future values of the macroeconomic variables. Our model then becomes a MIMIC (multiple indicator multiple cause) model.[7] The "indicators," i.e., the variables which are affected by the latent variables include both the vector of commodity prices and the actual realization of the future macroeconomic variables. The "causes" of the latent variables include any variable which is useful in forecasting macroeconomic variables. Thus the causes include our z's.

To account for market information that is unavailable to us, we first generalize eqn. (10), using the first-differenced specification that we adopted in eqn. (12):

$$E_t(\Delta x_{t+j}) = \theta_j(L)\Delta x_t + \phi_j(L)\Delta z_t + f_j v_t \tag{13}$$

$E_t(\Delta x_{t+j})$ is now a latent variable - an unobserved forecast of Δx_t based on the observed current and past values of Δx_t and Δz_t, but <u>also</u> based on the unobserved residual vector v_t. Equation (13) is still very special in that the same residual v_t affects the forecast of all future x's. This means that the forecast of future x's can be written as:

$$E_t(\Delta x_{t+j}) = \theta_j'(L)\Delta x_t + \phi_j'(L)\Delta z_t + f_j' E_t(\Delta x_{t+1}) \tag{14}$$

In other words, a forecase of x_{t+1} is sufficient, when combined with the observable x's and z's, to generate forecasts of x_{t+j}, $j > 1$.

We include latent variables, J_t, which are a subset of $E_t(\Delta x_{t+1})$. Thus they are the expectation at t of the value at t+1 of certain variables y, which are part of the vector x. Then:

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[7]See Goldberger (1972).

$$J_t = E_t(\Delta y_{t+1}) = \theta_j''(L)\Delta x_t + \phi_j''(L)\Delta z_t + f_j'' v_t \tag{15}$$

By (14), forecasts of y beyond t+1 depend only on J_t and current and lagged x's and z's. From (15) it is apparent that the latent variables have the property that the vector of residuals w_t in the equation:

$$\Delta y_{t+1} = J_t + w_t \tag{16}$$

is uncorrelated with any information available at t. Finally, we write the individual commodity prices at t as:

$$\Delta P_{i,t} = \sum_{k=0}^{K} \alpha_{ik} \Delta x_{t-k} + g_i J_t + \epsilon_{i,t} \tag{17}$$

where g_i is a vector of coefficients. The system we estimate then consists of (15), (16), and (17). The vector of latent variables J has multiple causes, namely the z's, and multiple indicators, namely the current prices and future y's.

It should be apparent that our procedure is closely related to the more traditional instrumental variables method of estimating rational expectations models. Consistent estimates of g_i could also be obtained by using the current and lagged z's as instruments for Δy_{t+1} in a regression equation which is given by (17), where J_t is replaced by Δy_{t+1}. One important feature that our procedure shares with the instrumental variables approach is that we also assume that certain variables (the z's) affect commodity prices only through their effect on agents' expectations of certain future variables.

Like our procedure, the instrumental variables approach gives consistent estimates of g_i, even when the instrument list is not exhaustive. However, the residuals from an instrumental variables regression cannot be used directly to test for excessive co-movement of commodity prices. These residuals are constructed using the actual realized values of future macroeconomic variables. Since the market forecast must by necessity differ from these realized values, the residuals in all the equations will tend to be correlated.

We estimate (15), (16) and (17) by maximum likelihood. This maximum likelihood estimation is done under the maintained assumption that the v's, w's and ϵ's are normally distributed. The contemporaneous variance-covariance matrix for the v's as well as that for the w's is left unrestricted. We assume that v's are uncorrelated with ϵ's and w's at all leads and lags, and that the same is true for the correlation between ϵ's and w's. We first estimate the model under the assumption that the variance covariance matrix for the ϵ's is diagonal so that our explanatory and latent variables account for all the correlation in commodity prices. This assumption is then tested by reestimating the model under the assumption that contemporaneous variance-covariance matrix of the ϵ's is unrestricted.

We use the same variables as in the regression model of Section 3. We focus on two latent variables which represent the current forecasts of next period's inflation and next period's rate of growth of the Index of Industrial Production. Thus we are assuming that the money supply and the stock market affect commodity prices only via their ability to predict inflation and output.[8]

Estimation is done using LISREL.[9] Apart from obtaining parameter estimates LISREL computes the value of the likelihood function according to eqn. (1). This likelihood can be computed under both the hypotheses that

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[8]In some sense this is more restrictive than in the earlier regression model because there the money supply and the stock market were potential predictors of all other x's as well.

[9]The input is the correlation matrix Ω of all the variables of interest. Thus this matrix includes the correlations among the changes in commodity prices, the x's , the z's and the future values of inflation and production growth. See Joreskog and Sorbom (1986).

the model explains all co-movements of commodity prices (so that the ϵ's are uncorrelated) and that it does not. A standard likelihood ratio test can then be used to gauge the statistical validity of the restriction that the ϵ's are uncorrelated.

5. The Explanatory Power of Latent Variables.

The results of our basic latent variable estimation procedure are presented in Table 4. The variables η_π and η_y are latent variables which represent the market's forecasts of, respectively, inflation between period t and period t+1, and growth in industrial production between t and t+1. The first seven columns of Table 4 represent the equations explaining commodity prices while the last two columns represent the equations explaining the latent variables.

As is apparent from this table the latent variables help explain commodity prices. In the regressions explaining prices, both latent variables have generally positive and often statistically significant coefficients. To see that the latent variables are important, note that the R^2's are much higher when the latent variables are included than in the corresponding equations of Table 2.

After estimating the model with the constraint that the covariance matrix of the ϵ's is diagonal, we reestimate it without that constraint. Even this less constrained model now incorporates some constraints since we maintain the assumption that the v's and w's are uncorrelated with the ϵ's and that the z's affect prices only through the latent variables. These secondary restrictions are accepted by the data since the χ^2 statistic associated with the 25 restrictions implied by this relatively unrestricted model is 32.2.

Having estimated both the restricted and unrestricted models, we do a likelihood ratio test on the covariance restrictions. The test statistic is 49.7 This statistic, which measures the extent to which the 21 restrictions on the off diagonal elements of the covariance matrix are violated is still significantly different from zero at the 1% level. Therefore, we find that even after including latent variables there is still excess co-movement of commodity prices. This is further evidence against the standard competitive pricing model. It is worth noting that although we still reject the model, the evidence against it is weakened when latent variables are included, since the χ^2 statistic in the OLS case was 89.4.

We have also tried several variations of our basic model. In particular, we estimated two models with only one latent variable. The first has a latent variable that represents the market forecast of future inflation, and the second has a latent variable that represents the market forecast of growth in industrial production. The χ^2 statistics of the hypothesis of no excess co-movement are 48.4 and 56.4 for the first and second models respectively. From this we note that forecasted inflation has more to do with joint movement of commodity prices than does forecasted production growth.

Also note that the evidence against the hypothesis of no excess co-movement is slightly weaker when we include only the latent variable for inflation than when we include both. This suggests that simply adding latent variables will not necessarily resolve the puzzle of excess co-movement. One explanation for this finding is that our relatively unconstrained model fits worse when the only latent variable is the market's forecast of inflation. Indeed, the χ^2 statistic testing the constraints imposed by the relatively unconstrained model is 47.6, which, given that the model imposes 27 restrictions, is statistically significant at the 1% level. Therefore this finding may be due to the fact that there is less evidence against the hypothesis that money and the stock market affect commodity prices through forecasts of both inflation and output growth than there is against the hypothesis that they do so through only one of these forecasts.

We have also tried to extend the number of lags included in our latent variable models. However, we then failed to achieve convergence of the likelihood function, presumably because of the large number of unimportant parameters being estimated. On the other hand, we did succeed in obtaining estimates of the latent variable models that include a lagged dependent variable. In all of these models (one includes two latent variables and the other two include one latent variable), the hypothesis of a diagonal covariance matrix for the ϵ's is rejected at the 1% level.

6. Concluding Remarks.

Common movements in the prices of unrelated commodities should be traceable to changes in current values or expected future values of macroeconomic variables. In this paper we have shown that these kinds of variables do not account for much of the observed co-movement of commodity prices. This is the case whether expectations are based solely on observable macroeconomic variables, or are based also on unobserved latent variables. There are two possible explanations for this finding. One is that our model is simply incomplete - perhaps some important macroeconomic variables are missing from our specification. Given our extensive experimenting we doubt that this is the case, but this possibility cannot be ruled out on the basis of the available data.

The other explanation is that the actors in commodity markets react in tandem to noneconomic factors. These reactions might be due to the presence of equilibrium "sunspots", "bubbles" or simply changes in "market psychology". In any case, this would represent a rejection of the standard competitive model of commodity pricing in the presence of storage.

While we have focused on commodity markets, our approach should also be applicable to the analysis of other storable assets, including financial assets. For instance, in the standard model of corporate equity valuation, price is the present value of expected future earnings. Thus co-movements in equity prices across different companies should be due to factors which affect the earnings of all of those companies. If the companies chosen are sufficiently different, these common factors must be macroeconomic in nature. Again, these changing forecasts of macroeconomic variables can be based on either currently observable data or on unobservable information contained in latent variables. This paper suggests an approach for testing whether actual co-movements in stock prices are indeed due to these economic factors, or whether they are driven in part by "herd" behavior.

APPENDIX

Monthly cash price data for January 1960 through December 1985 came from the following sources:

Cocoa: Through April 1984, Bureau of Labor Statistics, "Spot Cocoa Bean Prices in New York." May 1984 onwards, United Nations Monthly Bulletin of Statistics, average daily closing price of nearest 3-month future, New York Cocoa Exchange.

Copper: Commodity Yearbook, "Producers' Prices of Electrolytic (Wirebar) Copper, Delivered U.S. Destinations," American Metal Market. Data are monthly averages of daily wholesale delivered cash prices.

Cotton: Commodity Yearbook, "Average Spot Price of U.S. Cotton, 1-1/16 inches, Strict Low Middling at Designated Markets, Agricultural Marketing Service, USDA.

Crude Oil: Platts Oil Price Handbook and Oilmanac, Annual Editions, "Average Wholesale Price of Crude Petroleum as Collected by the Independent Petroleum Association of America."

Gold: Handy and Harmon cash price. A monthly average of daily spot prices.

Lumber: Bureau of Labor Statistics, "Aggregate Price Index for Lumber and Primary Lumber Products."

Wheat: Commodity Yearbook, "Average Price of Number 1 Hard Winter Wheat, at Kansas City," Agricultural Marketing Service, USDA.

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TABLE 1
Correlations of Commodity Prices

	WHEAT	COTTON	COPPER	GOLD	CRUDE	LUMBER	COCOA
WHEAT	1.000						
COTTON	0.253	1.000					
COPPER	0.051	0.152	1.000				
GOLD	-0.020	0.045	0.322	1.000			
CRUDE	0.103	0.098	0.032	0.245	1.000		
LUMBER	-0.059	0.125	0.113	0.126	-0.085	1.000	
COCOA	-0.014	0.044	0.052	0.135	0.014	0.122	1.000

TABLE 2
OLS Regressions

	WHEAT	COTTON	COPPER	GOLD	CRUDE	LUMBER	COCOA
π	.277	-.082	.071	.135	.334	-.077	-.065
	(3.2)	(-0.9)	(0.8)	(1.7)	(4.2)	(-0.9)	(-0.7)
$\pi(-1)$	-.160	.206	-.010	.200	.167	.157	.122
	(-1.8)	(2.3)	(-0.1)	(2.5)	(2.1)	(1.9)	(1.4)
Y	-.001	.081	.030	-.050	-.087	.043	.125
	(-0.1)	(1.2)	(0.5)	(-0.8)	(-1.4)	(0.7)	(1.9)
Y(-1)	.080	.046	.053	-.075	-.054	.065	.111
	(1.2)	(0.7)	(0.8)	(-1.3)	(-0.9)	(1.1)	(1.7)
R	-.061	.158	.457	.139	-.437	.324	.239
	(-0.2)	(0.4)	(1.3)	(0.4)	(-1.3)	(0.9)	(0.7)
R(-1)	-.017	-.246	-.517	-.406	.267	-.513	-.281
	(-0.1)	(-0.7)	(-1.4)	(-1.2)	(0.8)	(-1.5)	(-0.8)
E	-.054	-.076	.151	.345	-.142	.012	.073
	(-0.8)	(-1.2)	(2.4)	(5.9)	(-2.4)	(0.2)	(1.1)
E(-1)	-.027	.075	.056	-.069	.030	.151	.060
	(-0.4)	(1.2)	(0.9)	(-1.2)	(0.5)	(2.5)	(0.9)
M	.131	-.075	.179	.120	.026	.160	.013
	(2.0)	(-0.7)	(2.8)	(2.1)	(0.4)	(2.7)	(0.2)
M(-1)	-.018	.094	-.078	.117	.048	.065	.028
	(-0.3)	(1.4)	(-1.2)	(1.9)	(0.8)	(1.0)	(0.4)
S	-.003	.095	.055	.078	.106	.050	.080
	(-0.1)	(1.5)	(0.9)	(1.4)	(1.9)	(0.9)	(1.3)
S(-1)	-.086	-.044	-.104	-.081	-.150	.093	-.031
	(-1.4)	(-0.7)	(-1.7)	(-1.4)	(-2.6)	(1.5)	(-0.5)
R^2	.06	.05	.08	.23	.21	.17	.07

TABLE 3

χ^2 Statistics for Group Exclusions of the Explanatory Variables

	(1) χ^2 with 14 degrees of freedom, 1 lag of each variable	(2) χ^2 with 49 degrees of freedom, 6 lags of each variable
INF	73.22**	127.29**
INDST	29.48**	71.56*
TBILL	29.32**	93.24**
EXCH	62.06**	166.41**
MI	36.29**	81.93**
STOCK	20.44	101.05**
Diagonal Correlation Matrix:	89.36**	99.44**

* Significant at 5% level
** Significant at 1% level

TABLE 4
Latent Variable Model

	WHEAT	COTTON	COPPER	GOLD	CRUDE	LUMBER	COCOA	η_π	η_y
η_π	1.362	1.380	1.998	1.709	2.078	-1.865	0.506		
	(1.9)	(1.9)	(2.2)	(2.1)	(2.3)	(-1.2)	(0.9)		
η_y	-0.270	0.338	0.567	0.676	-0.245	2.383	0.352		
	(-0.6)	(0.8)	(1.1)	(1.4)	(-0.5)	(2.2)	(1.0)		
π	-0.318	-0.651	-0.759	-0.572	-0.561	0.789	-0.270	0.426	-0.032
	(-1.0)	(-1.9)	(-1.8)	(-1.5)	(-1.4)	(1.6)	(0.0)	(7.9)	(-0.4)
$\pi(-1)$	-0.585	-0.183	-0.522	-0.240	-0.479	0.981	0.005	0.298	-0.111
	(-2.1)	(-0.7)	(-1.5)	(-0.8)	(-1.4)	(1.6)	(0.0)	(5.5)	(-1.5)
Y	0.126	0.014	-0.097	-0.211	0.057	-0.767	0.031	-0.030	0.318
	(0.7)	(0.1)	(-0.5)	(-1.1)	(0.3)	(-1.9)	(0.2)	(-0.7)	(5.6)
Y(-1)	0.058	-0.066	-0.088	-0.227	-0.126	-0.105	0.045	0.045	0.107
	(0.6)	(-0.7)	(-0.8)	(-2.2)	(-1.2)	(-0.6)	(0.6)	(1.1)	(1.9)
R	-0.932	-0.863	-1.513	-1.218	-1.800	0.521	-0.318	0.715	0.460
	(-1.6)	(-1.5)	(-2.1)	(-1.8)	(-2.6)	(0.5)	(-0.7)	(3.5)	(1.6)
R(-1)	0.658	0.615	1.219	0.802	1.333	-0.232	0.240	-0.582	-0.555
	(1.3)	(1.2)	(1.9)	(1.3)	(2.1)	(-0.2)	(0.6)	(-2.8)	(-2.0)
E	-0.202	-0.227	-0.096	0.151	-0.358	0.171	0.015	0.109	0.020
	(-1.8)	(-2.0)	(-0.7)	(1.2)	(-2.7)	(0.8)	(0.2)	(2.7)	(0.4)
E(-1)	0.128	0.186	0.254	0.087	0.229	-0.066	0.099	-0.098	0.014
	(1.1)	(1.6)	(1.8)	(0.7)	(1.7)	(-0.3)	(1.1)	(-2.5)	(0.3)
M								0.037	0.089
								(1.7)	(2.7)
M(-1)								0.014	0.039
								(0.8)	(1.4)
S								0.036	0.040
								(1.9)	(1.5)
S(-1)								-0.053	0.010
								(-2.2)	(0.3)
R^2	0.09	0.13	0.26	0.38	0.30	0.43	0.09	0.96	0.82