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# THE EXCESS CO-MOVEMENT OF COMMODITY PRICES*

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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 behaviour under rational expectations, is that we do not need data on inventory stocks. Our test relies instead on the joint behaviour of prices across a range of commodities, and the fact that those prices should only move together in response to common macroeconomic shocks.

This excess co-movement casts doubt on the standard competitive commodity price model. A possible explanation for it is that commodity price movements are to some extent the result of 'herd' behaviour in financial markets. (By 'herd' behaviour 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 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 rising 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.

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. affect current and expected future demands (and possibly supplies) of all commodities, and hence affect all their current prices. For example, a rise in interest rates should lower commodity prices; higher interest rates depress

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future aggregate demand and hence commodity demands, and raise 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 our data set, and the nature of the price correlations. As we will see, price changes are correlated, and the correlations are larger the longer the intervals across which the changes are measured. In Section II 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 variable. In Sections III and IV we show how a latent variable model can be used to account for this possibility. We find that latent variables representing unobserved forecasts of inflation and industrial production are indeed significant explanations of commodity prices. However, even after allowing for these latent variables, there is still excess co-movement left over. Section V concludes by discussing some limitations of our analysis and possible reasons for our findings.

## I. THE CORRELATION OF COMMODITY PRICES

We study monthly price changes for seven commodities: wheat, cotton, copper, gold, crude oil, lumber, and cocoa. This is a broad spectrum of commodities that are as unrelated as possible. For example, the agricultural products we have chosen are grown in different climates and have different uses. None of the commodities are substitutes or complements, none are co-produced, and none is used as a major input for the production of another. Barring price movements due to common macroeconomic factors, we would expect these prices to be uncorrelated.[1]

We use United States average monthly cash prices from April 1960 to November 1985. Ideally, these data should correspond to a current price quotation for immediate delivery of a homogeneous good. However, all commodities are at least somewhat heterogeneous, 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 Appendix B.

Table 1 shows a correlation matrix for the monthly changes in the logarithms of these prices. The likelihood ratio test described below implies that individual correlations that exceed 0·112 in magnitude are significant at the 5% level. Nine out of the 21 correlations meet this criterion. Gold is correlated 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

[1] Limited experimentation with other sets of commodities, including replacing gold with platinum, had little effect on our results.

Table 1

*Correlations of Monthly Log Changes in 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 | 0·043 | 0·052 | 0·135 | 0·013 | 0·122 | 1·000 |

$\chi^2(21) = 114·6$.

Table 2

*Correlations of Nonoverlapping Quarterly Log Changes in Commodity Prices*

| | Wheat | Cotton | Copper | Gold | Crude | Lumber | Cocoa |
|---|---|---|---|---|---|---|---|
| Wheat | 1·000 | — | — | — | — | — | — |
| Cotton | 0·300 | 1·000 | — | — | — | — | — |
| Copper | 0·095 | 0·254 | 1·000 | — | — | — | — |
| Gold | 0·136 | 0·138 | 0·391 | 1·000 | — | — | — |
| Crude | 0·142 | 0·063 | 0·018 | 0·419 | 1·000 | — | — |
| Lumber | 0·023 | 0·225 | 0·152 | 0·212 | −0·096 | 1·000 | — |
| Cocoa | 0·050 | 0·085 | 0·228 | 0·214 | −0·043 | 0·302 | 1·000 |

$\chi^2(21) = 53·5$.

is equal to the identity matrix. As shown in Morrison (1967), the ratio of the restricted and unrestricted likelihood functions is

$$\lambda = |R|^{N/2}, \tag{1}$$

where $|R|$ is the determinant of the correlation matrix. Our test statistic is therefore $-2\log\lambda$, which is distributed as $\chi^2$ 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, we readily reject the hypothesis that these commodity prices are uncorrelated.

The correlations of commodity price changes are much larger for longer holding periods. Tables 2 and 3 show correlations for (nonoverlapping) 3-month and 12-month changes in the logarithms of monthly prices. Observe that for annual changes, 19 out of 21 correlations exceed 0·2. As the $\chi^2$ statistics show, as a group the correlations remain significant at the 1% level. Nonetheless, the significance levels for the quarterly and annual changes are lower than for the monthly ones, because there are many fewer non-overlapping yearly than monthly observations.

A better measure of the statistical significance of the quarterly and yearly correlations is obtained by using all of the available data, i.e. using overlapping

Table 3

*Correlations of Nonoverlapping Annual Log Changes in Commodity Prices*

| | Wheat | Cotton | Copper | Gold | Crude | Lumber | Cocoa |
|---|---|---|---|---|---|---|---|
| Wheat | 1·000 | — | — | — | — | — | — |
| Cotton | 0·504 | 1·000 | — | — | — | — | — |
| Copper | 0·430 | 0·352 | 1·000 | — | — | — | — |
| Gold | 0·606 | 0·462 | 0·521 | 1·000 | — | — | — |
| Crude | 0·354 | 0·246 | 0·325 | 0·548 | 1·000 | — | — |
| Lumber | 0·313 | 0·458 | 0·099 | 0·275 | −0·176 | 1·000 | — |
| Cocoa | 0·272 | 0·289 | 0·241 | 0·233 | −0·030 | 0·582 | 1·000 |

$\chi^2(21) = 56{\cdot}3$.

observations. $\chi^2$ statistics computed as above using all overlapping observations give values of 194·9 for quarterly differences and 517·7 for annual differences. These statistics are not distributed as $\chi^2(21)$ because the use of overlapping data introduces serial dependence. We therefore computed, via Monte Carlo, 15,000 draws of our test statistic, $-2 \log \lambda$, under the null hypothesis that the monthly price changes are i.i.d. and uncorrelated across commodities. The highest values that we drew for these statistics were 121·3 for quarterly price changes and 504·1 for yearly changes. We can therefore conclude that the observed quarterly and annual correlations are highly significant.

Of course these correlations might be due to common macroeconomic factors, such as changes in current or expected future inflation or aggregate demand. In addition, macroeconomic variables may explain more of the price movements over longer horizons (swamping the commodity-specific noise), which may account for the larger correlations that we find for longer holding periods. We explore these possibilities below.

## II. 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 affect commodity demands and supplies. For example, as 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, macroeconomic variables can affect prices by affecting expectations about future supplies and demands. Commodities are storable, so expectations about future market conditions influence the demand for storage and hence current prices. This means that unexpected changes in macroeconomic variables which are useful for forecasting can have an immediate effect on commodity prices. For example, higher interest rates can immediately reduce prices by increasing the required rate of return on storage. Higher interest rates can also raise prices, by reducing capital investment by suppliers of a number of commodities, thereby reducing future supplies. In addition, a change in interest rates might change expectations about future aggregate economic activity, which would affect expected future commodity demands, and again, current prices.

We can formalise these arguments with a simple model.[2] Write the *net* supply of commodity $i$ at time $t$, $Q_{i,t}$, as:

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

where $p_{i,t} = \log P_{i,t}$, and $P_{i,t}$ is the price of commodity $i$ at $t$. The index $a_{i,t}$ captures changes in both supply and demand. It depends on both commodity specific variables (e.g. a strike by copper miners or bad weather), as well as current and lagged values of $\mathbf{x}_t$, a vector of macroeconomic variables (such as the index of industrial production, interest rates, inflation, etc.) that can affect many commodities. We define a set of commodities to be unrelated if there are negligible cross-price effects (so that $a_{i,t}$ does not include the prices of other commodities), and if any commodity specific variable that affects $a_{i,t}$ does not affect $a_{j,t}$, $j \neq i$.

The evolution of inventory, $I_{i,t}$, is given by the accounting identity:

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

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

$$r_t = [\mathrm{E}_t P_{i,t+1} - C_{i,t} - P_{i,t}]/P_{i,t}, \tag{4}$$

where $r_t$ is the required rate of return, $\mathrm{E}_t$ 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 the capitalised flow of its marginal convenience yield over the period.

The convenience yield is the flow of benefits that one obtains from holding stocks, e.g. an assurance of supply as needed, ease of scheduling, etc. At 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 will also depend on macroeconomic variables.[3] For example, an increase in industrial production raises the consumption of industrial commodities, and therefore increases desired stocks. We model $c_{i,t}$, the logarithm of $C_{i,t}$, as a linear function of $I_{i,t}$:

$$c_{i,t} = n_{i,t} + \gamma_i I_{i,t}, \tag{5}$$

[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 while they assume i.i.d. shocks, 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).

where $n_{i,t}$ is a function of current and past values of $\mathbf{x}_t$, the vector of macroeconomic variables.

Equation (4) says that prices at $t$ depend on expected future prices. Thus current prices depend on expected future conditions in the industry, and as we show in Appendix A, they are functions of current and expected future values of $\mathbf{x}_t$. We assume that forecasts of $\mathbf{x}_t$ are based on current and past values of $\mathbf{x}_t$, and also on current and past values of a vector $\mathbf{z}_t$ of exogenous economic variables that do not directly affect commodity prices (e.g. the money supply and the stock market):

$$\mathrm{E}_t\,\mathbf{x}_{t+j} = \boldsymbol{\theta}_j(\mathrm{L})\,\mathbf{x}_t + \boldsymbol{\varphi}_j(\mathrm{L})\,\mathbf{z}_t, \tag{6}$$

where $\boldsymbol{\theta}_j(\mathrm{L})$ and $\boldsymbol{\varphi}_j(\mathrm{L})$ are matrix polynomials in the lag operator L. As the Appendix shows, this leads to the following estimating equation:

$$\Delta p_{i,t} = \sum_{k=0}^{K} \boldsymbol{\alpha}_{ik}\,\Delta\mathbf{x}_{t-k} + \sum_{k=0}^{K} \boldsymbol{\beta}_{ik}\,\Delta\mathbf{z}_{t-k} + \epsilon_{i,t}, \tag{7}$$

where $\epsilon_{i,t}$ is serially uncorrelated, and under our null hypothesis, $\mathrm{E}(\epsilon_{i,t}\,\epsilon_{j,t}) = 0$ for all $i \neq j$. To allow for the possibility that $\epsilon_{i,t}$ is serially correlated, we also estimate the following equation:

$$\Delta p_{i,t} = \sum_{k=0}^{K} \boldsymbol{\alpha}_{ik}\,\Delta\mathbf{x}_{t-k} + \sum_{k=0}^{K} \boldsymbol{\beta}_{ik}\,\Delta\mathbf{z}_{t-k} + \rho_i\,\Delta p_{i,t-1} + \epsilon_{i,t}. \tag{7'}$$

Equations (7) and (7′) embody a simple notion: the prices of unrelated commodities should move together exclusively in response to market participants' changing perceptions of the macroeconomic environment.

*Estimation*

We estimate (7) and (7′) for each of our seven commodities using OLS for the period April 1960 to November 1985. Since our results are nearly the same for the two specifications, we focus on (7). The vector $\mathbf{x}_t$ includes the Index of Industrial Production ($Y$), the consumer price index ($\pi$), an (equally weighted) index of the dollar value of British pounds, German marks, and Japanese yen ($E$), and the nominal interest rate on 3-month Treasury bills ($R$).[4] The vector $\mathbf{z}_t$ includes the money supply, M1 ($M$), and the S & P Common Stock Index ($S$). The model is first estimated with the current and one-month lagged values of these variables, and then is re-estimated with the current values and lags of one to six months.

Table 4 shows estimation results for equations that include $\mathbf{x}_t$ and $\mathbf{z}_t$ current and lagged one month. Summing coefficients of current and lagged variables, we see that increases in inflation and M1 are associated with increases in the prices of all the commodities, and increases in interest rates with price declines. The effects of other variables are mixed, but as Table 5 shows, each variable

[4] The interest rate is in level rather than first-differenced form. This is consistent with the first difference of the interest rate affecting the rate of change of commodity prices. We include the level of interest rates because it may well be a good predictor of future inflation and because equation (4) suggests that levels of interest rates may help predict individual commodity price changes.

Table 4
*OLS Regressions*
(t-statistics in parenthesis)

| | Wheat | Cotton | Copper | Gold | Crude | Lumber | Cocoa |
|---|---|---|---|---|---|---|---|
| $\pi$ | 0·273 | −0·081 | 0·070 | 0·135 | 0·333 | −0·079 | −0·064 |
| | (3·1) | (−0·9) | (0·8) | (1·7) | (4·1) | (−1·0) | (−0·7) |
| $\pi(-1)$ | −0·161 | 0·204 | −0·009 | 0·203 | 0·170 | 0·155 | 0·120 |
| | (−1·8) | (2·3) | (−0·1) | (2·5) | (2·1) | (1·9) | (1·4) |
| $Y$ | −0·001 | 0·080 | 0·027 | −0·058 | −0·088 | 0·040 | 0·124 |
| | (−0·01) | (1·2) | (0·4) | (−1·0) | (−1·4) | (0·6) | (1·9) |
| $Y(-1)$ | 0·082 | 0·045 | 0·055 | −0·070 | −0·051 | 0·066 | 0·109 |
| | (1·3) | (0·7) | (0·9) | (−1·2) | (−0·9) | (1·1) | (1·7) |
| $R$ | −0·007 | 0·165 | 0·421 | −0·009 | −0·466 | 0·321 | 0·264 |
| | (−0·02) | (0·4) | (1·1) | (−0·03) | (−1·3) | (0·9) | (0·7) |
| $R(-1)$ | −0·76 | −0·254 | −0·485 | −0·268 | 0·298 | −0·508 | −0·303 |
| | (−0·2) | (−0·7) | (−1·4) | (−0·8) | (0·9) | (−1·5) | (−0·8) |
| $E$ | −0·056 | −0·077 | 0·141 | 0·325 | −0·146 | −0·002 | 0·068 |
| | (−0·9) | (−1·2) | (2·2) | (5·5) | (−2·4) | (−0·0) | (1·1) |
| $E(-1)$ | −0·019 | 0·070 | 0·067 | −0·064 | 0·033 | 0·158 | 0·051 |
| | (−0·3) | (1·1) | (1·1) | (−1·1) | (0·6) | (2·7) | (0·8) |
| $M$ | 0·133 | −0·039 | 0·207 | 0·120 | 0·001 | 0·182 | 0·026 |
| | (2·0) | (−0·6) | (3·2) | (2·1) | (0·002) | (3·0) | (0·4) |
| $M(-1)$ | −0·045 | 0·088 | −0·063 | 0·175 | 0·061 | 0.064 | 0·018 |
| | (−0·7) | (1·3) | (−1·0) | (2·8) | (1·0) | (1·0) | (0·3) |
| $S$ | −0·003 | 0·094 | 0·050 | 0·077 | 0·111 | 0·053 | 0·081 |
| | (−0·05) | (1·5) | (0·8) | (1·4) | (1·9) | (0·8) | (1·3) |
| $S(-1)$ | −0·084 | −0·044 | −0·119 | −0·097 | −0·145 | 0·082 | −0·029 |
| | (−1·3) | (−0·7) | (−1·9) | (−1·7) | (−2·5) | (1·4) | (−0·5) |
| $R^2$ | 0·06 | 0·05 | 0·09 | 0·24 | 0·21 | 0·18 | 0·07 |
| DW | 1·34 | 1·2 | 1·48 | 1·40 | 1·51 | 1·10 | 1·87 |

has a statistically significant impact on commodity prices as a whole. That table presents likelihood ratio tests for group exclusions of explanatory variables from all seven price equations. Column (1) applies to equations with one lag, and column (2) to six. Each statistic is twice the difference of the log likelihood functions for the unrestricted and restricted models, and is distributed as $\chi^2$ with degrees of freedom equal to the number of restrictions (14 and 49 respectively). Except for stock returns in column (1) and industrial production in column (2), these statistics are significant at the 1 % level.

Denote by $\hat{\epsilon}_t$ the vector of residuals $(\hat{\epsilon}_{1,t}, \ldots, \hat{\epsilon}_{7,t})'$, and let $\boldsymbol{\Omega}$ be the covariance matrix of $\hat{\epsilon}$. If our model is complete, $\boldsymbol{\Omega}$ should be diagonal. We test whether it is using the technique described in Section I; the results are included in Table 5. The test statistic is significant at the 1 % level for both versions of the model.[5] The data reject a diagonal covariance matrix more strongly when we include six lags of the explanatory variables. This may be because in small samples the addition of irrelevant explanatory variables automatically reduces the variance of the $\hat{\epsilon}_t$'s without reducing the covariances commensurately.

[5] The following *individual* residual correlations were significant at the 5 % level: wheat–cotton (0·267), cotton–copper (0·148), copper–gold (0·281), gold–crude oil (0·227), and gold–lumber (0·118).

Table 5

*$\chi^2$ Statistics for Group Exclusions of the Explanatory Variables*

| | (1) $\chi^2$ with 14 degrees of freedom, 1 lag of each variable | (2) $\chi^2$ with 49 degrees of freedom, 6 lags of each variable |
|---|---|---|
| (1) *INF* | 73·22** | 127·29** |
| (2) *INDST* | 29·48** | 71·56* |
| (3) *TBILL* | 29.32** | 93·24** |
| (4) *EXCH* | 62·06** | 166·41** |
| (5) *MI* | 36·29** | 81·93** |
| (6) *STOCK* | 20·44 | 101·05** |
| Diagonal correlation matrix: | 89·36** | 99·44** |

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

Table 6

*$R^2$s With and Without Commodity Prices as Additional Explanatory Variables*

| Holding Period... | Monthly | | Quarterly | | Annual | |
|---|---|---|---|---|---|---|
| Dependent Variable | Without | With | Without | With | Without | With |
| Wheat | 0·056 | 0·135 | 0·136 | 0·237 | 0·577 | 0·889 |
| Cotton | 0·053 | 0·154 | 0·278 | 0·367 | 0·401 | 0·887 |
| Copper | 0·090 | 0·181 | 0·179 | 0·233 | 0·701 | 0·906 |
| Gold | 0·244 | 0·333 | 0·373 | 0·398 | 0·908 | 0·960 |
| Crude | 0·211 | 0·261 | 0·402 | 0·482 | 0·944 | 0·974 |
| Lumber | 0·177 | 0·187 | 0·279 | 0·298 | 0·753 | 0·818 |
| Cocoa | 0·069 | 0·085 | 0·159 | 0·209 | 0·872 | 0·890 |

To account for serial correlation in the residuals (as reflected in the Durbin–Watson statistics in Table 4), we also estimated (7′), which includes a lagged dependent variable. To test for excess co-movement in this case, we cannot utilise the technique employed in Section I. Instead we compare the likelihoods of models estimated both with and without the constraints imposed. Including the current values and one lag of the explanatory variables, the likelihood ratio test for a diagonal residual correlation matrix is 71·2. This is lower than for the regressions shown in Table 4, but still highly significant.

These results show that excess co-movement is statistically significant, but say little about its magnitude. In particular, we would like to know how much of the total variation in commodity prices is explained by this co-movement. This can be determined by comparing the $R^2$s for the OLS regressions in Table 4 with $R^2$s for regressions which explain the price change of each commodity using current changes in the prices of all of the other commodities as additional explanatory variables. These $R^2$s are shown in Table 6. Except for gold, crude oil, and lumber, the $R^2$s for the monthly regressions on the macro variables are low; most of the variance of price changes is unexplained. When commodity prices are added, the $R^2$s increase substantially, and for wheat, cotton, and copper, the change in $R^2$ (which measures the marginal explanatory power of commodity price co-movements) exceeds the $R^2$ when only macro variables are included.

Table 6 also shows the $R^2$s for estimates of (7) using non-overlapping 3- and 12-month differences. (The explanatory variables are the same, but now we use 3- and 12-month changes in the logs of prices, industrial production, etc.) The marginal explanatory power of commodity price co-movements tends to increase when we use these quarterly and annual data.[6] For example, other commodity price changes explain nearly half of the total variation in annual cotton price changes. Table 6 thus shows that commodity price co-movements account for a substantial fraction of individual price movements.

We also examined the sensitivity of our results to the choice of sample period, using monthly data and one lag of each explanatory variable. Leaving out the period October 1973 to December 1974 (during which commodity prices may have been broadly affected by OPEC, which may have also affected macroeconomic variables), the statistic for the absence of co-movements falls to 77·1. Extending the sample to October 1986 results in a statistic of 75.4, and shortening the sample so that it ends in November 1984 gives 83·0.[7] These statistics are all highly significant.[8]

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 this in the next two sections.

## III. A LATENT VARIABLE MODEL

In the previous section we tested whether correlations among commodity prices can be attributed to the correlation of each price with observable macroeconomic variables that are predictors of future commodity market conditions. This approach has a serious limitation: individuals have more information about future **x**s than can be obtained from *any set* of current and past **x**s and **z**s which are directly observable. Thus (6) is too restrictive. Some of the news about future macroeconomic variables is qualitative and difficult to include in the kinds of regressions reported above. This qualitative information could in principle affect all commodities and could thus be a source of correlation among their prices.

A natural way of capturing such information about the future is by

[6] The $R^2$s for the regressions that use only macroeconomic explanatory variables increase substantially as we lengthen the holding period, which partly explains the larger raw correlations of commodity price changes for longer holding periods shown in Tables 1–3.

[7] We focus on the 1960:4 to 1985:11 period because of the major change in U.S. government intervention in the cotton market that occurred in 1986.

[8] We also considered the weather as an explanator that could affect all commodities, and included U.S. data on heating degree days, cooling degree days, temperature, and precipitation. This had virtually no effect on our results; the resulting $\chi^2$ was 87·7.

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.[9] The 'indicators,' i.e. the variables which are affected by the latent variables, include both the vector of commodity prices and the actual realisations of future macroeconomic variables. The 'causes' of the latent variables include any variable which is useful in forecasting macroeconomic variables. Thus the causes include our **zs**.

To account for information unavailable to us, we first generalise (6):

$$\mathrm{E}_t(\Delta \mathbf{x}_{t+j}) = \boldsymbol{\theta}_j(\mathrm{L})\, \Delta \mathbf{x}_t + \boldsymbol{\varphi}_j(\mathrm{L}) \Delta \mathbf{z}_t + \mathbf{f}_j\, \mathbf{v}_t. \tag{8}$$

Here, $\mathbf{f}_j$ is a matrix, and $\mathrm{E}_t(\Delta \mathbf{x}_{t+j})$ is an unobserved forecast of $\Delta \mathbf{x}_t$ based on the observed current and past values of $\Delta \mathbf{x}_t$ and $\Delta \mathbf{z}_t$, and on the unobserved residual vector $\mathbf{v}_t$. We now consider a subset of the variables $\mathbf{x}$, which we denote by $\mathbf{y}$. Define the vector of latent variables $\mathbf{J}_t$ as follows:

$$\mathbf{J}_t = \mathrm{E}_t(\Delta \mathbf{y}_{t+1}) = \boldsymbol{\theta}'(\mathrm{L})\, \Delta \mathbf{x}_t + \boldsymbol{\varphi}'(\mathrm{L})\, \Delta \mathbf{z}_t + \mathbf{f}' \mathbf{v}_t, \tag{9}$$

where $\boldsymbol{\theta}'(\mathrm{L})$ and $\boldsymbol{\varphi}'(\mathrm{L})$ are matrix polynomials. We now make the strong assumption that $\mathbf{f}'$ is of full rank. This means that

$$\mathrm{E}_t(\Delta \mathbf{x}_{t+j}) = \boldsymbol{\theta}''_j(\mathrm{L})\, \Delta \mathbf{x}_t + \boldsymbol{\varphi}''_j(\mathrm{L})\, \Delta \mathbf{z}_t + \mathbf{f}''_j\, \mathbf{J}_t. \tag{10}$$

In other words, knowledge of $\mathbf{J}_t$ is sufficient, when combined with the observable **xs** and **zs**, to generate forecasts of $\mathbf{x}_{t+j}$, $j \geqslant 1$. We can then write the log change in the price of commodity $i$ (which depends on all future **xs**) as:

$$\Delta p_{i,t} = \sum_{k=0}^{K} \boldsymbol{\alpha}_{ik}\, \Delta \mathbf{x}_{t-k} + \mathbf{g}_i \mathbf{J}_t + \epsilon_{i,t}, \tag{11}$$

where $\mathbf{g}_i$ is a vector of coefficients.

The latent variables we include are the expectation at $t$ of the value at $t+1$ of $\mathbf{y}$. Therefore, the vector of residuals $\mathbf{w}_t$ in the equation

$$\Delta \mathbf{y}_{t+1} = \mathbf{J}_t + \mathbf{w}_t \tag{12}$$

is uncorrelated with any information available at $t$. The system we estimate then consists of (9), (11), and (12). The vector of latent variables **J** has multiple causes, namely the **zs**, and multiple indicators, namely the current prices and future **ys**.

Our procedure is closely related to the more traditional instrumental variables method of estimating rational expectations models. Consistent estimates of $\mathbf{g}_i$ could also be obtained by using the current and lagged **zs** as instruments for $\Delta \mathbf{y}_{t+1}$ in a regression equation which is given by (11), where $\mathbf{J}_t$ is replaced by $\Delta \mathbf{y}_{t+1}$. As in the instrumental variables approach, we assume that certain variables (the **zs**) affect commodity prices only through their effects on agents' expectations of future variables.

Like our procedure, instrumental variables gives consistent estimates of $\mathbf{g}_i$,

[9] See Goldberger (1972) and Aigner *et al.* (1984).

even when the instrument list is not exhaustive. But 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 realised values of future macroeconomic variables. Since the market forecast must by necessity differ from these realised values, the residuals in all the equations will tend to be correlated.

We estimate (9), (11) and (12) by maximum likelihood, under the maintained assumption that the **v**s, **w**s and $\epsilon$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 the **v**s are uncorrelated with the $\epsilon$s and **w**s at all leads and lags, and that the same is true for the correlation between $\epsilon$s and **w**s. We first estimate the model under the assumption that the covariance matrix for the $\epsilon$s is diagonal so that our explanatory and latent variables account for all of the correlation in commodity prices. This assumption is then tested by re-estimating the model with an unrestricted contemporaneous covariance matrix for the $\epsilon$s.

We use the same variables as in the regression model of Section II, and include 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 assume that the money supply and the stock market affect commodity prices only via their ability to predict inflation and output.[10]

Estimation is done using LISREL.[11] Besides yielding parameter estimates, LISREL computes the value of the likelihood function, making likelihood ratio tests straightforward.

## IV. THE EXPLANATORY POWER OF LATENT VARIABLES

Estimation results for this latent variable model are presented in Table 7. The latent variables $\eta_\pi$ and $\eta_y$ represent the market's forecasts of inflation between period $t$ and period $t+1$, and growth in industrial production between $t$ and $t+1$ respectively. The first seven columns of Table 7 represent the equations explaining commodity prices while the last two columns represent the equations explaining the latent variables. As this table shows, latent variables help explain commodity prices. Both latent variables have generally positive and statistically significant coefficients. Also, the $R^2$s are much higher when latent variables are included than in the corresponding equations of Table 4.

After estimating the model with the constraint that the covariance matrix of the $\epsilon$s is diagonal, we re-estimate it without that constraint. Even this less constrained model now incorporates some constraints since we still assume that the **v**s and **w**s are uncorrelated with the $\epsilon$s and that the **z**s affect prices only through the latent variables. We test these secondary restrictions by

[10] 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.

[11] The input is the correlation matrix $\boldsymbol{\Omega}$ 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).

Table 7
*Latent Variable Model*

| | Wheat | Cotton | Copper | Gold | Crude | Lumber | Cocoa | $\eta_\pi$ | $\eta_y$ |
|---|---|---|---|---|---|---|---|---|---|
| $\eta_\pi$ | 1·334 | 1·483 | 2·037 | 1·876 | 2·247 | −1·648 | 0·563 | — | — |
| | (1·8) | (1·9) | (2·1) | (2·1) | (2·3) | (−1·2) | (0·9) | | |
| $\eta_y$ | −0·262 | 0·249 | 0·611 | 0·703 | −0·324 | 2·290 | 0·345 | — | — |
| | (−0·6) | (0·5) | (1·1) | (1·3) | (−0·6) | (2·4) | (0·9) | | |
| $\pi$ | −0·308 | −0·698 | −0·773 | −0·641 | −0·636 | 0·689 | −0·294 | 0.425 | −0·033 |
| | (−0·9) | (−2·0) | (−1·8) | (−1·5) | (−1·4) | (1·1) | (−1·0) | (7·9) | (−0·4) |
| $\pi(-1)$ | −0·577 | −0·226 | −0·529 | −0·288 | −0·540 | 0·892 | 0·014 | 0·298 | −0·111 |
| | (−2·0) | (−0·7) | (−1·5) | (−0·8) | (−1·5) | (1·7) | (0·1) | (5·5) | (−1·5) |
| $Y$ | 0·123 | 0·046 | −0·110 | −0·216 | 0·087 | −0·699 | 0·034 | −0·031 | 0·315 |
| | (0·7) | (0·3) | (−0·5) | (−1·0) | (0·4) | (−2·0) | (0·2) | (−0·8) | (5·6) |
| $Y(-1)$ | 0·059 | −0·061 | −0·095 | −0·238 | −0·125 | −0·094 | 0·043 | 0·047 | 0·108 |
| | (0·6) | (−0·6) | (−0·8) | (−2·2) | (−1·1) | (−0·6) | (0·6) | (1·2) | (2·0) |
| $R$ | −0·920 | −0·887 | −1·564 | −1·349 | −1·875 | 0·476 | −0·351 | 0·697 | 0·428 |
| | (−1·6) | (−1·4) | (−2·1) | (−1·9) | (−2·5) | (0·5) | (−0·7) | (3·4) | (1·5) |
| $R(-1)$ | 0·651 | 0·618 | 1·268 | 0·911 | 1·378 | −0·231 | 0·265 | −0·564 | −0·525 |
| | (1·2) | (1·2) | (1·9) | (1·4) | (2·1) | (−0·3) | (0·6) | (−2·8) | (−1·9) |
| $E$ | −0·200 | −0·236 | −0·101 | 0·131 | −0·375 | 0·151 | 0·005 | 0·106 | 0·012 |
| | (−1·8) | (−2·0) | (−0·7) | (1·0) | (−2·6) | (0·8) | (0·1) | (2·7) | (0·3) |
| $E(-1)$ | 0·125 | 0·199 | 0·256 | 0·103 | 0·248 | −0·039 | 0·097 | −0·096 | 0·017 |
| | (1·1) | (1·7) | (1·8) | (0·8) | (1·7) | (−0·2) | (1·0) | (−2·5) | (0·3) |
| $M$ | — | — | — | — | — | — | — | 0·034 | 0·104 |
| | | | | | | | | (1·5) | (2·9) |
| $M(-1)$ | — | — | — | — | — | — | — | 0·021 | 0·048 |
| | | | | | | | | (1·1) | (1·6) |
| $S$ | — | — | — | — | — | — | — | 0·035 | 0·034 |
| | | | | | | | | (2·0) | (1·2) |
| $S(-1)$ | — | — | — | — | — | — | — | −0·054 | 0·009 |
| | | | | | | | | (−2·2) | (0·2) |
| $R^2$ | 0·08 | 0·13 | 0·26 | 0·39 | 0·31 | 0·39 | 0·09 | 0·65 | 0·35 |

constructing a likelihood ratio statistic which compares our less constrained model with an unconstrained alternative. This statistic is distributed as $\chi^2(25)$ when the restrictions are valid.[12] We obtain a value of 35·5, which is insignificant at the 5% level.

Having estimated both the restricted and less restricted models, we perform a likelihood ratio test on the 21 restrictions implied by a diagonal covariance matrix. (This test measures how much worse the entire model – equations (9), (11), and (12) – fit the data when the covariance matrix of $\epsilon$ is constrained to be diagonal. Asymptotically, it is equivalent to a Wald test of whether the estimated covariance matrix of $\epsilon$ in the unrestricted model is diagonal.) The test statistic is 49·7, which is smaller than the value of 88·6 that we obtained in the OLS case, but is still significant at the 1% level. Thus, even after including latent variables there is still excess co-movement of commodity prices.

[12] Ignoring the **x**s, the model has 7 prices, 2 future macroeconomic variables, and 4 instruments, for a total of 78 covariances. The test statistic for the less restricted model has 25 degrees of freedom because that model includes 53 free parameters: 21 covariances of the $\epsilon_t$s, 14 $g_t$s in (11), 8 $\phi$s in (9), 3 elements of the covariance matrix for (9), 1 covariance of the $\mathbf{w}_t$s in (12), and the 6 free covariances of our instruments.

Another way of gauging the performance of the model is to look at the correlations among the estimated $\epsilon_t$s in the unrestricted model. We found that three individual correlations were significant at the 5% level: wheat–cotton (0·222), cotton–gold (0·113), and copper–crude oil (0·121).

We estimated several variations of the basic model, including two models with only one latent variable. In the first, the latent variable is expected future inflation, and in the second it is the expected rate of growth in industrial production. The test statistics, which again are distributed as $\chi^2(21)$ under the null hypothesis of no excess co-movement, are 48·2 and 57·0 respectively, which are both significant at the 1% level. Thus, forecast inflation explains more of the joint movements of commodity prices than does forecast 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. Hence simply adding latent variables may not resolve the puzzle of excess co-movement. The reason is that while adding latent variables raises the log likelihoods of both the constrained and unconstrained models, our test statistic is the difference between the two.[13]

We also estimated a latent variable version of (7′) which includes lagged dependent variables. The results change very little. The test statistic for the absence of co-movement remains equal to 49·7 when there are two latent variables, and becomes 46·3 and 40·3 respectively when the only latent variables are expected inflation and the expected change in industrial production. Finally, we tried to extend the number of lags, but failed to achieve convergence of the likelihood function, presumably because of the large number of unimportant parameters being estimated.

## V. CONCLUDING REMARKS

Common movements in the prices of unrelated commodities should be traceable to changes in current or expected future values of macroeconomic variables. We have shown that such variables do not fully explain the observed co-movement of commodity prices. This is the case whether expectations are based solely on observable macroeconomic variables, or are also based on unobserved latent variables.

Three possible limitations of our analysis may account for this finding. One is that our model is incomplete – some important variables are missing from our specification. Indeed, a major limitation of our approach is that we can never be sure we have included all relevant macroeconomic variables and latent variables. However, our extensive experimenting with alternative variables always resulted in excess co-movement.

A second possibility is that our macroeconomic variables are not truly

[13] Eliminating the latent variable for industrial production makes the fit of the less constrained model deteriorate substantially. The test statistic for this model relative to an unconstrained alternative is 51·8. This is significant at the 1% level since this less constrained model imposes 27 restrictions. Thus 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.

exogenous. If changes in several individual commodity prices directly affected some of the macro variables, our coefficient estimates for the macro variables would be biased. As a result, the estimated residuals would include a mixture of shocks to the macro variables and shocks to those commodity prices which affect the macro variables. This could lead to non-zero off-diagonal correlations. These correlations would remain zero, however, if only one commodity affected the macro variables. Indeed, oil is the only one of our commodities likely to have such effects. Therefore we doubt that the endogeneity of macro variables can explain our results.

A third possibility is the assumption of normality, which underlies most of our tests. Distributions of commodity price changes are known to be leptokurtic and thus non-normal, and this may result in spurious residual correlations. Unfortunately, we know of no way to test restrictions in a latent variable model without assuming normality, so the possible implications of leptokurtosis remain as questions for future research.

If there is indeed excess co-movement, how can we explain it? One possibility is that common price movements are the result of liquidity constraints: a fall in the price of one commodity lowers the price of others because it impoverishes speculators who are long in several commodities at once. This effect arises when capital markets are imperfect, and must be distinguished from simple portfolio rebalancing. The portfolio rebalancing that follows changes in individual commodity prices only affects other commodity prices if it affects discount rates. This in turn requires the sort of endogeneity of macro variables considered above.

Another possibility is that actors in commodity markets simply 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 price formation in the presence of storage.

Some of these explanations for our finding of excess co-movement may also help to account for the dependence of our results on the length of the holding period. We found that as the holding period is increased from a month to a quarter or a year, the amount of unexplained co-movement rises as well. This, too, may be due to the exclusion of relevant macroeconomic variables. Suppose that changes in macro variables affect commodity prices slowly. (For example, an unusual monthly change in inflation might have to persist for some time before it affects perceptions about the future.) Such slow effects are consistent with our finding that macro variables explain more of the movements in commodity prices over longer holding periods. Then any excluded macro variable will also explain more of the price movements for longer holding periods. This means that its exclusion increases the unexplained co-movement as the holding period is increased.

The liquidity effects discussed above could also explain the dependence of our results on the holding period. These effects should be larger the larger is the change in any single commodity's price. The variance of price changes is larger the longer the horizon, so we would expect liquidity effects to become more significant as the horizon increases.

Finally, commodity prices may exhibit considerable high-frequency mean-reverting noise. If so, neither macroeconomic variables nor prices of other commodities will explain a large fraction of individual monthly price changes.

More research is needed to test these various hypotheses. Hopefully additional work will help to disentangle the causes of the excess co-movement of commodity prices that we have found.

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## Appendix A

Here we derive (7) from (2)–(6) and a linearisation. First, rewrite (4) as:

$$1+r_t+\epsilon_t = (P_{t+1}-C_t)/P_t.$$

Here, $\epsilon_t$ is the unexpected return from holding the commodity. We will linearise $(P_{t+1}-C_t)/P_t$ around the arbitrary point $(\hat{P}_{t+1}, \hat{P}_t, \hat{C}_t)$:

$$(P_{t+1}-C_t)/P_t \approx (\hat{P}_{t+1}-\hat{C}_t)/\hat{P}_t + (P_{t+1}-\hat{P}_{t+1})/\hat{P}_t - (C_t-\hat{C}_t)/\hat{P}_t - (\hat{P}_{t+1}-\hat{C}_t)(P_t-\hat{P}_t)/\hat{P}_t^2.$$

We now approximate $(C_t-\hat{C}_t)/\hat{C}_t$ by $\log C_t - \log \hat{C}_t$, and similarly for the other variables. Using lower case letters to denote logarithms of the respective upper case letter, we obtain:

$$(P_{t+1}-C_t)/P_t \approx (\hat{P}_{t+1}-\hat{C}_t)/\hat{P}_t + (\hat{P}_{t+1}/\hat{P}_t)(p_{t+1}-\hat{p}_{t+1}) - (\hat{C}_t/\hat{P}_t)(c_t-\hat{c}_t) - [(\hat{P}_{t+1}-\hat{C}_t)/\hat{P}_t](p_t-\hat{p}_t).$$

We take our linearisation around the steady state of the competitive equilibrium. At this steady state, $\hat{C}_t/\hat{P}_t = h$ and $\hat{C}_{t+1}/\hat{C}_t = s$ for all $t$, where $h$ and $s$ are constants. This implies that $\hat{P}_{t+1}/\hat{P}_t = s$ as well. Thus:

$$1+r_t+\epsilon_t \approx s-h+\log(h)h-\log(s)s+sp_{t+1}-hc_t-(s-h)p_t.$$

Taking expectations on both sides:

$$sE_t p_{t+1}-hc_t-(s-h)p_t-r_t-1+s-h+\log(h)h-\log(s)s = 0. \tag{A 1}$$

Using (5) and denoting $h/s$ by $\delta$, (A 1) becomes:

$$E_t p_{t+1}-(1-\delta)p_t-\delta(n_t+\gamma I_t)-r_t/s-\phi = 0, \tag{A 2}$$

where $\phi = s-h+\log(h)h-\log(s)s-1$ is a constant. Let $\tilde{n}_t = n_t - r_t/s\delta$, and combine (2), (3), and (A 2) to get the following difference equation for $I_t$:

$$E_t I_{t+1}-(2-\delta+b\delta\gamma)I_t+(1-\delta)I_{t-1}-\delta b\tilde{n}_t-a_{t+1}+(1-\delta)a_t-b\phi = 0. \tag{A 3}$$

This difference equation has two characteristic roots, $k$ and $d$, which depend on $b$, $\gamma$, and $\delta$. Using standard methods, one can show that if $b > 0$, $\gamma > 0$, and $0 < \delta < 1$, one root lies between 0 and 1, and the other is greater than 1. There thus exists a unique non-explosive solution to (A 3) (explosive solutions would violate the transversality condition), which we write as:

$$I_t = \phi' + kI_{t-1} + (1/d)\, E_t \sum_{j=0}^{\infty} (1/d)^j [a_{t+j+1} - (1-\delta)\, a_{t+j} + \delta b \tilde{n}_{t+j}] \qquad \text{(A 4)}$$

where $\phi'$ is a constant. Equation (A 4) describes the change in inventories in terms of current and expected future values of $a_t$ and $\tilde{n}_t$. To see that price is also a function of current and expected future values of the *a*s and $\tilde{n}$s combine (2), (3) and (A 4) and reinsert commodity specific subscripts:

$$p_{i,t} = (k_i - 1) I_{i,t-1}/b_i + \frac{1}{b_i}\left[(1/d_i)\, E_t \sum_{j=0}^{\infty} (1/d_i)^j (a_{i,t+j+1} - (1-\delta)\, a_{i,t+j} + \delta b_i \tilde{n}_{i,t+j}) - a_{i,t}\right]$$

where we have ignored the constant. Recall that $a_{i,t}$ and $c_{i,t}$ both depend on current and lagged values of $\mathbf{x}_t$. Therefore, $p_{i,t}$ depends on expected future values of $\mathbf{x}_t$, so that an equation is needed to forecast $\mathbf{x}_t$.

Assuming that forecasts of future **x**s are based on (6), we obtain:

$$p_{i,t} = \sum_{k=0}^{K} \boldsymbol{\alpha}_{ik}\, \mathbf{x}_{t-k} + \sum_{k=0}^{K} \boldsymbol{\beta}_{ik}\, \mathbf{z}_{t-k} + u_{i,t}.$$

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 *not* explained by the macroeconomic variables $\mathbf{x}_t$. 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 assume that the $u_{i,t}$s follow a random walk so that $E_t(u_{i,t+j}) = u_{i,t}$ for $j > 0$, and changes in $u_{i,t}$ are serially uncorrelated. This leads to equation (7) in the text. Since the $u_{i,t}$s could have a richer temporal structure, we also allow for serial correlation by introducing a lagged dependent variable as in (7′).

## Appendix B

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

*Cocoa*: Up to January 1985, Bureau of Labor Statistics, 'Spot Cocoa Bean Prices in New York.' February 1985 onwards, average daily cash price quoted in Chicago for Accra delivery.

*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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