

DO COMMODITY PRICES STILL SHOW EXCESS CO-MOVEMENT?

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ABSTRACT

Pindyck and Rotemberg [19] find that short-run variations in certain commodity prices are more highly correlated than one would expect on the basis of microeconomic and macroeconomic analysis. The authors, whose sample spans 1960-1985, conjecture that this excess co-movement may reflect liquidity constraints in capital markets and herd behavior on the part of speculators as well as limitations of models and data. Using a sample of commodity prices from 1975 to 2004, this paper updates the earlier study and applies additional techniques of robust estimation and time series analysis. Pindyck and Rotemberg's finding of short-run excess co-movement is strongly confirmed.

INTRODUCTION

Pindyck and Rotemberg [19], hereafter PR, find that short-run variations in certain commodity prices are more highly correlated than one would expect on the basis of microeconomic and macroeconomic analysis. Selecting seven raw materials whose substitution elasticities in production and consumption should be negligible, the authors examine the correlation matrix computed from monthly logarithmic changes in the prices between April 1960 and November 1985. A likelihood-ratio test based on the correlation matrix strongly rejects the null hypothesis of no correlation among the price changes. A similar result is obtained when each price-change series is regressed on a set of macroeconomic variables and the correlation matrix of the residuals is tested. These and other experiments lead PR to conclude that there is indeed excess co-movement in commodity prices, and they speculate about its sources. "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....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" [19, p. 1186].

According to the authors, many traders and brokers implicitly assume the existence of excess co-movement among prices of raw materials: "Analyses of futures and commodity markets issued by brokerage firms, or that appear in 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” [19, p. 1173].

For several reasons it is timely to review and update the hypothesis of excess co-movement. As discussed below, new data on commodity prices and macroeconomic variables are available; moreover, developments in robust estimation and time series analysis make it possible to probe the data more intensively. In addition, there is a renewed interest in commodities. As the twenty-first century begins, markets for several raw materials –notably metals and some cereal grains— are cycling upward, allegedly spurred by strong economic growth in China and elsewhere [1, 2, 5, 18]. However, the consequences of higher commodity prices for overall inflation are still ambiguous (10, 12, 14, 22). In these circumstances, new evidence on excess co-movement should improve our understanding of commodity markets and the inefficiencies to which they may be subject.

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IMPROVEMENTS IN DATA AND METHODOLOGY

The PR sample includes the early 1970s, a tumultuous period during which many commodity prices rose dramatically as governments in producing nations tried to establish cartels and capture windfall profits (rents). During this extraordinary boom, the inclination of market participants to engage in herd behavior may have been unusually strong [4]. In general, the PR sample period seems unsuitable for several of the commodities in their data set, as Deb et al. [7, pp. 282-283] remark: “Specifically, the price of crude petroleum varied little from 1960 to 1970, and from 1970 to late 1973; the price of cocoa was subject to intervention between 1970 and 1976, and its variation over this period consisted of six sharp changes. The price of wheat before 1972 also shows a very different pattern of volatility compared with what comes later. Finally, it is well known that between 1960 and 1968 the official US price of gold was constant, and only later does this series show any movement. The consequent lack of homogeneity in the sample data makes it difficult to conduct meaningful tests of excess co-movement for these commodities.”

In the second place, the last fifteen years have seen important advances in robust estimation and outlier detection. These improvements in methodology can perhaps be applied to a problem raised in the PR paper: the excess co-movement could be an artifact of “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” [19, p. 1186]. Throughout this paper, standard parametric statistics are compared to their robust counterparts whenever possible.

A third motive for another look at excess co-movement is the availability of new techniques for the treatment of time series data. An assumption implicit in the PR methodology is that the monthly log changes in prices are stationary random processes; that assumption can now be subjected to a unit root test. If stationarity is verified, each series of price changes can then be filtered by Box-Jenkins procedures to improve the accuracy of the key likelihood-ratio test for non-correlation.

Apart from the incentives of new data and new tools, the principal motive for revisiting excess co-movement is the one identified by PR: the hypothesis suggests chronic imperfections or irrational decision-making in the trading and financing of

raw materials. “Excess co-movements due to irrational trading behaviour pose a problem for hedgers whose behaviour is based on price movements driven by market fundamentals, and for whom pervasive ‘fads’ and ‘herd’ mentality would be serious impediments. On the other hand, if the phenomenon is relatively isolated, or if it can be attributed to causes other than herd or fad behaviour, then it would be inappropriate to deduce strong conclusions from its presence” [7, pp. 275-276].

Several researchers have proposed models to explain the well-documented instability of commodity prices [e. g. 6, 23]. However, this author is not aware of a theoretical framework that would account for the endemic market failures suggested by excess co-movement. In any case, a new finding of excess co-movement should make the case for such a theory more compelling.

The next two sections of this paper examine in some detail the evidence for and against excess co-movement with emphasis on the update of PR’s original results. The final section offers some conclusions.

EVIDENCE OF EXCESS CO-MOVEMENT

The PR raw materials are cocoa, copper, cotton, gold, lumber, crude oil and wheat, “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” [19, p. 1174]. The PR sample begins in April 1960 and ends in November 1985. Transforming the prices to monthly log changes, the authors compute the correlation matrix R for $n = 307$ observations and $p = 7$ commodities. Following Morrison [17, pp. 111-144], they apply a likelihood ratio test to the null hypothesis that the log price changes are uncorrelated—in other words, R is an identity matrix. The alternative hypothesis is that at least one correlation is not zero. The resulting test statistic is based on the determinant of R , specifically

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

Under the null hypothesis

$$-2 \ln \lambda = -n \ln |R| \tag{2}$$

has asymptotically a chi-square distribution with $p(p-1)/2 = 21$ degrees of freedom. For the PR data, the test statistic is 114.6, which greatly exceeds conventional significance levels. (With 21 degrees of freedom, the 90th percentile of chi-square is 29.62, the 95th percentile is 32.67, and the 99th percentile is 38.93).

Accordingly, PR conclude that there is substantial correlation among the seven commodity prices despite their presumably negligible substitution elasticities. Of course, one can argue that, in general, any null hypothesis will be rejected if the sample size is large enough. On the other hand, the PR test statistic contradicts the hypothesis of non-correlation decisively, not marginally; and while many elements of R are small in magnitude, several correlations are fairly large and stable at conventional levels of statistical significance: cotton and wheat, 0.253; gold and crude oil, 0.245; copper and gold, 0.322. Correlations like these could provide substantial

profit opportunities for market participants, and the persistence of the correlations may indicate market inefficiencies.

Deb et al. [7] challenge PR's conclusions on several grounds: (i) commodity prices exhibit heteroscedasticity and therefore need to be modeled using GARCH methods; (ii) the log price changes are typically fat-tailed, so the normal distribution is an inappropriate model; and (iii) PR's sample period is so exceptional that it cannot provide a valid test of excess co-movement. Objections (ii) and (iii) seem compelling, and solutions to those problems will be explored below. With respect to issue (i), Deb et al. use GARCH models to examine the PR commodities and several other sets of raw materials during the sample period 1974-1992. "The analysis of these data provide evidence of [excess co-movement] when tests in the OLS and univariate GARCH framework are used. We find, however, that these tests over-reject the respective null hypotheses when the data-generating process is typical of time series of commodity prices. On the other hand, there is no evidence of [excess co-movement] when tests in a multivariate GARCH framework are applied. We find that these tests have the correct size and good power in small samples" [7, p. 289].

The authors use t-distributions with one or two degrees of freedom to model fat-tailed log price changes. While it may be suitable for these symmetric "innovation" outliers, GARCH estimation is not robust against the "additive" outliers often encountered in economic time series [20, pp. 273-284]. These anomalies produce clusters of bad leverage points that GARCH models may tend to over fit. As the authors remark, "in view of the difficulty of simultaneously handling a number of commodities in a multivariate GARCH framework, other alternatives with time-varying second moments could be employed to investigate common volatility" [7, p. 290].

Like PR, this paper uses a sample of monthly log changes for the prices of the seven raw materials; the time series start in February 1975 and end in January 2004, so $N = 348$ observations. (Sources for all the data used in this paper are described in an appendix.) Since nonstationarity would invalidate the likelihood-ratio test, each series is first subjected to an augmented Dickey-Fuller (ADF) test. The results appear in Table 1, where the null hypothesis of nonstationarity is rejected at the one percent level for all seven commodity prices. The autoregression on which the test is based includes an intercept and fifteen lags, the maximum number indicated by Schwert's formula [11, p. 644]. When fewer lags are included, the null hypothesis tends to be rejected even more decisively.

TABLE 1
AUGMENTED DICKEY-FULLER TESTS

Commodity	T test
Cocoa	-4.390
Copper	-4.283
Cotton	-5.576
Gold	-3.801
Lumber	-5.201
Crude	-5.596
Wheat	-4.616

All tests are significant at the 1 % level.

Since the monthly log changes of commodity prices are apparently stationary, the next step is to compute R. Table 2 displays the 21 correlations, which range in magnitude from practically zero to 0.283 for copper and gold. As previously mentioned, the larger correlations indicate non-negligible opportunities for arbitrage profits and would not be expected to persist in the absence of market failures. The value of the likelihood-ratio test statistic (2) is 73.62, smaller than PR's result but again well above the usual cut-off points. Therefore, excess co-movement cannot be rejected in this recent sample; the basic PR finding is replicated.

**TABLE 2
CORRELATIONS OF MONTHLY LOG CHANGES**

Cocoa	Copper	Cotton	Gold	Lumber	Crude	Wheat
Cocoa	1.000					
Copper	0.127**	1.000				
Cotton	0.021	0.178**	1.000			
Gold	0.084	0.283**	0.051	1.000		
Lumber	-0.019	0.049	0.092*	0.045	1.000	
Crude	0.016	0.084	0.005	0.150**	0.124*	1.000
Wheat	0.089*	0.117*	-0.001	0.111*	0.024	0.013
	1.000					

Significant at the 5 % level (*) or at the 1 % level (**) in a one-tail test

However, this conclusion might be affected by observations that are grossly inconsistent with the assumption of multivariate normality underlying the likelihood-ratio test. It is well known that the usual estimate of R is quite vulnerable to such outliers. Rousseeuw and Leroy [20, chapter 7] discuss the minimum covariance determinant (MCD) estimator, which identifies and downweights anomalous data, producing a highly robust and statistically consistent version of the correlation matrix. This technique is implemented using the MCD algorithm of Rousseeuw and van Driessen [21] followed by an efficient M estimator as implemented in S-plus [13]. The resulting test statistic is 82.76, not very different from the value cited in the previous paragraph; so it seems that the excess co-movement is not merely an artifact of stray observations.

Another premise of the likelihood-ratio test is that the components of R represent a random sample; in other words, the monthly log changes should not be autocorrelated. Given a pair of stationary time series, each produced by a sequence of independent normal innovations, the problem is to estimate the correlation between the pair. As Jenkins and Watts [15, pp. 338-340] pointed out many years ago, maximum-likelihood estimation of the correlation requires that each series first be filtered to remove autocorrelation; then the cross correlation can be computed from the two filtered series. This is essentially a feasible generalized least squares adjustment to improve statistical efficiency. In the absence of this adjustment, the estimated correlations will often be too large in absolute value, suggesting co-movement where none in fact exists.

For each series of monthly log changes in prices, the first column in Table 3 shows the significance level of the Ljung-Box Q-statistic, a standard indicator of

autocorrelation [11, p. 622]. The null hypothesis of statistical independence is rejected for all seven commodities. To explore the consequences of removing the autocorrelation, a purely empirical filtering strategy is adopted: a Box-Jenkins model is estimated for each time series [11, pp. 620-624; 9, pp. 16-22]. The model may have several lagged values in any of three components: seasonal autoregression (SAR), ordinary autoregression (AR), or a moving average (MA). The second column of Table 3 displays the significance level of the Q-statistic applied to the residuals from each Box-Jenkins model while the third column shows the number of lags in each component of the model. A comparison of the first and second columns indicates that Box-Jenkins filtering has removed most if not all of the autocorrelation. The next step is to compute R for the filtered residuals and calculate the likelihood-ratio test statistic (2), whose value turns out to be 64.60. So filtering leads to a modest reduction in the chi-square value, which nevertheless continues to offer substantial evidence of excess co-movement.

TABLE 3
AUTOCORRELATIONS OF MONTHLY LOG CHANGES

	Before BJ fit*	After BJ fit*	Number of lags in Box-Jenkins model		
			SAR	AR	MA
Cocoa	0.002	0.208	3	3	0
Copper	0.000	0.576	0	7	0
Cotton	0.000	0.161	0	0	3
Gold	0.000	0.112	0	7	5
Lumber	0.000	0.191	0	2	4
Crude	0.000	0.276	3	5	0
Wheat	0.000	0.148	7	7	0

* Significance level of Ljung-Box Q-statistic

THE ROLE OF MACROECONOMIC EFFECTS

According to PR [19, p. 1176], “Commodity prices may have common movements because of changes in macroeconomic variables that affect demands and / or supplies for broad sets of commodities.” These macroeconomic effects may be direct or via expectations about future events. As an obvious example of a direct impact, GDP growth increases the demand for a broad range of raw materials. As to indirect impacts, “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” [19, pp. 1176-1177].

In Appendix A of their paper, PR derive in detail a reduced-form estimating equation in which each commodity’s log price change reacts to actual and expected variations in commodity specific variables and macroeconomic variables. In bare outline, the derivation of the estimating equation is as follows: the *net* supply of commodity *i* at time *t* is

$$Q_{it} = a_{it} + b_t \ln P_{it} \quad (3)$$

where P is the commodity's price. According to PR [19, p. 1177], "The index a_{it} captures changes in both supply and demand. It depends on both commodity specific variables (e. g. a strike by copper mines 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_{it} does not include the prices of other commodities), and if any commodity specific variable that affects a_{it} does not affect a_{jt} , $j \neq i$." By definition, inventory changes according to

$$I_{it} = I_{i,t-1} + Q_{it}. \quad (4)$$

Then the time path of P is given implicitly by

$$r_t = (E_t P_{i,t+1} - C_{it} - P_{it}) / P_{it} \quad (5)$$

"where r_t is the required rate of return, E_t is the expectation conditional on all information available at time t , and C_{it} is the one-period holding cost of the commodity, less the capitalized flow of its marginal convenience yield over the period" [19, p. 1177]. In particular,

$$\ln C_{it} = n_{it} + d I_{it} \quad (6)$$

and n_{it} depends on the macroeconomic variables \mathbf{x}_t . According to equation (5), "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)...As the Appendix shows, this leads to the following estimating equation" [19, p. 1178]:

$$\Delta \ln P_{it} = \sum a_{ik} \Delta \mathbf{x}_{t-k} + \sum b_{ik} \Delta \mathbf{z}_{t-k} + e_{it} \quad (7)$$

where e_{it} is a normal random variable with zero expectation and the summations are over lags from $k = 0$ to $k = K$.

To investigate whether excess co-movement is attributable to macroeconomic effects, PR estimate the reduced form equation (7) by ordinary least squares (OLS); there is one such equation for each commodity. In the absence of more specific prior information, they assume that the vectors \mathbf{x}_t and \mathbf{z}_t and the lag length K do not differ among the raw materials, so estimation by the method of seemingly unrelated regressions (SUR) would offer no gain in statistical efficiency. This is also true if, for a particular commodity, some elements of \mathbf{x}_t and \mathbf{z}_t or their lagged values were to be deleted from (7) on theoretical or statistical grounds [11, pp. 343-344].

TABLE 4
OLS REGRESSIONS ON MACROECONOMIC VARIABLES

	Crude	Cocoa Wheat	Copper	Cotton	Gold	Lumber
Constant		0.002	0.007	0.000	0.008*	0.009
TBR	0.009	0.001				
TBR(-1)	0.004	0.011	-0.001	0.002	-0.004	0.004
IP	-0.001	-0.003	0.004	0.011*	-0.011*	-0.005
IP(-1)	0.127	0.141	-0.143	0.138	0.089	0.185
ER	-0.159	0.052	-0.057	0.224	-0.112	-0.445*
ER(-1)	-0.564	0.133	-1.125**	-0.083	-1.249**	-2.116**
CPI	-0.322	-0.251	-0.143	-0.010	-0.037	-0.867**
CPI(-1)	8.667**	-0.022	-0.373	-0.922	1.552	0.083
M1	2.255	-0.113	-0.161	0.444	1.819	1.712
M1(-1)	-0.037	0.352	-0.023	-0.155	-0.035	0.338*
S&P	0.229	-0.027	-0.020	0.065	-0.005	0.101
S&P(-1)	-0.145	0.123	0.004	0.085	-0.073	-0.006
R-squared	-0.258**	-0.073	0.017	0.017	-0.040	-0.034
D-W	1.967	0.001				
		0.109	0.153	0.323	0.176	0.204
		0.106				
		1.928	1.907	1.775	1.958	2.016
		1.963				

* significant at the 5 % level

** significant at the 1 % level

TBR = first difference of the 3-month U. S. Treasury bill rate

IP = first difference of the log of the U. S. index of industrial production

ER = first difference of the log of the trade-weighted dollar exchange rate

CPI = second difference of the log of the U. S. consumer price index

M1 = second difference of the log of the U. S. money stock

S&P = first difference of the log of the S&P 500 index of equity prices

A one-month lag in a time series is denoted by (-1).

PR specify x_t and z_t using six U. S. time series: the three-month Treasury bill rate together with log changes of the index of industrial production, the dollar's exchange rate, the consumer price index, the money stock (M1), and the Standard and Poor index of equity prices. In one experiment, PR include in the regression the current value of each macroeconomic variable and its one-month lag. They report that, while there are many low t-statistics, "each variable has a statistically significant impact on commodity prices as a whole" [19, pp. 1178-1179]. When the set of OLS

residuals is assembled in a correlation matrix, the resulting likelihood-ratio test statistic is equal to 89.36. A similar result is obtained when the regression model includes six lagged values of each independent variable. “After accounting for commodity price movements that are due to common macroeconomic factors, price changes remain correlated across commodities” [19, p. 1181].

In the adaptation of PR’s macroeconomic regression to the more recent data set used in this paper, the independent variables are first subjected to ADF tests of the type described previously. Unsurprisingly, several nominal time series exhibit nonstationarity, specifically the Treasury bill rate and the log changes in the consumer price index and the money stock. These series are therefore differenced to achieve stationarity. Table 4 displays the OLS regressions with a one-month lag for each independent variable and a Hildreth-Lu correction for first-order autoregression in the residuals [11, pp. 273-276; 9, pp. 6-10]. As previously mentioned, SUR is not helpful in this context; however, the OLS results can be supplemented by applying canonical correlation to the two sets of variables (the log price changes and the macroeconomic variables). Omitting lagged values of \mathbf{x}_t and \mathbf{z}_t , the largest squared canonical correlation is 0.254, which is statistically significant [17, pp. 167, 210-211; 3]; so one can reject the hypothesis that the raw materials prices are independent of macroeconomic effects.

To ascertain whether excess co-movement persists after macroeconomic factors have been taken into account, the likelihood-ratio test (2) is applied to the residuals from the regressions in Table 4; and a value of 61.69 is obtained. With a six-month lag for each independent variable, the result is practically identical. As a robustness check, the macroeconomic regressions are also computed by reweighted least squares using as a starting point the least trimmed squares (LTS) estimator [20, pp. 132-135]. While OLS is notoriously sensitive to anomalous observations in either the dependent variable or the independent variables, LTS can cope with substantial amounts of contamination. As additional insurance, the correlation matrix of the robust residuals is estimated by MCD, producing a test statistic equal to 61.09 with one-month lags or 51.57 with six-month lags.

The results cited in the last two paragraphs support PR’s conclusion: although macroeconomic effects can explain part of the correlation in commodity prices, there remains a statistically significant component of excess co-movement.

CONCLUSIONS

In attempting to update PR’s results, this paper has not replicated every experiment in the earlier paper. For example, the authors study the effects of aggregating their monthly data to the quarterly and annual frequencies; and they estimate a latent-variable version of the macroeconomic-effects model. These and other interesting explorations only strengthen the impression of persistent excess co-movement that this paper has verified using more recent data and methodology.

Future research on the PR hypothesis might include a broader set of variables that reflect global integration in recent decades; after all, U. S. data by themselves may no longer capture the full range of macroeconomic impacts on markets for raw materials. For example, it would be appropriate to consider international industrial production indexes, surveys of consumer sentiment and business outlook, and financial and monetary indicators. Moreover, it might be

interesting to follow the lead of Deb et al. [7] in expanding the set of PR commodities.

In the PR paper and this update, conclusions have been drawn from a sequence of statistical operations. For example, an ADF test was followed by the likelihood ratio test (2), then adjustments were made for outliers and autocorrelation; and similar steps were used in the macroeconomic modeling. A consequence of this approach is that the nominal significance levels are not strictly correct, and the actual power of the tests is reduced. Leamer [16] provides an elegant examination of this problem; the subtitle of his book (“ad hoc inference with nonexperimental data”) is a succinct description of the econometrician’s plight. On the other hand, recent improvements in computer hardware and software have made it practical to perform non-classical tests, notably the bootstrap and Bayesian inference [11, chapter 16 and appendix E]; their application to the hypothesis of excess co-movement is another opportunity for future research.

Like the PR paper, this update has focused on correlations among *stationary* transformations of commodity prices. On the other hand, much recent research on economic time series has emphasized long-run relationships among variables exhibiting random-walk behavior or, less often, deterministic trends [11, pp. 649-660]. It is tempting to apply cointegration analysis to the PR problem, presumably working with the logarithms of commodity prices instead of the log changes. However, that analysis seems premature because we lack an operational theory of excess co-movement based on imperfections or irrationality in commodity markets. In the absence of specific hypotheses and the data to test them, cointegration methods pose the risk mentioned by Thomas Doan [8, p. 245]: “It’s one thing to test a restriction...that is rooted in economic theory. It’s quite another to blindly estimate a ‘cointegrating vector’ and to rely upon asymptotic distribution theory to save us from an incorrect inference” arising from the spurious-regression problem raised by Granger and Newbold and by Phillips [11, pp. 632-634].

DATA APPENDIX

Commodity prices are from the International Financial Statistics (IFS) Online Service provided by the International Monetary Fund at the website <http://imfstatistics.org/imf>. Although no raw material is completely standardized as to its characteristics and its geographical source, the PR commodity set has been matched as closely as possible. COCOA = the price of Ghanaian cocoa beans, COPPER and GOLD are London Metals Exchange prices, COTTON = the Liverpool price of U. S. cotton, LUMBER = the price of Malaysian hardwood logs, CRUDE = the average world price of crude petroleum, and WHEAT = the U. S. Gulf Coast price.

The macroeconomic variables are from <http://www.economagic.com>. TBR is the three-month U. S. Treasury bill rate in the secondary market; IP is the Federal Reserve Board’s index of U. S. industrial production; ER is an index of the exchange value of the trade-weighted U. S. dollar; CPI is the U. S. consumer price index for all urban consumers from the Bureau of Labor Statistics; M1 is the narrow definition of the U. S. money stock from the Federal Reserve Board; and S&P is the Standard and Poor index of the average closing prices of 500 common stocks.

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