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Do Commodity Traders Herd?

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Abstract

We test for herding using data on aggregate trader positions for four commodities over 20 years. We show that while the positions of commodity traders are highly related, the relatedness falls short of herding. The cross-commodity relatedness in trader positions is almost entirely explained by common demand and supply factors.

Keywords: commodity comovement, herding, speculation

JEL Classifications: E32, G10, G14, Q11, O13

1. Introduction

Traders in commodity markets are thought to frequently conform to the actions of other traders rather than using the information available to them. For instance, in the absence of significant new information, the financial press commonly reports on the sentiment of the day—that the bears (or bulls) collectively dominated the trading across many commodities. The implication appears to be that commodities speculators have a tendency to follow the crowd, that is, to herd.[1]

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[1] The term, herding, is used in different ways in the literature. In a common definition, herding in financial markets occurs when traders buy or sell the same asset without economic justification (Avery and Zemsky, 1998). In another definition, herding occurs when several traders buy or sell within a general asset class (Sias, 2004). Studies report herding in corporate investing (Scharfstein and Stein, 2003), the adoption of technology (Kislev and Shchori-Bachrach, 1973) and earnings forecasts (Welch, 2000).

This implication of herding is also found in the literature on commodity price behavior. Pindyck and Rotemberg (1990) demonstrate that prices of seemingly unrelated commodities (such as wheat, cotton, lumber, and cocoa) move together, even after controlling for macroeconomic indicators, such as inflation, industrial production, and interest rates. The authors suggest that herding may be behind this "excess comovement" in commodity prices. Other researchers revisit the excess comovements hypothesis using a variety of test procedures. For instance, Deb, Trivedi and Varangis (1996) report that price comovement results are sensitive to the neglected structural breaks in prices in the 1970s, and to the controls for conditional heteroskedasticity in the price data. Malliaris and Urritia (1996) employ cointegration analysis to reject the long-term independence of six commodity futures price series. However, these researchers focus on relations among commodity prices, not commodity traders, so the evidence on herding remains limited.

In this paper we examine the comovements among the futures positions of large hedgers, large speculators and small traders across four commodities, wheat, corn, oats, and soybeans. The central question is whether the cross-commodity correlations in the aggregate positions of traders are explained by fundamental factors, such as production and inventories, that is, whether there are excess comovements in trader positions. A finding of excess comovements in trader positions would be consistent with herding.

Studies of herding sometimes depict it as an irrational response to sentiment, fad, or popular advise (e.g., Shiller, 1984; De Long, Shleifer, Summers and Waldmann, 1990 and Shleifer and Summers, 1990).[2] It follows that herding generally works to the detriment of the market. Bannerjee (1992) notes that the sequential decision process implied by herding reduces information in the market. At the very least, if the herders' information is flawed, herd behavior can lead to short-run mispricing, impeding the decision-making abilities of hedgers (Avery and Zemsky, 1998). The implications of herding can be even broader for commodity markets. For instance, if herding is the cause of the high correlation in the prices of commodities, it bears the blame for impeding the diversification of revenues that would otherwise be enjoyed by commodity-exporting countries.

Our study is distinguishable from prior work on herding in two important respects. First, our data on trader positions allow us to provide direct evidence on herding. Prior research on herding among individual traders is based on price behavior, rather than on patterns of ownership. For instance, much of the evidence that individual stock investors herd is based on the positive correlation between the returns of small firms and the discount to net asset value of closed-end mutual funds (for example, Chen, Kan and Miller, 1993; Neal and Wheatley, 1998; Nofsinger and

[2] However, not all researchers regard herding as flawed or irrational. For instance, in the literature on herding among institutions (e.g., Graham, 1999; Wermers, 1999), herding can also occur due to traders following the same signals or models ("investigative herding"), taking positions on assets with the same characteristics ("characteristic herding") or mimicking other traders to maintain a performance rank ("reputational herding").

Sias, 1999). Further, our data set distinguishes between the positions of large traders and small traders, allowing us to also investigate whether herding is more prevalent in either group. It is widely believed that small traders are more likely to seek safety in consensus (for instance, Cote and Sanders, 1997; Hong and Kubik, 2003). A reasonable hypothesis, therefore, is that small traders are more likely to herd.

The second distinguishing feature of this paper is that we more completely control for the fundamentals driving the cross-commodity relatedness in trader positions. We use production and inventory data at the commodity level. Prior studies that examine commodity price comovements attempt to control for common fundamentals, but only through macroeconomic indicators (e.g., Pindyck and Rotemberg, 1990). In our opinion, it is unreasonable to expect broad macroeconomic indicators to satisfactorily reflect the demand-supply conditions in individual commodities. In fact, there is evidence that macroindicators explain very little of the variation in commodity prices. For instance, Bessembinder and Chan (1992), Bailey and Chan (1993), and Bjornson and Carter (1997) find that Pindyck- and Rotemberg-type methods, where prices are regressed on macroindicators, perform poorly. For instance, the largest adjusted R^2 in Bjorn and Carter is 0.03. In contrast, there is evidence that factors, such as weather, have a relatively large effect on individual commodity price behavior (for instance, Roll, 1984; Brunner, 2002; Deaton and Laroque, 2003). Such evidence suggests that an empirical model for commodity-trader behavior ought to also consider market-level variables.

Our main findings are as follows: (1) There are strong cross-commodity correlations in trader positions over the past 1983–2002 years. (2) The cross-commodity correlation for small traders is higher than for large speculators, but is similar to that for large hedgers. (3) Macroeconomic variables, such as interest rates, real gross domestic product (GDP) and the dollar index fail to explain the cross-commodity correlations for each of the trader groups. (4) Market-level indicators, such as carried-over inventories and harvest size, in conjunction with the macroindicators, explain the majority of the correlations for each group of traders. This result suggests that the high correlations in trader positions are driven primarily by fundamentals.

2. Methods

Let p_t represent the net contractual position (long minus short) of a group of traders for a commodity, D_t the net demand for the commodity, and X_t a matrix of macroeconomic indicators. A general approach to assess the "rationality" of the imbalance in the positions of the traders is to assess the explanatory power of the regression:

$$p_t = f(D_t, X_t) + u_t, \tag{1}$$

where u_t is the unexplained portion of the traders' positions, and f is the function to be estimated. The rational component of the trader positions is influenced by economic conditions, represented here by X_t.

We can test for excess comovements in the trader positions for commodities i and j by testing for the relatedness of the residuals from the regressions:

$$\begin{aligned} p_{i,t} &= f(D_{i,t}, X_t) + u_{i,t}, \\ p_{j,t} &= f(D_{j,t}, X_t) + u_{j,t}. \end{aligned} \tag{2}$$

The excess comovement hypothesis is supported if $\rho\{u_{i,t}, u_{j,t}\} > 0$. By including the market-level factors (D), we avoid presumptions on the relatedness (in fundamentals) of commodities i and j. That is, the above approach applies to commodities that are barely related in their fundamentals (such as lumber and corn), as well as to those that are highly related in that they are jointly produced (as in soy oil and soy meal) or consumed (paper and print ink).

Let z_t represent the production of a commodity at t (say harvest size), s_t its total supply, and I_t the inventories at time t. The market clears at:

$$D_t + I_t = s_t = z_t + (1 - \delta)I_{t-1}, \tag{3}$$

where δ is the per-period deterioration rate of inventories. We assume the deterioration rate δ is constant, and drop it. From (2) and (3) we have

$$\begin{aligned} p_{i,t} &= f(s_{i,t} - I_{i,t}, X_t) + u_{i,t}, \\ p_{j,t} &= f(s_{j,t} - I_{j,t}, X_t) + u_{j,t}, \end{aligned} \tag{4}$$

which is a partial equilibrium formulation that considers the effects of both current and expected demand and supply conditions.

In the theory of commodity prices, inventories are endogenous (see, for instance, Williams and Wright, 1991; Deaton and Laroque, 1992; Chambers and Bailey, 1996). In other words, we must estimate net contractual demand and inventory jointly. Therefore, to estimate Equation (4), we must (1) model the functional form of $f(.)$, and (2) address the endogeneity of the inventory variable. Since our objective is to identify the sources and not the manner of comovement, we adopt the flexible model for each commodity:

$$\begin{aligned} p_t = {} & \alpha_0 + \alpha_{1,1}(s_t - I_t) + \cdots + \alpha_{1,n}(s_t - I_t)^m \\ & + \alpha_{2,1}(s_t - I_t)X_t + \cdots + \alpha_{2,n}(s_t - I_t)^k X_t + \alpha_3 X_t + \varepsilon_t, \end{aligned} \tag{5}$$

where the orders of m and k are determined by the data through a cross-validation approach that is common in the nonparametric literature (e.g., Zhang, 1993).

The cross-validation approach involves selecting the order of m and k that minimize a criterion akin to the sum of square errors between the fitted and refitted dependent variable. Pre-selecting the order of m and k, we regress $p_t, D_t, \ldots, D_t^m, D_t X_t, \ldots, D_t^k X_t$, respectively, on the instruments $1, s_t, s_t^2, \ldots, s_t^m, X_t, s_t X_t, \ldots, s_t^k X_t$ to obtain the values $\hat{p}_t, \hat{D}_t, \ldots, \hat{D}_t^m, \hat{D}_t X_t, \ldots, \hat{D}_t^k X_t$. We apply ordinary least squares (OLS) to $\hat{p}_t = \alpha_{10} + \alpha_{11}\hat{D} + \cdots + \alpha_m \hat{D}^m + \alpha_{21}\hat{D}X_t + \ldots \alpha_{2k}\hat{D}^k X + X'\beta + \mu_t$ with the first observation deleted and compute the fitted value for the first observation, $\hat{\hat{p}}_1$. Similarly, we apply OLS with the ith ($i = 2, \cdots N$) observation deleted and then compute $\hat{\hat{p}}_i$.

The optimal m, k are those that minimize the criterion $s(m, k) = \sum_{t=1}^{T} (\hat{p}_t - \hat{\hat{p}}_t)^2$. The endogeneity of the inventory variable will be addressed by an instrumental variable approach with 1, s_t, $s_t{}^2$, . . $s_t{}^{m+1}$, s_tX_t, $s_t{}^2X_t$, . . $s_t{}^{k+1}X_t$ as instruments.

3. Data

We use data on the number of contracts held by the long and short traders in four commodity futures markets from January 1983 through September 2002. The commodities are wheat, oats, soybeans and corn, all traded at the Chicago Board of Trade. We limit the investigation to the four commodities because they are the only ones that have long, continuous time series of harvest size, production, consumption, yield and planted acres available. They also have well-known sources of supply, namely carried-over inventories and harvest. There are little or no U.S. imports of these commodities.

3.1. Trader positions

The trader positions come from the Commitment of Traders (COT) Report compiled by the Commodity Futures Trading Commission (CFTC). The COT report provides the contractual positions for three groups of futures traders: commercial traders or larger hedgers, noncommercial traders or large speculators, and small traders. The holdings of small traders fall below the CFTC's threshold for trader categorization, and no distinction in motive, hedging or speculation, is provided for these traders. The monthly commitments of traders are averaged quarterly (at the end of November, February, May, and August) to match the sampling of the commodity-specific data. The long positions must equal short positions in futures markets, so that an imbalance between long and short positions in one group of traders means that there is, on aggregate, an imbalance of the same magnitude (but in the opposing sign) in the remaining groups. It follows that the COT data are not suitable for tests on intracommodity herding.

A general concern regarding the data on large speculators is that these traders have a monetary incentive to misrepresent themselves as large hedgers. The margin requirements for hedgers in most futures markets are generally lower. However, as long as there is no temporal relatedness in the misrepresentation of speculators across commodities, any misrepresentation in the large trader categories ought not to affect our results.[3]

3.2. Net trader positions

We employ a standardized measure of net trader positions. We define $L_{j,t}$ and $S_{j,t}$, respectively, as the number of long and short contracts outstanding for trader type j averaged over quarter t. The measure is

[3] COT data are frequently used to test the effects of trader positions on the variability in prices. For instance, Chatrath and Song (1999) use COT data for five commodities to test whether the positions of speculators and small traders are associated with large jumps in prices.

$$p_t = (L_{j,t} - S_{j,t})/(L_{j,t} + S_{j,t}), \tag{6}$$

which is the standardized difference in long and short positions. An alternate measure, $(L_{j,t} - S_{j,t})/Total_t$, where $Total_t$ is the aggregate open interest for quarter t, produced very similar results. The standardization of the difference in long and short positions is intended to control for the significant and positive trend in contracts outstanding noted in the four commodities. Despite the standardization of net positions, nonstationarity is suspected in p_t for each trader group in each of the four commodities. For these series, standard Augmented Dickey Fuller (ADF) tests cannot reject the null of a unit root at the 5% level of significance. On the other hand, the ADF tests consistently reject the null of a unit root for the first-differenced series. As we are concerned with the short-run comovements in trader positions, the empirical tests are conducted on the first difference of p_t.

3.3. Macro- and market-level data

Quarterly data on inventories (on-farm, off-farm, total), harvest size, yield per acre, and planted acres come from the U.S. Department of Agriculture. The macroeconomic indicators, industrial production, GDP, consumer price index (CPI), three-month secondary market Treasury bill yield, and the broad dollar index, come from the Federal Reserve Bank data files.

4. Results

Many of our conclusions are based on correlations between trader positions across the four commodities. Significance levels for correlation coefficients are based on Morrison's likelihood ratio test statistic, $-2^*\log(\lambda)$, $\lambda = |R|^{0.5^*N}$, where $|R|$ is the determinant of the correlation matrix and N is the sample size. The test statistic is distributed χ^2 with 1 degree of freedom. For the full sample, this implies that a correlation coefficient of 0.15 (0.18) is significant at the 10% (1%) level. We report Spearman's Rank correlation coefficients to provide a robustness check.

4.1. Trader commitments: Size and imbalances

Table 1 reports that large hedgers have the largest holdings (number of contracts outstanding), followed by small traders and large speculators. Small traders account for a fairly large proportion (30–40%) of the outstanding contracts. The relative imbalance between long and short positions is generally negative for large hedgers. This is not surprising, since we expect the majority of agricultural commodity hedgers to be producers rather than consumers. And, as expected, the imbalances for speculators and

Table 1

Quarterly trader positions Q1/1983–Q3/2002

The CFTC data on the positions of large hedgers, large speculators, and small traders are sampled monthly and averaged over quarters ending November, February, May, and August. Figures in the first three columns are means and standard deviations in parenthesis. Figures in the final three columns are intracommodity correlations in the changes to the imbalance ratios of the three trader groups. The imbalance ratio is $IR = (L_{j,t} - S_{j,t})/Total_t$ where $L_{j,t}$ and $S_{j,t}$, respectively, are the average number of long and short positions outstanding for trader type j for quarter t, and *Total* is the total number of contracts across trader groups. Values below (above) the diagonal of each correlation matrix are Pearson (Spearman Rank) coefficients.

	Trader positions			Correlations of changes in IR		
	Long	Short	Imbalance (IR)	Hedgers	Speculators	Small traders
Panel A: Wheat						
Hedgers	26,384	34,735	−0.117	1.000	−0.846	−0.651
	(16,232)	(19,152)	(0.122)			
Speculators	14,364	11,345	0.042	−0.856	1.000	0.230
	(9,694)	(10,587)	(0.100)			
Small traders	6,836	21,505	0.075	−0.712	0.246	1.000
	(7,579)	(4,932)	(0.080)			
Panel B: Corn						
Hedgers	131,810	134,260	−0.010	1.000	−0.913	−0.695
	(64,433)	(57,870)	(0.059)			
Speculators	40,100	26,022	0.055	−0.903	1.000	0.230
	(32,024)	(25,091)	(0.089)			
Small traders	83,973	95,600	−0.046	−0.709	0.340	1.000
	(26,716)	(29,930)	(0.080)			
Panel C: Oats						
Hedgers	3,213	7,162	−0.342	1.000	−0.669	−0.774
	(1,622)	(3,493)	(0.143)			
Speculators	1,498	561	0.083	−0.653	1.000	0.129
	(974)	(555)	(0.065)			
Small traders	5,360	2,347	0.260	−0.800	0.064	1.000
	(2,221)	(723)	(0.129)			
Panel D: Soybeans						
Hedgers	45,646	65,407	−0.137	1.000	−0.866	−0.529
	(19,217)	(28,804)	(0.142)			
Speculators	22,701	11,896	0.067	−0.886	1.000	0.109
	(16,603)	(8,804)	(0.106)			
Small traders	49,986	41,030	0.071	−0.600	0.160	1.000
	(11,489)	(8,996)	(0.065)			

small traders generally run counter to that for hedgers (note that the intracommodity imbalances sum to zero).[4]

Table 1 also reports intracommodity Pearson and Spearman's Rank correlations among the three trader groups. There is a strong negative relation between the

[4] Hedgers (speculators), as a group, are perennially net-short (net-long) in most commodities. Keynes (1930) uses this fact to explain backwardation in futures prices.

Table 2

Correlations of quarterly changes in net trader positions Q1/1983–Q3/2002

Net trader position for a commodity is $(L_{j,t} - S_{j,t})/(L_{j,t} + S_{j,t})$ where $L_{j,t}$ and $S_{j,t}$, respectively, are the average number of long and short positions outstanding for trader type j for quarter t. The first difference of this measure is employed in the computations. Statistics below (above) the diagonal are Pearson (Spearman Rank) correlations.

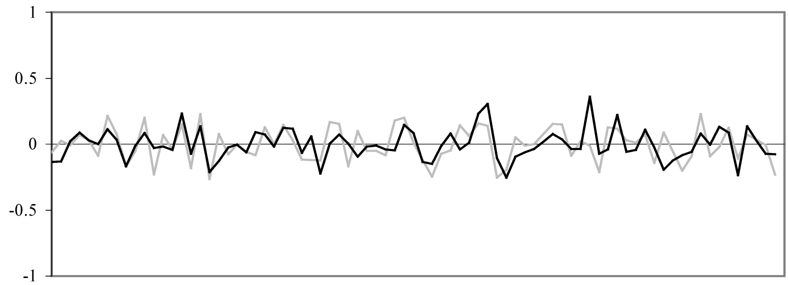
	Wheat	Corn	Oats	Soy
Panel A: Large hedger				
Wheat	1.00	0.16	0.37	0.11
Corn	0.22	1.00	0.18	0.57
Oats	0.36	0.22	1.00	0.32
Soy	0.11	0.56	0.31	1.00
Panel B: Large speculators				
Wheat	1.00	0.18	0.37	0.05
Corn	0.17	1.00	0.02	0.51
Oats	0.39	0.08	1.00	0.18
Soy	0.07	0.48	0.16	1.00
Panel C: Small traders				
Wheat	1.00	0.30	0.26	0.18
Corn	0.38	1.00	0.15	0.52
Oats	0.30	0.21	1.00	0.18
Soy	0.25	0.51	0.20	1.00

changes in relative imbalances in the positions of commercial and noncommercial traders. There is generally a weak positive relation between the changes in the relative imbalances in large speculator and small trader positions.

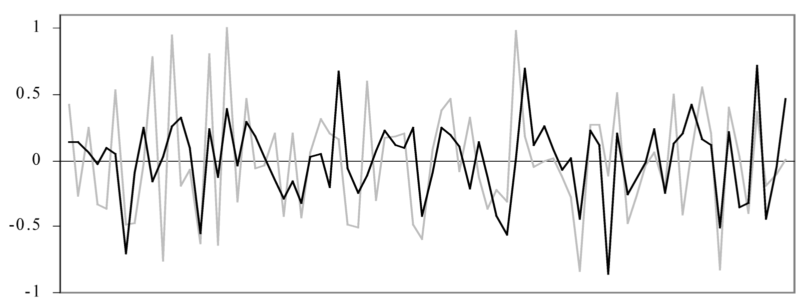
4.2. Intercommodity correlation of trader commitments

Our results on herding begin in Table 2, which reports correlations in the quarterly changes in net trader positions. The statistics indicate high degrees of correlation for five of the six pairings for large hedgers, four of the six pairings for large speculators, and all of the pairings for small traders. For large hedgers and large speculators, the cross-commodity correlations are the highest for the corn-soybeans pairing (0.56 and 0.48, respectively) and the wheat-oats pairing (0.36 and 0.39, respectively). For small traders, the correlation coefficients are the largest for the corn-soy (0.51) and the wheat-corn (0.38) pairings. With one exception, the correlations are slightly higher for small traders than for large speculators. We find generally similar results using monthly rather than quarterly data. Therefore, the Table 2 results fail to provide strong support for the hypothesis that herding occurs more commonly among small traders.

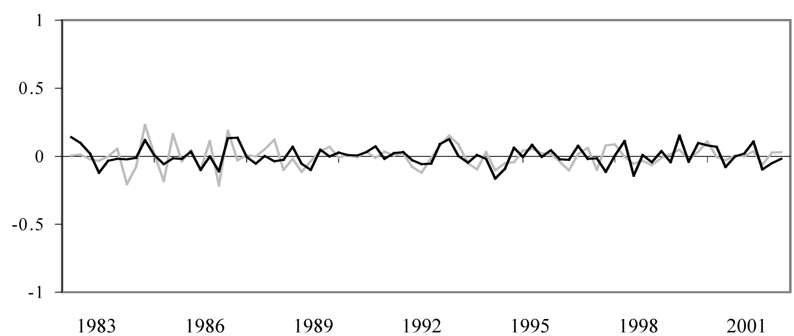
The close and positive relationship across the four commodity markets is brought out in Figure 1, which plots the changes in net trader positions for corn and soybeans. The plots for other pairings (not shown) are similar. The changes in net positions are more dramatic for the large speculators, even though the net positions are standardized.



A. Large hedgers



B. Large speculators



C. Small traders

Figure 1

Changes in net trader positions in soybeans (bold line) and corn

For each of the trader groups, a large swing in the positions for one commodity tends to be accompanied by a large swing in the other commodity. Further, the quarterly changes in net positions appear to be negatively autocorrelated, with only a few changes following through in the same direction. Thus, it appears that a large amount

Table 3

Correlation of fundamental factors for four commodities

Pearson correlations (below diagonal) and rank correlations (above diagonal). Data for the detrended changes in yield per acre and planted acres are annual, and the detrended and deseasonalized changes in the supply and disappearance are quarterly.

	Changes in yield per acre				Changes in planted acres			
	Wheat	Corn	Oats	Soy	Wheat	Corn	Oats	Soy
Wheat	1.00	0.58	0.80	0.61	1.00	0.79	0.82	0.80
Corn	0.78	1.00	0.75	0.89	0.94	1.00	0.68	0.77
Oats	0.92	0.86	1.00	0.71	0.94	0.89	1.00	0.91
Soy	0.83	0.95	0.87	1.00	0.96	0.93	0.97	1.00
	Changes in supply				Changes in disappearance			
	Wheat	Corn	Oats	Soy	Wheat	Corn	Oats	Soy
Wheat	1.00	−0.18	0.88	−0.27	1.00	−0.24	0.78	−0.39
Corn	−0.29	1.00	−0.03	0.83	0.53	1.00	−0.19	0.53
Oats	0.89	−0.26	1.00	−0.07	0.91	0.52	1.00	−0.18
Soy	−0.32	0.96	−0.27	1.00	0.30	0.75	0.34	1.00

of buying is often followed quickly by a large amount of selling. These patterns suggest an absence of a systematic and prolonged buildup of net long (or net short) positions by speculators and small traders. This in itself is not inconsistent with herding, since herders are often thought to be short-term oriented (for instance, see Wermers, 1999). On the other hand, the patterns are inconsistent with the notion that the intercommodity correlations in the trader positions between 1983 and 2003 are a result of "passive investing" trends in commodities.

4.3. Correlation of commodity fundamentals

Table 3 reports the correlations for a set of commodity fundamentals—detrended changes in production yield, planted acres, and deseasonalized and detrended supply and disappearance, the difference between supply and ending inventories. The Pearson correlations range from 0.78 to 0.95 for changes in yield, from 0.89 to 0.97 for changes in planted acres, and from 0.34 to 0.91 for changes in disappearance. For changes in supply, the highest correlations are 0.89 and 0.96 for the wheat-oats and corn-soybeans pairings, but we also find strongly negative correlations for wheat-soybeans, wheat-corn, and oats-soybeans. A striking feature of the results in Table 3 is that the fundamentals appear to be related for pairs of commodities with no obvious complementarity or substitutability, for instance, wheat and soybeans. This means that commodities that would typically be considered unrelated by researchers who study commodity comovements (e.g., Pindyck and Rotemberg, 1990; Deb, Trivedi and Varangis, 1996) are actually highly related in their fundamentals.

Table 4

Explanatory power of the macro and equilibrium models

Panel A reports the explanatory power of the OLS regression of change in net positions on contemporaneous and lagged change in CPI, change in real GDP, change in the dollar index, and the Treasury bill rate. Panel B reports the explanatory power of the equilibrium model estimated using two-stage least squares (2SLS).

	Wheat	Corn	Oats	Soy
Panel A: Macro model-adjusted R^2				
Large hedgers	0.01	0.00	0.08	0.01
Large speculators	0.01	0.02	0.07	0.02
Small traders	0.00	0.07	0.02	0.01
Panel B: Equilibrium model R^*				
Large hedgers	0.79	0.79	0.88	0.76
Large speculators	0.78	0.78	0.84	0.82
Small traders	0.73	0.76	0.82	0.69

The correlations could be the result of crops competing for acreage, and sharing weather shocks and changes in technology. However, most of the fundamentals are more highly related than the changes in net trader positions in Table 2. In other words, the results raise the possibility that the close relationship between the trader positions in Table 2 arise mostly from the even more highly related tendencies in fundamentals.

4.4. *Performance of the macro and equilibrium models*

Panel A, Table 4 reports the adjusted R^2 and residual correlations from the macro model, where the differenced net trader positions for each trader group are regressed on contemporaneous and lagged values of three macroindicators, the differenced real GDP, differenced dollar index, and undifferenced interest rate (as in Pindyck and Rotemberg, 1990).[5] The macroindicators explain little of the variance in the changes in net trader positions. For large hedgers, the adjusted R^2 ranges from 0.01 (wheat) to 0.08 (oats). A similar range is found for large speculators and small traders. It is also evident that the macro model fails to explain the high correlation in the changes in net trader positions. The weak explanatory power of the macro model is consistent with earlier studies that show that macroeconomic indicators generally do not explain commodity price behavior.

Panel B of Table 4 reports on the explanatory power of the equilibrium model. The two-stage estimation of the equilibrium model (Equation (5)) is conducted with a polynomial order $m = k = 4$, selected in the interest of both maintaining reasonable

[5] The coefficients from the 12 regressions are omitted. None of the coefficients is significant at the 1% level, and only changes in real GDP is significant at the 10% level for the corn, oats and soybeans regressions. The lack of explanatory power of the macrovariables is consistent with Pindyck and Rotemberg (1990). Other variables, such as industrial production, alternate interest rates, and narrower foreign exchange indexes, fail to improve the model's performance; these results are available from the authors.

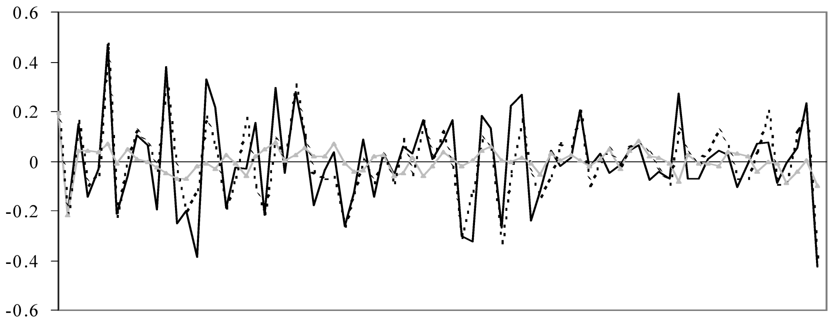
degrees of freedom, and its performance in explaining the trader behavior. As in the macro model, X_t contains the three current and lagged macroindicators. The explanatory power of the estimation is R^*, defined here as one minus the ratio of the residual variance and the variance of the dependent variable. The equilibrium model outperforms the macro model in explaining price behavior. The R^* is fairly similar across commodities and trader groups. It ranges between 0.76 and 0.88 for large hedgers, 0.78 and 0.86 for large speculators, and 0.69 and 0.82 for small traders. Thus we do not find compelling evidence that small trader positions are more difficult to "explain" than large trader positions. More important, the results indicate that net demand and expected net demand for a particular commodity explains the majority of the variation in the trader positions of that commodity. Other fundamental factors that we do not directly control for in this study (such as temperature and rainfall) are likely to explain some of the remaining variations in the positions.

Figure 2 provides a comparison of the explanatory performance of the macro and equilibrium models for wheat. The patterns for the other commodities are similar in their implications. It is evident that the predicted value from the macro model (solid, patterned line) captures little of the sharp changes in the trader positions (solid, dark line). On the other hand, the predicted value from the equilibrium model (broken line) traces the peaks and valleys remarkably well. To summarize, the macro model is almost entirely ineffective in explaining commodity price behavior, while the equilibrium model explains a substantial amount of price variation. As both employ fundamental variables, it is clear that the latter will provide a much better opportunity to investigate the existence of excess comovements.

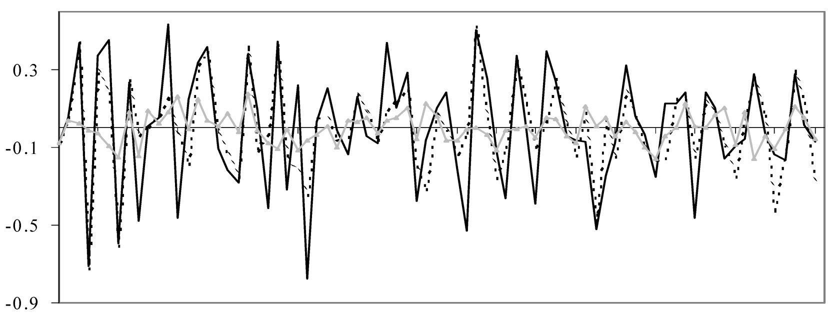
4.5. Residual correlations

Table 5 reports the correlations of the residuals from estimations of the macro and equilibrium models. The correlations for the macro model residuals (Panel A) are not much different from the correlations for the changes in net trader positions reported in Table 2. For instance, the wheat-oats and corn-soybeans correlations are almost unchanged. This is not surprising given the weak explanatory power of the macro model. On the other hand, the correlations of the residuals from the estimation of the equilibrium model are greatly reduced from Table 2 and generally statistically insignificant. Further, the sharp decline in residual correlations is evident across both groups of traders. Thus our results show that commodity-specific (market-level) factors explain the majority of the correlation among the trader positions in the four commodities. In other words, our results provide strong support against the hypothesis of herding among the traders in these commodities.

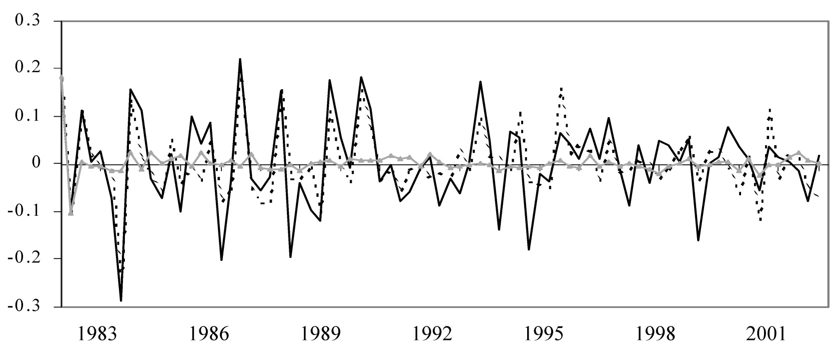
We run a set of robustness tests, which confirm the superiority of the equilibrium model in explaining trader behavior. A potentially important issue to be resolved is whether (or to what extent) the difference in the estimation techniques across the macro and equilibrium frameworks played a role in the results. As described earlier, the macro model is estimated with a linear specification while the equilibrium model



A. Large hedgers



B. Large speculators



C. Small traders

Figure 2

Actual versus predicted changes in net positions for wheat: actual (bold line), equilibrium (broken line), macro (patterned line)

Table 5

Residual correlations

Panel A reports the Pearson (below diagonal) and rank (above diagonal) correlations for residuals from the OLS estimation of the macro model. Panel B reports the correlations for the residuals from the two-stage least squares (2SLS) estimation of the equilibrium model.

	Wheat	Corn	Oats	Soy
Panel A: Macro model				
Large hedgers				
Wheat	1.00	0.18	0.40	0.14
Corn	0.22	1.00	0.21	0.60
Oats	0.39	0.20	1.00	0.28
Soy	0.11	0.58	0.28	1.00
Large speculators				
Wheat	1.00	0.24	0.37	0.10
Corn	0.17	1.00	0.13	0.56
Oats	0.39	0.18	1.00	0.13
Soy	0.07	0.50	0.13	1.00
Small traders				
Wheat	1.00	0.29	0.28	0.14
Corn	0.38	1.00	0.20	0.46
Oats	0.31	0.33	1.00	0.21
Soy	0.22	0.49	0.22	1.00
Panel B: Equilibrium model				
Large hedgers				
Wheat	1.00	−0.05	0.14	0.07
Corn	−0.11	1.00	−0.03	0.10
Oats	0.12	−0.08	1.00	0.09
Soy	0.09	0.12	0.13	1.00
Large speculators				
Wheat	1.00	0.05	0.08	0.07
Corn	−0.06	1.00	−0.05	−0.12
Oats	0.08	0.04	1.00	0.10
Soy	0.08	−0.03	0.11	1.00
Small traders				
Wheat	1.00	0.01	0.12	−0.00
Corn	0.06	1.00	0.02	0.13
Oats	0.12	−0.03	1.00	0.06
Soy	−0.07	0.10	0.06	1.00

is implemented with a fifth-order polynomial. In an alternate specification of the macro model, we employ a fifth-order polynomial on the macroindicators to examine the extent to which such a specification improves the explanatory power and the extent to which the specification effects the residual correlations. The explanatory power is only marginally improved, and the residual correlations show no noteworthy change for any of the pairings. Thus, it appears that the inputs of the two models, rather than their econometric implementation, cause most of the disparity in the results of residual correlations.

5. Conclusions and implications

We examine comovements in the quarterly changes in trader positions across wheat, corn, oats, and soybeans futures over a 20-year interval. The main question addressed is whether the correlations in trader positions reflect "excess comovement" (or herding) across the commodities that is not explained by fundamental factors, such as production and inventories. The results show that the positions of large hedgers, large speculators and small traders are highly related across the four commodities. We find that various macroeconomic indicators, such as interest rates, inflation and the dollar index, explain very little of either the behavior of trader positions or the cross-commodity relatedness of the trader positions. On the other hand, commodity-specific factors provide decisive results. These factors explain a relatively large portion of the changes in net trader positions in each commodity, and explain the vast majority of their relatedness across the four commodities. In other words, we find no excess comovements in the positions of commodity traders.

The findings suggest that commodity fundamentals are more closely related than previously recognized. For instance, Pindyck and Rotemberg (1990) assume that the market-level fundamentals for commodities, such as copper and lumber, are unrelated. In another important study of price comovements, Deb, Trivedi and Varangis (1996) assume the commodities to be unrelated if they are neither jointly produced nor jointly consumed. By their metric, sugar is unrelated to coffee or cocoa and lumber and oil ought to be unrelated to each other and to nine other commodities, including, wheat and cotton. Our results show that the comovements among fundamental factors can be extremely high, highlighting the problems inherent in studies that test for excess comovements without explicitly considering the relatedness in fundamentals.

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