HEDGING AND SPECULATIVE TRADING IN AGRICULTURAL FUTURES MARKETS

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Regulators and industry participants have expressed concern that excessive speculation harms agricultural futures markets. Such harm may arise if speculators cause prices to systematically differ from the price sequence that would arise in markets populated by equally informed traders with rational expectations (RE). We show theoretically that, when traders exhibit differences of opinion (DO) about the expected value of the commodity, futures prices may diverge from the RE equilibrium. Moreover, we develop a testable prediction, namely that positions held by different trader groups are correlated with prices in a DO equilibrium but not correlated in a RE equilibrium. We find strong empirical support for the DO-type environment; changes in positions held by managed money traders are positively correlated with prices, and changes in positions held by producers are negatively correlated. In the context of our DO model, this finding implies that prices change by more on average than producers think they should and by less than managed money thinks they should. However, the evidence suggests that neither group is systematically more prescient than the other.

JEL codes: G1, Q1.

In popular descriptions of futures markets, traders are classified by reference to occupation, trading strategy, or business entity—the farmer/producer, refinery/processor, day trader, hedge fund, or index fund. These generalizations also underlie many of the classic models that economists use to describe futures and other financial markets. In such models, heterogeneous groups such as hedgers and speculators (Keynes), rational and noise traders (DeLong et al.), or informed traders and liquidity providers (Easley and O'Hara) interact in the market to generate equilibrium price dynamics. Groups are often symbiotic in these models, but there are also environments in which some groups of traders may exacerbate price dynamics (e.g., Hong, Scheinkman, and Xiong).

Regulators have repeatedly voiced concerns during periods of unusual price dynamics about whether particular traders—namely, speculators—cause such volatility and potentially harm futures markets. Specifically, regulators question whether speculators' trades affect fundamental prices and thereby interfere with effective risk management and price discovery. As former Commodity Futures Trading Commission (CFTC) Chairman Gensler recently stated:[1] "CFTC data published in 2011 shows the vast majority of trading volume in key futures markets—more than 80 percent in many contracts—is day trading or trading in calendar spreads. Only a modest proportion of average daily trading volume results in reportable traders changing their net long or net short futures positions for the day. This means that about 20 percent or less of the trading is done by traders who bring a longer-term perspective to the market on the price of the commodity." CFTC Commissioner

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[1] Remarks of Chairman Gary Gensler before the International Monetary Fund Conference. See http://www.cftc.gov/PressRoom/SpeechesTestimony/opagensler-137.

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Chilton expressed the same sentiment:[2] "Speculators are necessary liquidity providers to our markets, and while they perhaps are not driving prices to uneconomic levels, they certainly have an effect on prices—above and beyond where they might otherwise go—and American consumers and taxpayers are shouldering that burden."

Regulators express their concern using the term "excessive speculation," which is found in legislation since at least the Grain Futures Act of 1922. It also appears in the Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010. Although its use in regulation is unclear, most economists would define excessive speculation as trading that causes prices to differ from "fundamentals," where fundamentals are the price sequence that would result from competitive markets populated by equally informed traders with rational expectations. We adopt this definition to motivate our analysis.[3]

Our purpose in this article is to examine whether differences of opinion among traders may cause prices to deviate from a rational expectations (RE) equilibrium. In our difference-of-opinion (DO) model, traders do not believe that prices fully incorporate the available information about fundamentals. Rather, they trust their own information signals when choosing positions. Thus, the DO model may lead to unusual price dynamics, which may appear in the regulator's eye to be cases of excessive speculation.

We extend the DO literature by considering the different implications of a DO and an RE model for the positions held by particular trader groups. In contrast, previous applications focus on how the DO environment affects price dynamics and trading volume (e.g., Banerjee; Banerjee, Kaniel, and Kremer; Banerjee and Kremer). Specifically, we examine how positions taken by trader groups thought to be speculators (or hedgers) relate to market prices in a DO model, and we do the same for an RE model. In effect, we try to unravel whether a DO model explains why speculators are often criticized during periods of unusual price dynamics.

In our DO model, traders receive private signals about the value of the commodity and rely on those signals to choose positions. Each trader is aware that the other received a private signal, but she believes her own signal to be correct; in essence, traders agree to disagree. In contrast, traders in an RE model believe that prices fully aggregate information and therefore the other trader's private signal carries some information about the value of the commodity. We show that the DO equilibrium implies that positions held by trader groups are correlated with prices. Specifically, positions are positively correlated with prices for the trader group that receives the strongest signal and negatively correlated for the other group. In an RE equilibrium, traders condition on the price, and the correlation between positions and prices, is zero. This implication provides an empirical basis for testing the two models.

We use disaggregated Commitments of Traders (DCOT) data published by the CFTC to test the DO theory for corn, soybeans, wheat, cotton, lean hogs, and live cattle. The DCOT reports weekly aggregate futures positions held by five trader groups: merchants or producers, swap dealers, managed money, other large traders, and nonreporting small traders. To varying degrees, all groups except for the producer category have been associated with the term "speculators."

Our empirical results provide strong support for the DO-type environment in futures markets, particularly for managed money and producer trader groups. Our results show that the positions of managed money traders are positively correlated with price changes, whereas the positions of producers are negative correlated. This result provides support for the DO model and indicates that managed money traders (i.e., hedge funds) have strong price signals that they use to formulate trade decisions and that these signals do affect prices. In essence, prices change by more on average than producers think they should and by less than managed money thinks they should. Our results do not reveal which group is correct on average or in any particular episode. Given the finding in Fishe and Smith that essentially no trader in either group has significant predictive ability, it is likely that neither group is systematically more prescient than the other. These findings are robust to volatility and seasonal effects and suggest a theoretical explanation for why

[2] See http://www.cftc.gov/PressRoom/SpeechesTestimony/chiltonstatement022412.

[3] This definition of excessive speculation is the same as that often used in finance to define a bubble (Gilles and LeRoy). In the popular press, the word bubble is often used to refer to long swings in prices away from fundamentals, whereas excessive speculation is a term used to suggest too much volatility. Shiller showed that these two phenomena are in fact the same.

managed money traders may bring unwanted attention from regulators.

We also find evidence that the position changes of the DCOT trader groups are not synchronized, which supports the view that these participant groups hold different opinions when changing positions. Thus, there is indirect support for the DO model from the relative behavior of position changes.

Our modeling results also provide a framework for the interpretation of the Commitment of Traders data, whereas the previous literature has been less directed at testing a specific theoretical model. Results from extant research have suggested that position changes by trader groups do not Granger-cause futures returns (Büyükşahin and Harris), but there appears to be a relationship between diminished price volatility and increased activity by managed money traders (Brunetti, Büyükşahin, and Harris), and also those same traders may be connected to the rise in correlations across asset groups (Büyükşahin and Robe).

Conceptual Framework

We start with the premise that all traders contend with a tradeoff between risk and reward. This tradeoff looks different for a firm with a large position in the underlying commodity because a large component of its portfolio return comes from the covariance between its spot and futures positions. We define such firms as *hedgers*. Firms without a position in the underlying commodity are *speculators*. In our environment, there are two time periods and two traders, each of whom takes a position in period 1 and realizes profits in period 2. Each trader maximizes expected utility by choosing how many positions to take in the futures contract. In addition to futures, the hedging trader holds Z units of the underlying commodity.

We specify a constant absolute risk aversion utility function. The hedger maximizes

$$V_H = E_H\left[-\exp\left(-\gamma(\Delta F_2\, Q_H + P_2\, Z)\right)\right], \tag{1}$$

and the speculator maximizes

$$V_S = E_S\left[-\exp\left(-\gamma \Delta F_2\, Q_S\right)\right], \tag{2}$$

where γ denotes the risk aversion parameter, $\Delta F_2 \equiv F_2 - F_1$ denotes the change in the futures price, Q_i denotes the futures position of trader i, and P_2 denotes the period 2 spot price of the commodity. We add subscripts to the expectations operator to allow for differences of opinion across traders based on their information sets.

Traders enter period 1 with homogeneous expectations about the period 2 futures price, given by $F_0 \equiv E_0[F_2]$. Both traders understand that there is a normally distributed fundamental shock in period 1 and another normally distributed fundamental shock in period 2. However, neither trader observes the true fundamental value until it is revealed in the spot market in period 2. At the beginning of period 1, each trader i receives a signal μ_i, which is a noisy estimate of the period 1 fundamental shock. We derive the period 1 futures price based on how traders interpret these signals.

Following Banerjee, Kaniel, and Kramer, we consider two environments to describe how traders interpret the period 1 signal. In the RE setting, each trader uses the actions of the other to infer her signal and thereby update her own estimate of the period 2 price. In the DO setting, traders agree to disagree; they believe their own signal is perfect and ignore the signal received by the other trader. Mathematically, both traders know that the period 2 futures price is generated by $F_2 = F_0 + \varepsilon_1 + \varepsilon_2$, and that the shocks are distributed as *iid* normal—that is, $\varepsilon_t \sim N(0, \sigma_F^2)$. The two environments are as follows:

(*a*) RE: The signals are generated according to

$$\begin{bmatrix}\mu_H \\ \mu_S\end{bmatrix} = A\varepsilon_1 + \begin{bmatrix}v_H \\ v_S\end{bmatrix}, \quad \begin{bmatrix}v_H \\ v_S\end{bmatrix} \sim N(0, \Omega) \tag{3}$$

where $A = [1 \quad 1]'$. Both traders know this signal generating process. The noise terms v_i are independent of the true shocks ε_1 and ε_2.

(*b*) DO: The signals are generated by the same process as (3), but each trader believes that her signal is the truth; the hedger believes $\mu_H = \varepsilon_1$, and the speculator believes that $\mu_S = \varepsilon_1$.

Consistent with the findings of Fishe and Smith that few, if any, traders consistently show superior predictive ability, both DO traders receive relevant information about the fundamental value. We do not need to assume that pure noise traders exist to obtain our results. Moreover, the information received by each trader is the same in the DO environment as the RE environment. The difference between the two settings is how each trader views both her own signal and the other trader's signal, which is how we obtain different equilibrium prices across the two settings.

We also allow for the hedger to face basis risk, but for brevity we specify the basis risk to be uncorrelated with the fundamental shocks. Thus, we specify the period 2 spot price as $P_2 = F_2 + u$, where u denotes a normally distributed basis term defined such that $\mathrm{cov}[F_2, u] = 0$. This specification implies that $\mathrm{cov}[F_2, P_2] = \mathrm{var}[F_2]$ and therefore that the standard hedge ratio equals one. If we were to dispense with the $\mathrm{cov}[F_2, u] = 0$ assumption, then our solutions for positions and prices would have an extra term representing the ratio, $\mathrm{cov}[F_2, P_2]/\mathrm{var}[F_2]$.

Because shocks are Gaussian, the utility functions in equations (1) and (2) are lognormally distributed. Using the formula for the expectation of a lognormal random variable and maximizing with respect to Q_i yields

$$(4) \qquad Q_H = \frac{\gamma^{-1} E_H[\Delta F_2]}{\mathrm{var}_H[F_2]} - Z$$
$$Q_S = \frac{\gamma^{-1} E_S[\Delta F_2]}{\mathrm{var}_S[F_2]}.$$

In equilibrium, $Q_H + Q_S = 0$, which implies that the period 1 futures price is

$$(5) \qquad F_1 = \left(\frac{1}{\mathrm{var}_H[F_2]} + \frac{1}{\mathrm{var}_S[F_2]} \right)^{-1} \times \left(\frac{E_H[F_2]}{\mathrm{var}_H[F_2]} + \frac{E_S[F_2]}{\mathrm{var}_S[F_2]} - \gamma Z \right).$$

The futures price is a weighted average of the expected price across traders adjusted for a risk premium. The differences between the equilibrium prices in the RE and DO environments arise from differences in the conditional mean and variance of F_2, and we show these differences and their implications for futures positions next.

RE Equilibrium

In an RE equilibrium, each trader believes that the price efficiently aggregates information (Banerjee, Kaniel, and Kramer; Grossman). Thus, conditional on the 2×1 vector of signals, μ, the formula for the mean of a conditional normal distribution implies that the expected futures price is

$$(6) \qquad E[F_2 \mid \mu] = F_0 + E[\varepsilon_1 \mid \mu] = F_0 + A' \left(AA' + \sigma_F^{-2} \Omega \right)^{-1} \mu.$$

Similarly, the conditional variance is

$$(7) \qquad \mathrm{var}[F_2 \mid \mu] = 2\sigma_F^2 - \sigma_F^2 A' \left(AA' + \sigma_F^{-2} \Omega \right)^{-1} A.$$

These moment expressions do not differ across traders because in equilibrium both traders have the same information.

Plugging (6) and (7) into (5) implies that the futures price is

$$(8) \qquad F_1 = F_0 + A'(AA' + \sigma_F^{-2}\Omega)^{-1}\mu - \frac{\gamma Z \sigma_F^2}{2} \left(2 - A'(AA' + \sigma_F^{-2}\Omega)^{-1} A\right).$$

The change in price from period 0 has two components. The first is a weighted average of the signals, and the second is a risk aversion term generated by the hedger. In the first term, the weighting vector on the signals equals $A'(AA' + \sigma_F^{-2}\Omega)^{-1}$. Recalling that A is a vector of ones, this weighting vector depends on $\sigma_F^{-2}\Omega$, the variance of the noise in each trader's signal relative to variance of the fundamental shock ε_1. In other words, $\sigma_F^{-2}\Omega$ is an inverse measure of signal precision. Because all traders know the signal generating process in an RE equilibrium, the realized price assigns more weight to the trader with the least noisy signal.

The second component of the change in price in (8) comes from the motivation of the hedger to take futures positions to offset spot price risk. In fact, this term is the risk premium because

$$(9) \qquad E[\Delta F_2] = \frac{\gamma Z \sigma_F^2}{2} \left(2 - A' \left(AA' + \sigma_F^{-2}\Omega\right)^{-1} A\right).$$

The risk premium increases with spot exposure Z because the hedger has to pay a larger premium to induce the speculator to take a larger position. The risk premium is also larger when the noise in each trader's signal is larger—that is, when Ω is large relative to σ_F^2.

We obtain the positions taken by each trader by substituting (9) and (7) into (4):

$$(10)\quad Q_H = -0.5A'\left(AA' + \sigma_F^{-2}\Omega\right)^{-1} AZ$$
$$Q_S = 0.5A'\left(AA' + \sigma_F^{-2}\Omega\right)^{-1} AZ.$$

These expressions show that positions do not depend on the signal in an RE equilibrium. Traders agree *ex post* about the value of the commodity, so positions are determined by the supply and demand for hedging, rather than the differential signals. It follows that, holding Z constant, the futures price F_1 is contemporaneously uncorrelated with positions. Next, we show that this result does not hold in the DO equilibrium.

DO Equilibrium

In a DO equilibrium and conditional on her own signal, each trader views the moments of the period 2 futures price as

$$(11)\quad \begin{array}{ll} E_H[F_2] = F_0 + \mu_H & E_S[F_2] = F_0 + \mu_S \\ \mathrm{var}_H[F_2] = \sigma_F^2 & \mathrm{var}_S[F_2] = \sigma_F^2. \end{array}$$

Plugging these moments into (5) implies that the futures price is

$$(12)\quad F_1 = F_0 + \frac{\mu_H + \mu_S}{2} - \frac{\gamma Z}{2}\sigma_F^2.$$

As was the case for the RE equilibrium, the change in futures price has a component that reflects information and a component that reflects the risk premium. These expressions are simpler than those in (8) because the traders have a simpler view of the world—each takes her own signal as truth and views the other trader's signal as uninformative about the fundamental value.

For the hedger, the expected payoff on holding futures is

$$(13)\quad E_H[\Delta F_2] = F_0 + \mu_H - \left(F_0 + \frac{\mu_H + \mu_S}{2} - \frac{\gamma Z}{2}\sigma_F^2\right) = \frac{\mu_H - \mu_S}{2} + \frac{\gamma Z}{2}\sigma_F^2$$

and for the speculator it is

$$(14)\quad E_S[\Delta F_2] = \frac{\mu_S - \mu_H}{2} + \frac{\gamma Z}{2}\sigma_F^2.$$

Each trader expects to earn (or pay) a risk premium and to make money on the perceived incorrectness of the other trader's signal.

Plugging (13) and (14) into (4), optimal positions for each trader are

$$(15)\quad Q_H = \frac{\mu_H - \mu_S}{2\gamma\sigma_F^2} - \frac{Z}{2}$$
$$Q_S = \frac{\mu_S - \mu_H}{2\gamma\sigma_F^2} + \frac{Z}{2}.$$

Holding constant the spot exposure, the trader with the higher value signal desires to take a larger long (or smaller short) position, and the trader with the lower value signal desires to do the opposite. The risk aversion parameters moderate the incentive of each trader to take a large position to profit from the perceived ignorance of the other.

The only random variables in the position and price expressions are the signals. Because both prices and positions are affected by the signals, prices will tend to be correlated with positions. For hedgers, the covariance between prices and positions is

$$(16)\quad \mathrm{cov}[Q_H, F_1] = E\left[\left(\frac{\mu_H - \mu_S}{2\gamma\sigma_F^2}\right)\left(\frac{\mu_S + \mu_H}{2}\right)\right] = \frac{1}{4\gamma\sigma_F^2}\left(\mathrm{var}[\mu_H] - \mathrm{var}[\mu_S]\right)$$

and for speculators it is the negative of this quantity because $Q_S = -Q_H$. Thus, the covariance is positive for the trader with the largest variance in the value signal and negative for the other trader.

The correlation in (16), and the corresponding zero correlation for the RE equilibrium, provide the main contribution of this theory. Our model is quite similar to those in Banerjee; Banerjee, Kaniel, and Kramer; and Banerjee and Kremer, for example, but those authors specify that the signal variance is constant across traders. As a consequence, they do not generate a testable prediction about the correlation between positions and prices. Because the previous literature addresses equity markets in which researchers do not observe the holdings of particular traders or subgroups of traders, such a prediction was not relevant in their studies.

Empirical Implications

The main implication of our theory is that, in the DO equilibrium, prices are positively correlated with positions for the trader who tends to receive the higher value signal. In contrast, prices are uncorrelated with positions in an RE equilibrium. Because prices and positions are jointly determined in equilibrium, the models do not indicate the direction of causality between positions and prices, only correlation between them. However, finding a statistically significant relationship between positions and prices indicates rejection of the RE equilibrium. We test this implication of our model by regressing observed position changes for different trader types on futures price changes.

Our theoretical model presents a stylized view of the world designed to highlight the main correlation result. The model has only two time periods and two traders. We could relax these assumptions with no effect on our main result. Banerjee; Banerjee, Kaniel, and Kramer; and Banerjee and Kremer specify similar models with a continuum of investors in the stock market. They show that the two-period solution provides the same insights as the many-period model, but it is obviously more complicated. The number of traders in the model only matters if they behave strategically, but in our model they behave competitively. If we were to increase the number of traders in our model, then we would still find that the traders who receive signals with above-average variance tend to change positions in the same direction as prices and vice versa for traders who receive low variance signals.

Equations (10) and (15) imply that in both RE and DO settings, larger spot exposure for the hedger leads to larger absolute positions. In our application, we do not observe the underlying positions of hedgers, so we cannot measure how changes in these positions affect prices. This omission could confound our analysis. If variation in spot market exposure drives position changes, then we would expect to see position changes by hedgers positively correlated with prices and position changes by speculators negatively correlated with prices (de Roon, Nijman, and Veld).

We account for this potential confounding factor by reporting results by season. The spot exposure of agricultural crop hedgers is dominated by the annual harvest cycle. During the growing season, market participants face uncertainty about the size of the crop, so their spot exposure varies widely. However, after the crop is harvested, the available supply is essentially fixed until the next harvest. During this period, hedgers are solving a storage problem, so variations in spot exposure should have much smaller effects on price and position changes during this period. We test whether the relationship between prices and positions is weaker during the growing season than outside of it.

We also investigate whether hedging pressure effects may confound our DO test by examining the synchronicity of position changes. An essential feature of the DO environment is that traders receive different signals. In contrast, if hedging pressure were to drive position and price changes in an RE world, then we would observe synchronous trading among all nonhedgers as they respond to changes demand from a hedger. Thus, the more that trading by groups acting as speculators (or hedgers) contrasts with the trading of other speculators (or hedgers), the greater is the support for the DO-type equilibrium.

In addition to the signals, the absolute risk aversion and volatility parameters affect equilibrium prices and positions. We specify our conceptual model with homogeneous risk aversion. If risk aversion were to vary across traders, then the trader with smaller γ would be more willing to take large positions. A given signal for this trader would move prices by more than the same signal provided to a more risk-averse trader.[4] Thus, although we define a strong signal in (16) as one with high variance, we could similarly have conceptualized a strong signal as one that is received by a trader with relatively low risk aversion (i.e., one who is likely to trade aggressively on the signal).

Similar to risk aversion, high volatility mitigates the effect of the signals on positions in the DO setting. Thus, we may expect the

[4] If the risk aversion parameters are γ_H and γ_S for the two traders, then the DO equilibrium is characterized by $F_1 = F_0 + (\gamma_H + \gamma_S)^{-1}(\gamma_S\mu_H + \gamma_H\mu_S) - (\gamma_H^{-1} + \gamma_S^{-1})^{-1}\sigma_F^2 Z$ and $\text{cov}[Q_H, F_1] = (\gamma_S \text{var}[\mu_H] - \gamma_H \text{var}[\mu_S])/(\sigma_F^2(\gamma_H + \gamma_S)^2)$.

covariance between positions and prices to be higher when volatility is lower. We test this prediction empirically.

The DO equilibrium does not generate predictions for the correlation between volatility and positions. Given that the average difference in signals equals zero, equation (14) reveals that volatility has no effect on average positions in the DO environment. In the RE equilibrium, an increase in fundamental volatility holding all else constant increases the relative informativeness of the signal and therefore increases absolute positions, as seen in (9).

Data

Since 1924, the CFTC and its predecessors have published data on the level and direction of positions held by particular groups of traders in commodity futures markets through the Commitments of Traders (COT) reports. These data provide a snapshot of the positions held by large hedging and speculating traders, referred to as commercial and noncommercial traders in CFTC reports. Small traders, who hold fewer contracts than the market-specific reporting level set by the CFTC, are not required to report positions, and they are termed "nonreportable" positions in COT reports.

Over time, the CFTC increased the volume of information released publicly through these reports in two ways. First, the frequency of reporting increased from annual to monthly in 1962, to biweekly in 1992, and to weekly in 2000. Second, the categorization of traders has changed to reflect perceptions of increasingly heterogeneous trader motivations for taking long and short positions in commodity futures markets. In 2007, the CFTC began releasing a supplemental COT report describing the positions held by commodity index traders. Prior to 2007, commodity index trader positions were largely contained in the commercial category because swap dealers offset price risk due to the establishment of commodity index investment instruments through corresponding long futures positions. In 2009, the CFTC further disaggregated large trader classification into four groups—commercial, swap dealers, managed money, and other reportable—in the DCOT report. This disaggregation was backdated, so the DCOT data are available from June 2006.

Recent studies have used the COT and supplemental COT reports to test whether commercial and noncommercial positions forecast changes in price across many commodity markets. Generally, these studies suggest there is little, if any, predictive power in position data for commercial and noncommercial traders (e.g., Büyükşahin and Harris; Sanders, Irwin, and Merrin 2009). Similarly, commodity index trader positions possess little predictive power for returns (e.g. Sanders and Irwin). However, recent work shows that the increased presence of managed money traders may have reduced price volatility in crude oil futures and increased cross-asset price correlations among several commodities (Brunetti, Büyükşahin, and Harris; Büyükşahin and Robe).

In this article, we focus on the DCOT data for six high-volume agricultural commodities: corn, cotton, lean hogs, live cattle, soybeans, and wheat. These commodities, particularly corn, soybeans, and wheat, have thousands of independent traders holding a daily position, which supports the competitive assumption in our model (cf. table 2 in Fishe and Smith). The DCOT data offer the most refined, publicly available partition of participant positions and thus provide a closer connection to the notion of hedgers and speculators. The DCOT report divides participants into five groups: a "producer" group includes traders who self-report their business line as a producer, merchant, processor, or end user; a "swap" group consists of swap dealers; a "managed money" group consists of hedge funds and other managed money companies; an "other" group includes any other traders whose position size requires daily position reporting, such as floor brokers and traders; and a "nonreporting" group consists of smaller traders whose overnight positions are below reporting thresholds.

To generate the reported DCOT statistics, the CFTC first aggregates positions held by each trader across maturities. Then, it calculates the net position for each trader (total long minus total short) and the spread position (number of long positions that are offset by a short position in another maturity).[5] Next, it takes all traders with a positive net position in a group and computes the sum.

[5] For example, a trader who holds one hundred long contracts in the nearby, fifty short contracts in the next deferred, and another twenty-five short contracts in the second deferred would have a net position of +25 and a spread position of 75.

This number is reported as the total long positions held by the group. Similarly, it takes all traders with a negative net position in a group and computes the sum to obtain total short positions held by the group. Finally, it sums the spread positions across traders. The CFTC does not report spread positions for the producer or nonreporting groups, so they cannot be isolated in the analysis.

We also obtain futures price data from the Commodity Research Bureau. We use settlement prices of the nearby contract on the day corresponding to the DCOT measurement (almost always a Tuesday). We roll over to the next contract in the second week of the month before delivery. To measure price volatility, we use implied volatility calculated by the Commodity Research Bureau from at-the-money options using the Black model and realized price volatility calculated as the daily standard deviation of settlement prices over the past 20 trading days.

Group Characteristics and Synchronicity

Table 1 reports the average size of positions and position changes of the DCOT groups for the six commodities in our sample. Panel A shows the average weekly open interest as of the reporting date. Across all commodities, the producer group holds the largest outstanding positions, particularly on the short side, which is the classic hedge for most agricultural commodities. The swap dealer and managed money groups hold large net long positions on average, so these groups appear to act as counterparties to the producer group. With few exceptions, there are substantial long and short holdings for all groups in every commodity, which lends support to the view that traders in these groups may hold divergent opinions about the direction of futures prices.

Panel B of table 1 reports the average absolute change in open interest for each trader group, measuring the magnitude (not direction) of position changes from week to week. These are average data, but the magnitudes are instructive about which groups are likely to be large enough to affect prices. Producers and managed money generally make the largest average absolute changes. Thus, to the extent that prices respond to large buying or selling pressure, these may be the groups whose position changes affect prices. Swap dealers and the other groups have smaller but still sizable position changes, although for swap dealers, these changes are smaller as a proportion of their overall position size compared with producers and managed money. This is likely due to the swap dealer category representing passive index trader activity. Again, with few exceptions, nearly every trader group makes substantial week-to-week changes in their open interest in all markets.

Counting the long, short, and spread positions separately, we have thirteen groups in the CFTC data. To investigate whether the simultaneous trading activity of these various groups supports a DO or RE environment, we test these data for synchronicity using the index developed by Fisher and Konieczny. The index is

$$FK = \sqrt{\frac{T^{-1}\sum_{t=1}^{T}(q_t-\bar{q})^2}{\bar{q}(1-\bar{q})}} \tag{17}$$

where $q_t = n^{-1}\sum_{i=1}^{n} a_{it}$ and a_{it} is an indicator variable that equals one if group i takes a particular action to adjust its open interest position and zero otherwise. Therefore, q_t is the proportion of groups that change their position in the specified manner in week t. The synchronicity index FK takes a value between zero and one and may be interpreted as the fraction of groups acting in a coordinated or synchronous manner (Dias et al.).[6]

For long and short groups, we define a_{it} in two ways:

(*a*) Same direction:

For groups with long positions, $a_{it} = 1$ if the position increases in week t.

For groups with short positions, $a_{it} = 1$ if the position decreases in week t.

(*b*) Complementary direction:

For groups with long positions, $a_{it} = 1$ if the position increases in week t.

For groups with short positions, $a_{it} = 1$ if the position increases in week t.

By construction, a spread position expresses no opinion on price levels. When we include

[6] Dias et al. show that the *FK* index is a method-of-moments estimator of the proportion of synchronized participants in a given market.

Table 1. Descriptive Statistics for Disaggregated Commitment of Traders Data, 2006–12

	Commodity					
Trader Group	Corn	Cotton	Lean Hogs	Live Cattle	Soybeans	Wheat
	Panel A: Average Weekly Open Interest					
All open interest	1,224,799	184,201	201,582	283,294	508,552	410,556
Producer: long	229,146	27,301	14,522	27,999	90,802	39,349
Producer: short	659,088	107,178	87,299	125,777	282,135	164,306
Swap dealers: long	312,785	67,988	71,094	94,961	124,913	165,898
Swap dealers: short	23,084	10,999	830	3,904	9,384	16,210
Swap dealers: spread	28,744	4,206	3,473	3,037	13,479	16,269
Managed money: long	235,874	37,669	39,341	74,972	108,254	70,194
Managed money: short	62,063	21,799	22,783	28,227	23,967	59,916
Managed money: spread	82,320	6,957	18,830	27,776	36,104	36,426
Other reporting: long	120,205	14,513	10,838	12,646	46,016	19,505
Other reporting: short	57,241	13,820	15,627	22,944	25,983	33,381
Other reporting: spread	78,502	7,858	20,323	17,404	35,725	28,903
Nonreporting: long	137,221	17,709	23,161	24,500	53,259	34,012
Nonreporting: short	233,757	11,385	32,416	54,226	81,774	55,146
	Panel B: Average Absolute Weekly Change in Open Interest					
All open interest	24,307	5,848	5,190	5,702	13,334	9,053
Producer: long	10,128	2,838	2,019	1,335	6,299	2,913
Producer: short	18,128	5,212	3,576	3,399	10,380	6,046
Swap dealers: long	6,237	1,445	1,210	1,196	2,646	2,630
Swap dealers: short	1,804	854	329	91	739	1,444
Swap dealers: spread	3,441	802	770	828	1,453	1,847
Managed money: long	11,263	2,301	2,904	2,418	6,823	3,210
Managed money: short	9,087	2,252	2,794	1,959	4,105	4,598
Managed money: spread	5,473	894	2,237	1,684	2,712	2,418
Other reporting: long	6,104	1,125	1,215	1,164	3,322	1,809
Other reporting: short	3,895	1,307	1,766	1,309	2,036	2,045
Other reporting: spread	7,772	1,000	1,765	1,879	3,986	3,247
Nonreporting: long	5,872	1,257	1,607	1,390	3,144	2,014
Nonreporting: short	6,035	1,195	1,929	1,542	2,797	2,070

Note: The CFTC DCOT report provides end-of-day open interest data in number of contracts by business line as of the reporting day (usually a Tuesday). The "producer" group includes traders who self-report their business line as a producer, merchant, processor, or end user; a "swap" group consists of swap dealers; a "managed money" group consists of hedge funds and other managed money companies; an "other" group includes all other traders whose position size requires daily position reporting; and a "nonreportable" group consists of smaller traders whose overnight positions are below the reporting thresholds. The directional positions are long, short, and calendar spreads, with the possibility of some trader overlap between categories. The table reports the mean values of these data (panel A) and the mean absolute week-to-week change in these values (panel B) in our sample from June 2006 to March 2012.

spread positions in our synchronicity calculations, we define $a_{it} = 1$ if the position increases in week t.

Definition (a) is consistent with the long side, so either an increase in a long position or a decrease in a short position in week t sets $a_{it} = 1$. If traders across groups are acting on common signals, as in an RE model, then they would be expected to change positions in a similar direction—that is, their actions would appear to be synchronized, q_t would be close to one or zero, and the FK index would converge toward one.[7] For example, if most trading activity were driven by the hedging demands of the producer group, then the traders in the other groups would be synchronized with each other. Definition (b) is designed to assess whether increases in long positions by some groups tend to be met by increases in short positions by other groups. In the context of our conceptual model, we would expect groups trading on strong signals to trade opposite groups receiving weak signals.

If futures market trader groups do not change their open interest in a coordinated manner, then we would expect such changes

[7] In this application of the FK index, the index cannot equal one because increased long open interest or decreased short open interest by some groups must be accompanied by opposite changes by at least one other group, so q_t cannot equal one. For example, with thirteen groups, the maximum value of q_t is 12/13.

Table 2. Synchronicity Index Estimates

		Commodity					
Position Changes	Trader Group	Corn	Cotton	Lean Hogs	Live Cattle	Soybeans	Wheat
Same direction	All groups	0.23	0.24	0.23	0.24	0.24	0.23
	Only long groups	0.46	0.47	0.49**	0.43	0.47	0.47
	Only short groups	0.43	0.44	0.42	0.42	0.44	0.40
	Only spread groups	0.68**	0.69**	0.61	0.65**	0.63**	0.65**
Complementary direction	Long and short groups	0.38**	0.38**	0.40**	0.36**	0.39**	0.37**
	Producer short, swap, and managed money long groups	0.73**	0.73**	0.71**	0.68**	0.71**	0.69**

Note: We adapt the Fisher and Konieczny approach to synchronicity to examine whether groups defined in the DCOT report tend to act together—that is, respond to a common signal. The greater the fraction of the synchronicity index, then the greater the fraction of groups changing positions in the same direction, defined to be consistent with the long side (more long/less short) or a complementary direction (absolutely larger in either the long or short direction). This table shows the estimated value of the synchronicity index for same-direction changes for all groups combined, the long-side groups, the short-side groups, and the spread groups. Two sets of additional estimates are reported for the complimentary direction case: all long and short groups combined and the long side of the producer group combined with the short side of the swap and managed money groups. The asterisks indicate that the index is significantly different from zero at the 1% level.

to appear staggered or randomized through time. If these changes are uniformly staggered across participants, then the FK index is expected to equal zero for our combined comparisons. The null hypothesis consistent with the staggering of trade decisions is $H_0 : E[q_t] = \theta$ for all t. Under this null, a constant proportion (θ) of groups may randomly change positions each week. Dias et al. show that this hypothesis may be tested using a χ^2 goodness-of-fit statistic. The appropriate test statistic has the form:

$$(18) \quad Q = \sum_{t=1}^{T} \frac{N(q_t - \bar{q}^2)}{\bar{q}(1-\bar{q})} = (NT)FK^2$$

where under the null, $Q \sim \chi^2_{(T-1)}$. We implement this test using different combinations of these DCOT groups to isolate any synchronous patterns. Note that rejecting this null provides additional support for the view that at least some groups are engaged in synchronized trading in futures markets.

The first four rows of table 2 show the estimated value of the synchronicity index for all thirteen groups combined, the five long side, the five short side, and the three spread groups in the DCOT data. The results show no synchronicity in the all-groups case. Failure to reject the null hypothesis of uniformly staggered position changes implies that no set of trader groups tends to move together when all groups are compared. At this global level, groups do not appear to act on common signals. This result provides evidence against the notion that trading activity is driven by the hedging demands of one group, which are met synchronously by a set of other groups. Similarly, the only-long and only-short groups display no significant synchronicity. Thus, the various long-side traders tend not to move together, nor do the short-side traders, suggesting that these subgroups do not act on a common signal. However, the spread groups do appear to be synchronized, which implies that relative price or calendar-type information may be held in common by and drive position changes among spread participants.

To further investigate trading behavior, we calculate synchronicity statistics, where a_{it} indicates complementary changes in open interest across groups. We define the change in the short position to complement the long-side decision using definition (b). In the last two rows of table 2, we report FK indices for two combinations of traders groups—all long and short groups combined; and the short side of the producer group combined with the long side of the swap and managed money groups—to determine if the actions of these combinations of groups complement each other.

We find that the long-only and the short-only groups complement each other because increases in the long side are accompanied by increases in the short side, which, of course, must be true at some aggregation level for futures data. However, the estimated value of the index (average 0.38 over commodities) suggests that only three to four of these ten groups are acting synchronized, whereas the remaining groups may be thought to act on separate information signals.

The final row of table 2 shows that the producer short-side group—firms thought of as classic hedgers holding underlying positions—is synchronized with either the swap dealer long-side group *or* the managed money long-side group. Thus, producers tend to respond to the signals in a particular week in the opposite direction to swap dealers or managed money; when producers increase their short position, the other groups tend to increase their long position. This finding suggests that these two groups exhibit DO.

Connecting Position Changes and Prices

Our conceptual model predicts a nonzero correlation between changes in positions and changes in prices in a DO environment and a zero correlation in an RE environment. We test this prediction using a regression model. For each trader group i and commodity market j, we estimate the following regression model

$$(19) \quad \Delta POS_{ijt} = \alpha + \beta \Delta \ln F_{jt} + \varepsilon_{ijt}$$

where F_{jt} denotes the futures price. We define the position changes as the change in net positions (i.e., long minus short) for a particular trader type from week $t-1$ to t. To compare coefficient estimates across commodities and trader types, we standardize position changes by total market open interest—that is,

$$(20) \quad \Delta POS_{ijt} = \frac{Q_{ijt} - Q_{ij,t-1}}{OI_{j,t-1}}.$$

We estimate thirty regressions, one for each trader-type/commodity combination, using equation-by-equation ordinary least squares.[8] We estimate standard errors using the Newey–West estimator with three lags.[9]

Table 3 shows our results. We find that position changes for the managed money group move strongly with prices and those for the producer group move strongly against prices. Estimates of the price change coefficient β are significantly different from zero at the 1% level across all commodities in the producer and managed money regressions. There is no apparent difference in effects between the livestock and storable commodities. Swap dealers have small positive coefficients for all commodities, but they are only significant for wheat and soybeans. Nonreporting traders, which are small in size, typically have significant positive coefficients (except for live cattle), but these coefficients are much smaller than those for managed money. For the two groups most correlated with prices (producers and managed money), the R^2 is between 0.25 and 0.40 for corn, soybeans, and wheat, and a little lower for the other commodities. The R^2 is close to zero for the other cases. These results imply that we reject the hypothesis of an RE equilibrium. As with rejection of any null hypothesis, this finding does not confirm that the DO model is correct, but it does imply that the data are consistent with the DO environment.

Interpreting our results in the context of a DO equilibrium, it appears that managed money firms receive large signals and trade on them, and thereby affect prices. Because managed money is commonly a hedge fund, this group is generally regarded as speculators. The finding that their positions are positively correlated with price changes makes it understandable that they may be a target for regulators who show concerns about increasing commodity prices. However, it does not necessarily imply that trading by this group is "excessive" because their private signals must enter the market somehow. Traders in the producer group tend to take positions on the other side of the market, indicating that they receive smaller signals and thus believe the price change should be

[8] The ordinary least squares estimator for equation (19) is equivalent to estimation using by-commodity systems of equations. Estimating a system of seemingly unrelated regressions by commodity for all trader-types is unnecessary because the left-hand side variables in such a system must sum to zero and the right-hand side variables are identical. This implies that one equation is redundant and the estimated error variance is singular. Dropping one equation results in a system with no cross-equation restrictions, in which case the seemingly unrelated regression generalized least squares estimates are identical to equation-by-equation ordinary least squares.

[9] Our results are identical if we increase the number of lags to six or reduce it to one. The first order autocorrelation in the dependent variable is less than 0.4 in all but one case, and it is typically much less.

Table 3. Results from Regressions of Position Change on Price Changes

Trader Group	Corn	Cotton	Lean Hogs	Live Cattle	Soybeans	Wheat
Producer	−0.27**	−0.41**	−0.32**	−0.34**	−0.53**	−0.25**
	(0.03)	(0.07)	(0.05)	(0.05)	(0.05)	(0.03)
Swap dealers	0.01	0.04	0.03	0.03	0.05**	0.05**
	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)
Managed money	0.21**	0.24**	0.26**	0.37**	0.38**	0.20**
	(0.03)	(0.05)	(0.05)	(0.06)	(0.05)	(0.03)
Other reporting	0.03*	0.03	−0.04	−0.01	0.01	−0.02
	(0.01)	(0.02)	(0.03)	(0.03)	(0.02)	(0.01)
Nonreporting	0.02*	0.11**	0.07**	−0.05*	0.09**	0.02*
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)

Note: We estimate thirty different regression equations, one for each commodity-/trader-type combination. Each regression includes the price change as an explanatory variable. Newey–West standard errors are indicated in parentheses (three lags). An asterisk indicates statistical significance at 5%, and a double asterisk indicates significance at 1%.

smaller. These results do not indicate which trader group is more correct. In fact, Fishe and Smith find that essentially no traders in these groups possess significant predictive ability, so it is likely that the groups are equally likely to be correct.

Note that we define a large signal somewhat tautologically as one that generates a large change in positions. This could arise from a large change in the expected future price, from a smaller change about which a trader is very confident, or from greater access to capital. Moreover, less risk-averse traders will tend to respond more to a given signal than more risk-averse traders. Thus, our results suggest that managed money traders receive different signals than producers, and they respond more aggressively to these signals. We cannot discern whether this strong response comes from the large average size of the signals, the high precision of the signals, low risk aversion, or greater access to capital. This indeterminacy arises because we observe actions but not beliefs.

Position changes by the swap dealer, other-reporting, and nonreporting trader groups are weakly related to prices. This finding can be interpreted as implying that these groups receive signals that are stronger than producers but weaker than managed money. For example, small individual traders, which would be in the nonreporting group, are restricted to take only small positions. This restriction could be conceptualized as high risk aversion or as restricted access to capital, but it implies that their signals do not move prices. A zero β could also mean that a trader group does not trade on its beliefs about future prices but on changes in its underlying exposure, as long as the group's position changes are either small or predictable enough that they don't affect prices. For example, swap dealers tend to change positions in a mechanical fashion as the demand for index positions changes, so they have little price impact (see e.g., Sanders, Irwin, and Merrin 2010).

Using COT data, Sanders, Irwin, and Merrin (2009) estimate similar regressions to (19), except from a Granger causality perspective. They regress position changes on lagged log price changes and lagged position changes and find evidence that price changes lead position changes. Our results do not change if we add the lagged log price change and a lagged dependent variable to each equation.[10] The coefficient on the lagged dependent variable is about 0.3 for managed money traders, producers, and swap traders. It is typically close to zero for the other two groups. The lagged price coefficient is typically the same sign as on the contemporaneous price, but much smaller. The coefficient on contemporaneous price does not change here because the lagged dependent variable (lagged position changes) and the lagged price are essentially uncorrelated with the current price change.

[10] Results available in the online supplementary appendix.

Table 4. Results from Regressions of Position Change on Price Changes Interacted with Volatility Regime

Trader Group	Variable	Corn	Cotton	Lean Hogs	Live Cattle	Soybeans	Wheat
Producer	Price	−0.23**	−0.23**	−0.22**	−0.38**	−0.40**	−0.22**
		(0.03)	(0.07)	(0.08)	(0.07)	(0.04)	(0.03)
	Price × LowVol	−0.11*	−0.75**	−0.22*	0.10	−0.32**	−0.07
		(0.05)	(0.10)	(0.09)	(0.11)	(0.11)	(0.05)
Swap dealers	Price	0.02	0.02	0.03	0.08	0.08**	0.07**
		(0.01)	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)
	Price × LowVol	−0.01	0.09	−0.01	−0.11*	−0.09**	−0.06*
		(0.03)	(0.05)	(0.04)	(0.05)	(0.03)	(0.03)
Managed money	Price	0.17**	0.11*	0.13*	0.34**	0.23**	0.15**
		(0.03)	(0.04)	(0.06)	(0.08)	(0.04)	(0.03)
	Price × LowVol	0.12*	0.55**	0.30**	0.06	0.38**	0.16**
		(0.05)	(0.07)	(0.09)	(0.12)	(0.09)	(0.05)
Other reporting	Price	0.03*	0.03	−0.01	0.03	0.02	0.00
		(0.01)	(0.02)	(0.04)	(0.04)	(0.02)	(0.02)
	Price × LowVol	−0.01	−0.01	−0.07	−0.10	−0.02	−0.05*
		(0.02)	(0.05)	(0.05)	(0.07)	(0.03)	(0.02)
Nonreporting	Price	0.01	0.07**	0.07**	−0.07*	0.07**	0.01
		(0.01)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)
	Price × LowVol	0.01	0.12**	0.00	0.05	0.05*	0.03
		(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)

Note: We estimate thirty different regression equations, one for each commodity-/trader-type combination. Each regression includes the price change and the interaction of the price change with a dummy for whether implied volatility is below its mean as explanatory variables. Newey–West standard errors are indicated in parentheses (three lags). An asterisk indicates statistical significance at 5%, and a double asterisk indicates significance at 1%.

Volatility

Our theory implies that the connection between positions and prices is stronger when volatility is lower [see equation (16)]. Thus, we run the regression

$$(21) \quad \Delta POS_{ijt} = \alpha + \beta \Delta \ln F_{jt} + \gamma \Delta \ln F_{jt} \cdot 1\left(\sigma_{jt} < \bar{\sigma}_j\right) + \varepsilon_{jt}$$

where $1(\sigma_{jt} < \bar{\sigma}_j)$ is an indicator function for below average volatility. We use implied volatility to measure price fluctuations, although realized daily volatility in the past month produces very similar results.

Table 4 shows that, for five of the six commodities, the estimated γ coefficient in equation (21) is negative for managed money traders, positive for producers, and typically small for everyone else. The value of the coefficient varies across commodities, likely because the magnitude of volatility varies across commodities. Overall, consistent with the DO theory, low volatility exacerbates the price effect for the groups in which we find significant price results.

Spot Exposure

The results in tables 3 and 4 could be affected by the omission of changes in exposure to the underlying commodity as an explanatory variable. This explanation seems unlikely because our results already contradict the hedging pressure theory, which predicts that producer position changes are positively correlated with price changes (de Roon, Nijman, and Veld). Nonetheless, we investigate the possible role of hedging pressure. We hypothesize that, if underlying exposure is correlated with position changes, then hedging pressure should have a greater effect during the growing season, especially for the four crops in our sample. We run the regression

$$(22) \quad \Delta POS_{ijt} = \alpha + \beta \Delta \ln F_{jt} + \delta \Delta \ln F_{jt} \cdot 1\left(4 \le month_t \le 9\right) + \varepsilon_{jt}$$

where $1(4 \le month_t \le 9)$ is an indicator function for observation t occurring from April through September. If hedging pressure is important, we expect δ to be positive for

Table 5. Results from Regressions of Position Change on Price Changes Interacted with Growing Season

Trader Group	Variable	Corn	Cotton	Lean Hogs	Live Cattle	Soybeans	Wheat
Producer	Price	−0.21**	−0.31**	−0.43**	−0.24**	−0.47**	−0.24**
		(0.03)	(0.09)	(0.05)	(0.06)	(0.05)	(0.03)
	Price × GrowSeas	−0.11*	−0.28*	0.20*	−0.19	−0.11	−0.02
		(0.05)	(0.13)	(0.09)	(0.10)	(0.10)	(0.05)
Swap dealers	Price	0.00	0.02	0.06	0.06	0.06	0.06**
		(0.02)	(0.03)	(0.04)	(0.05)	(0.03)	(0.02)
	Price × GrowSeas	0.03	0.06	−0.05	−0.06	−0.01	−0.03
		(0.02)	(0.04)	(0.04)	(0.06)	(0.03)	(0.03)
Managed money	Price	0.16**	0.18**	0.32**	0.29**	0.32**	0.17**
		(0.03)	(0.06)	(0.05)	(0.06)	(0.06)	(0.03)
	Price × GrowSeas	0.09	0.17*	−0.10	0.16	0.11	0.06
		(0.05)	(0.09)	(0.09)	(0.11)	(0.09)	(0.05)
Other reporting	Price	0.03*	0.04	−0.04	−0.05	0.02	−0.02
		(0.01)	(0.03)	(0.03)	(0.05)	(0.02)	(0.01)
	Price × GrowSeas	−0.01	−0.04	0.01	0.08	−0.01	−0.02
		(0.02)	(0.04)	(0.05)	(0.07)	(0.03)	(0.02)
Nonreporting	Price	0.02	0.07**	0.10**	−0.06	0.08**	0.03
		(0.01)	(0.02)	(0.02)	(0.03)	(0.01)	(0.02)
	Price × GrowSeas	0.00	0.09*	−0.06	0.02	0.02	−0.01
		(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)

Note: We estimate thirty different regression equations, one for each commodity-/trader-type combination. Each regression includes the price change and the interaction of the price change with a dummy for April–September as explanatory variables. Newey–West standard errors are indicated in parentheses (three lags). An asterisk indicates statistical significance at 5%, and a double asterisk indicates significance at 1%.

producers and correspondingly negative for managed money traders.

Table 5 shows our regression estimates of (22), which do not support the hedging pressure view. We find that, when significant, the delta coefficient is positive for managed money traders and generally negative for the producer group. Thus, although spot market exposure is likely important to initial position decisions, it does not seem to significantly affect position changes during the growing season for the crop commodities in our sample.

Overall, these results are consistent with the synchronicity statistics in table 2 in showing that the predictions of the differences of opinion model are supported by our results and that managed money positions change in the opposite direction to producers' positions, but in the same direction as prices.

Conclusions

We provide a theoretical framework to show that the correlation between changes in log futures prices and positions held by traders in agricultural futures markets are inconsistent with an RE equilibrium and consistent with a DO equilibrium in which traders believe their own signal about the price more than they believe the signals of others. Our findings indicate that prices may deviate from fundamentals but do not indicate by how much or in which direction.

If managed money traders receive correct signals about prices, then the fact that producers and others appear to disagree with these signals slows price adjustment. In such cases, futures prices may differ from fundamentals because they under-react to shocks. In contrast, if managed money traders receive incorrect price signals, then they could drive prices away from fundamentals; the calculations in Smith suggest that the magnitude of such pricing errors is unlikely to be large. Alternatively, managed money and producers groups may offset each other to a limited extent in their price effects, such that managed money may move prices in one direction and producers may subsequently move it in the other, or vice versa. Fishe and Smith show that neither group has the ability to systematically predict prices, which implies that neither group consistently receives a better signal than the other. In future research, we will investigate the magnitude of the mispricing error implied by these results.

Supplementary material is available at http://oxfordjournals.org/our_journals/ajae/online.

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