Supply Shocks, Futures Prices, and Trader Positions

by

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1 Introduction

There is a sustained interest from market observers, policymakers, and academics in the relationship between commodity futures prices and futures market positions held by particular groups of traders. To satisfy this interest, the US Commodity Futures Trading Commission (CFTC) publishes weekly commitment of traders (COT) reports that describe the proportion of futures market open interest held in aggregate by different trader groups. The CFTC publicly identifies two broad trader groups, commercials and non-commercials, who are often interpreted to be, respectively, hedgers with an established commercial interest in the underlying physical commodity, and speculators without an established commercial interest. The CFTC has also provided, since 2006, a finer classification of traders through its Disaggregated COT reports.

The motivation and market impact of these trader groups are not well understood. Recent studies (Cheng and Xiong, 2013; Fishe, Janzen, and Smith, 2014; Kang, Rouwenhorst, and Tang, 2014) suggest that observed open interest and trading activity are not consistent with simple hedging models populated by equally informed risk averse hedgers and risk neutral speculators with rational expectations about future supply and demand shocks. In this context, inference about the cause of observed changes in prices and positions is confounded because prices and positions are jointly determined. Prices only move when trades occur. Since no group trades in isolation - each trade requires counterparties who take long and short sides - price changes are often accompanied by changes in open interest held by all trader groups. At the same time, traders may adjust their positions in response to the signals provided by changing prices. By observing only prices and positions, we can conclude little about whose buying and selling activity moves prices, how futures trading transfers risk, and why particular trader groups choose particular positions.

To begin to unravel the simultaneity problem present in observed prices and positions, we study the joint dynamics of prices and positions in response to exogenous changes in the supply and demand fundamentals in the underlying physical market. These changes represent both new information about the fundamental value and riskiness of the underlying commodity and changes to the size of the physical position of hedging traders. To make this problem concrete, we focus on a specific market, the Chicago Mercantile Exchange (CME) corn futures market, and a specific source of exogenous shocks to corn supply, the accumulated rainfall in the US corn belt.

We exploit the fact that rainfall is an important determinant of physical corn supply (Tannura, Irwin, and Good, 2008) and is plausibly exogenous to price and trading behavior in the corn futures market. This follows a long tradition of using weather to capture exogenous variation in prices dating to initial derivation of the theory of instrumental variables by Wright (1928).

Our hypothesis is that trader groups respond differently to supply shocks caused by rain, by changing futures positions because their trading behavior responds to price, or because their hedging needs change due to changes in expected output or due to changes in expected volatility for the remainder of the growing season. Therefore, our primary goal is to obtain an empirical characterization of the joint dynamics of prices and positions in response to supply shocks.

2 Analytical Framework

We consider an informal theoretical model of trading in a futures market, similar to Cheng, Kirilenko, and Xiong (2014), populated by two broad groups of traders, hedgers and speculators. Hedgers have a non-zero net position, either long or short, in the physical market for the commodity; speculators have no position in the physical market. Convention suggests that the net position of hedgers in the physical market is position, so that they demand a short hedging position in the futures market. We assume that in every trading period, each trader group reacts to a set of external shocks common to all trader groups when choosing futures market positions. Each group has a unique set of structural parameters that determine their response to external shocks. Observed prices and positions are an equilibrium generated by the change in external variables, the interaction between the two trader groups, and these structural parameters.

Similar to classical models of hedger and speculator interactions in a futures market (e.g. Telser, 1958), each group has a demand curve for futures positions. Denote the size and direction (long or short) of the net futures position demanded by each group as x_h and x_s, where the h subscript denotes hedgers and the s subscript denotes speculators. x is greater than zero for a net long position and less than zero for a net short position. Following Cheng, Kirilenko, and Xiong (2014), we specify the following demand functions for futures positions in terms of the period-to-period change in x_h and x_s:

$$dx_h = -\beta_h dF - \gamma_h dVIX - \eta_h dS - \theta_h dIV - \lambda_h dOil \tag{1}$$

$$dx_s = -\beta_s dF - \gamma_s dVIX - \eta_s dS - \theta_s dIV - \lambda_s dOil. \tag{2}$$

In these demand functions, dF represents the change in the futures price and the remaining variables represent the set of exogenous shocks that may affect the trader group's demand for futures positions. $dVIX$ is a measure of economy-wide risk as proxied by the VIX market volatility index. dS is a shock to the aggregate physical position held by all traders, that is a supply shock.

Cheng, Kirilenko, and Xiong (2014) call the physical market shock, dS, an "idiosyncratic" shock related to the physical market for the commodity. They assume that this shock affects only hedgers. We include it in the demand function for both groups since speculators may also act on news about fundamentals and contribute to price discovery. We also allow both groups to respond to expected corn price volatility shocks as measured by changes in options implied volatility (dIV) and shocks to external markets, especially crude oil, due to financialization effects or fundamental linkages ($dOil$).

A priori, we place no restrictions on the structural parameters. However, we expect that these parameters may have particular signs. In particular, we assume the demand curves for each group i are non-increasing in prices ($\beta_i \geq 0$), each group has financial constraints that may bind when markets are volatile ($\gamma_i \geq 0$), and each group is averse to price volatility in any particular commodity market ($\theta_i \geq 0$). Hedging pressure theory would suggest that hedgers would increase the overall size of their futures position as the size of their physical position increases, so that $\eta_h > 0$.

Because F, x_h, and x_s are jointly determined, equations 1 and 2 are unidentified. The market clearing condition $dx_h + dx_s = 0$ states that the sum of all positions must equal zero; every long must have a short counterparty. Using this condition, we solve for dF and dx_h as a function of the remaining shocks:

$$dF = -\frac{\gamma_h + \gamma_s}{\beta_h + \beta_s} dVIX - \frac{\eta_h + \eta_s}{\beta_h + \beta_s} dS - \frac{\theta_h + \theta_s}{\beta_h + \beta_s} dIV - \frac{\lambda_h + \lambda_s}{\beta_h + \beta_s} dOil \tag{3}$$

$$dx_h = \frac{\gamma_s \beta_h - \gamma_h \beta_s}{\beta_h + \beta_s} dVIX + \frac{\eta_s \beta_h - \eta_h \beta_s}{\beta_h + \beta_s} dS + \frac{\theta_s \beta_h - \theta_h \beta_s}{\beta_h + \beta_s} dIV - \frac{\lambda_s \beta_h - \lambda_h \beta_s}{\beta_h + \beta_s} dOil \tag{4}$$

Using an simple linear econometric model to estimate the empirical relationship between dF, dx_h and the other shocks allows us to draw (limited) inference about the magnitude and sign of the structural parameters.

The consistent estimation of the econometric model based on equations 3 and 4 relies upon the exogeneity of the shocks included in model. We argue that the market for an individual agricultural commodity is unlikely to contribute measurably to overall market volatility or the market for more widely used commodities such as crude oil. So long as we can find a plausibly exogenous measure of variation in physical production, we should be able to consistently estimate the effect of supply shocks. Below we suggest such a measure. Estimating the effect of price volatility is more difficult, since prices and price volatility are obvious jointly determined. We exclude corn price implied volatility from our empirical model and save this challenge for future work.

3 Data and Empirical Procedure

Our empirical analysis considers the case of corn in the US midwest. We study the impact of supply shocks on prices and positions in the Chicago Mercantile Exchange (CME) corn futures market. The CME corn futures market is the world's most liquid agricultural futures market. Daily turnover in corn futures has exceeded 300,000 contracts in recent years. This implies a yearly notional volume in excess of 1.5 trillion USD. By comparison, the market value of yearly US output has been in recent year close to 60 billion USD. Corn prices have ranged between 75 and 330 US dollars per ton between 1993 and 2014 in nominal terms.

3.1 Corn Supply and Demand

Corn futures prices for a given delivery month are sensitive to a myriad of factors including expected supply and demand at the time of delivery, the ability of existing inventories to buffer unanticipated variation in supply and demand, and attitudes toward risk among market participants. Regarding expected supply, there is a known relationship between rainfall and corn output in the US Midwest. Tannura, Irwin, and Good (2008) identified a significant and positive correlation between summer rain precipitation and corn yields in the states of Iowa, Illinois and Indiana for less than 5 inches (127 millimeters) of monthly rain in June, July and August. Because corn supply is highly sensitive to rainfall only during the growing season, we limit our analysis to the months of June, July, and August.

We focus on the new-crop December futures contract, which should be most sensitive to growing season supply shocks. The December contract is generally the most actively traded new-crop contract. Physical corn underlying the December corn futures contract is deliverable at Illinois River shipping stations at center of the US corn belt, so production in this region is an important driver of deliverable supply.

Moreover, corn production in this region is mainly rain-fed, so irrigation water is not used to ameliorate the effect of dry weather. According to the National Agricultural Statistics Service, approximately 90% of US corn production is not irrigated. Only two major corn producing states use significant irrigation, Nebraska and Kansas. Only Nebraska is included in our dataset and its production is less than 20% of the total output produced in the area under consideration in this paper. Table 1 presents corn production statistics for major producing states during for our sample period.

3.2 Rain

Daily rain precipitation data between June 1st, 1993 and August 31st, 2014 was obtained from the National Climatic Data Center (NCDC) administered by the National Oceanic and Atmosphere Administration (NOAA). Rain data is measured in millimetres fallen within a 24 hour period. We identified a list of 41 representative weather stations in the main corn producing states in the US Midwest, listed in Table 1.

In this paper we assume that a single variable measuring total rain over the US Midwest strongly predicts regional output and hence has an impact on prices and positions. This is clearly a simplification since rain and yields also exhibit variability across states in the US Midwest. However, attempts to identify the impact of local rain in the corn markets rain are likely to be hampered by spatial correlation in rainfall across neighboring states and the lesser economic importance of each individual state. The approach in the construction of the rain variable is very similar to that applied in Merener (2013) for the impact of rain on soybean prices.

We start by constructing a daily rain variable for the US Midwest, as a weighted average of precipitation in the six states in our sample. Daily rain in each state is the simple average of all weather stations in that state. We aggregate rainfall across states using a production weighting according to the contribution of each state to US Midwest corn output using quinquennial shares of production. Finally, we use our daily rainfall measure to calculate the cumulative rainfall in the US Midwest as the sum of daily rainfall since June 1st of each year. Figure 1 shows accumulated rain in the US Midwest and its departures from trend. For example, 1993 was a year with excessive precipitation while 2012 and 2013 suffered droughts.

3.3 Prices and Positions

We obtain daily prices for the December corn future contract of each year in our sample from Datastream. Data on positions was obtained directly from the CFTC. The CFTC publishes 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 non-commercial 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 *non-reportable* positions in COT reports.

Over time, the CFTC has increased the volume of information released publicly through these reports by changing the categorization of traders 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 (SCOT) report describing the positions held by commodity index traders. Prior to 2007, commodity index trader positions were largely contained in the commercial category because swaps 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, swaps dealers, managed money, and other reportable, in the disaggregated Commitment of Traders (DCOT) report. This disaggregation was backdated so the DCOT data are available from June 2006.

4 Results and Empirical Implications

We first test the effect of accumulated summer rainfall on December corn futures prices. Table 2 shows estimation results for a linear specification of weekly corn returns on changes in accumulated rain, the VIX index, and oil prices. The sample in the first column includes every week in June, July and August between 1993 and 2014. The second column limits the sample to those weeks in which accumulated rain minus its trend was below zero at the beginning of the week. That is, we limit the sample to periods where accumulated precipitation was below average. We find that the impact of additional rain is very strongly significant in the latter case as it is to be expected given the higher sensitivity of yields to rain under dry conditions. The point estimate of -0.0013 per additional millimeter of rain implies a -3.3% decrease in price for an additional inch of rain.

To place our estimate of the effect of rainfall on corn prices in context, note that precipitation during a typical summer storm is about one inch, and average accumulated summer rainfall in the US Midwest (Table 1) is approximately 12 inches. Therefore, the effect of a summer storm is statistically and economically significant in dry summers. The effect is much weaker when the sample includes every week in the June-August period, regardless of accumulated rain. Hence, in the remainder of this section we focus on empirical results for periods of accumulated rain below trend.

In Table 3 we estimate the impact of weekly changes in accumulated rain on changes in the net positions of commercial and non-commercial traders, according to the classification by the CFTC in its Commitments of Traders report. The effect is strongly significant and roughly opposite for both types of traders, as expected by the fact that they include the vast majority of market participants and the net position of all traders must sum to zero. The effect of an additional inch of accumulated rain in the net position of commercial traders implied by the 3,554 point estimate is an increase of 90.3 million bushels, roughly equivalent to 2.2 million tons. Hence, commercial traders tend to increase their net long position (or reduce their net short position) in response to an inch of rain during dry summers, while non-commercial traders simultaneously do the opposite for markets to clear. This estimate is also economically significant; the order of magnitude for open interest in corn has been 100 million tons and US production in recent years has exceeded 300 million tons.

The analysis of the simultaneous response of prices and positions to a positive supply shock caused by rain identified in Tables 2 and 3 shows that an additional inch of rain, which leads to more expected supply at the end of the growing season, and therefore lower prices, also leads to less selling by commercial traders. This is inconsistent with a basic model of hedging pressure where commercial traders are interpreted to be producers engaged in short hedging. In such a model, increased expected supply would lead to more commercials selling futures and a negative coefficient for accumulated rain in Table 3.

The econometric estimates for the effect of accumulated rain on prices and commercial positions correspond to the coefficients multiplying dS in Equations 3 and 4. Hence, their values are related to the underlying structural coefficients in Equations 1 and 2. It holds that

$$-\frac{\eta_h + \eta_s}{\beta_h + \beta_s} \approx -0.0013,$$

implying $\eta_h + \eta_s > 0$, and

$$\frac{\eta_s \beta_h - \eta_h \beta_s}{\beta_h + \beta_s} \approx 3554$$

which, under the assumption of $\beta_h \approx \beta_s$, leads to $\eta_s > \eta_h$. The last implication suggests that hedgers are less inclined to sell (or perhaps even willing to buy, with $\eta_h < 0$) in response to a positive supply shock, relative to the preferences of speculators. Again, this contradicts the characterization of traders in the commercial category as hedgers who respond to a larger aggregate physical (net long) position by increasing the size of their (short) hedge.

The response of the net positions of commercial and non-commercial traders can be decomposed in term of the underlying long and short positions for each type of trader. Their responses to shocks in accumulated rain are shown in Tables 4 and 5. The pattern that emerges is that commercial traders both strongly reduce their short position and strongly increase their long position in response to rain. Symmetrically, non-commercial traders strongly increase their short position and strongly reduce their long position in response to rain.

4.1 Results from Disaggregated Commitment of Traders Data

As a robustness check, we consider the finer classification of traders provided by the CFTC in its Disaggregated Commitment of Traders DCOT report. This data is only available since 2006. We estimate regressions similar to those in tables 2, 4 and 5, replacing positions held by commercial traders with those held by traders classified as Producer/Merchant/Processor/User and replacing positions held by non-commercial traders with those held by traders in the Managed Money category, who are commonly interpreted to be financial speculators.

Table 6 shows a negative impact of rain on prices, of similar magnitude to that reported in the second column of Table 2. This estimate is no longer significant at the 99% confidence level, a difference likely due to the attenuated sample period available for the DCOT data. The short Producer/Merchant/Processor/User response to rain, reported in Table 7, is strongly significant and qualitatively similar to that of commercial traders in Table 4. These supposedly hedging traders reduce their short position as expected supply increases. On the other hand, Table 8 shows that changes in the positions held by the Managed Money group are not strongly driven by supply shocks caused by rain.

4.2 *Momentum*

We include one lag of all variables in our econometric model to account for possible autocorrelation in prices and positions. In regressions where trader positions are the dependent variable, there are strong positive responses to lagged corn returns, as seen in tables 3, 4, 5 and 7, and 8. The results suggest that short commercial traders tend to increase their short positions and short non-commercial traders tend to decrease their short position following weeks where prices rise. This is line with the estimated impact for changes in accumulated rain because positive changes in expected supply tend to coincide with negative changes in price. The strong correlation between past price changes and positions suggests momentum or trend-following strategies may explain the behavior of one or more trader groups.

5 Conclusions

We consider the joint response of prices and positions in the corn futures market to exogenous supply shocks as measured by accumulated rainfall in the US midwest. This question is important because recent studies of CFTC position data for various trader groups suggests that the motivations of these groups are not well understood. Our empirical estimates suggest that the futures market positions held by the trader group commonly thought to be hedgers are not positively related to the size of the aggregate physical position as measured by accumulated rainfall, a known determinant of physical supply. Therefore, the behavior of prices and positions are either inconsistent with the simplest version of a hedging pressure model of a commodity futures market or the categories defined by commercials and producers/processors/merchants/users are not typically long in the physical market and hence do not need to be short in the futures market.

Our main result implies that trader groups cannot be characterized solely based on a conception of futures markets as a venue for one group to transfer price risk to another. This result is relevant to the longstanding question of the purpose of futures markets as venues for risk transfer and/or price discovery. Traders in hedger or speculator groups may act on private or public information about market fundamentals in expectation of trading profit. Firms in the hedger category may take both long and short positions in order to manage price risk in the physical market. In fact, large commodity trading firms typically categorized as hedgers are likely to have considerable information about physical supply and rarely want to take large unidirectional futures market positions. Future work will seek to reconcile the behavior of such firms with available data on trader positions.

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	Illinois	Iowa	Minnesota	Nebraska	Indiana	South Dakota
Corn prod. 1993 (1000 bu.)	1,300,000	880,000	322,000	785,200	712,800	160,650
Corn prod. 1993 (%US)	0.20	0.14	0.05	0.12	0.11	0.03
Corn prod. 2013 (1000 bu.)	2,106,000	2,213,900	1,328,400	1,613,950	1,009,200	812,000
Corn prod. 2013 (%US)	0.16	0.17	0.10	0.12	0.08	0.06
Mean summer rain (mm) 1993-2014	307.2	343.6	321.5	283.7	317.3	239.9
Std. Dev. summer rain (mm) 1993-2014	69.8	118.2	75.7	106.6	47.5	85.8
Weather Stations	Avon De Kalb Fairbury Hoopeston Hutsonville Jerseyville Mattoon Paw Paw Rantoul Greater Peoria Springfield	Audubon Cherokee Forest City Grundy Center Hawarden Kanawha Keosauqua Rathbun Dam Rockwell City Sioux City Des Moines Waterloo	Rochester St. Cloud Trempealeau Dam Austin	Canaday Hastings Kearney Nebraska City Grand Island Lincoln Omaha	South Bend Elliston Frankfort Laporte Muncie	Alexandria Huron

Table 1: Production and rain statistics for the main corn producing states in the US Midwest in 2013.

Figures

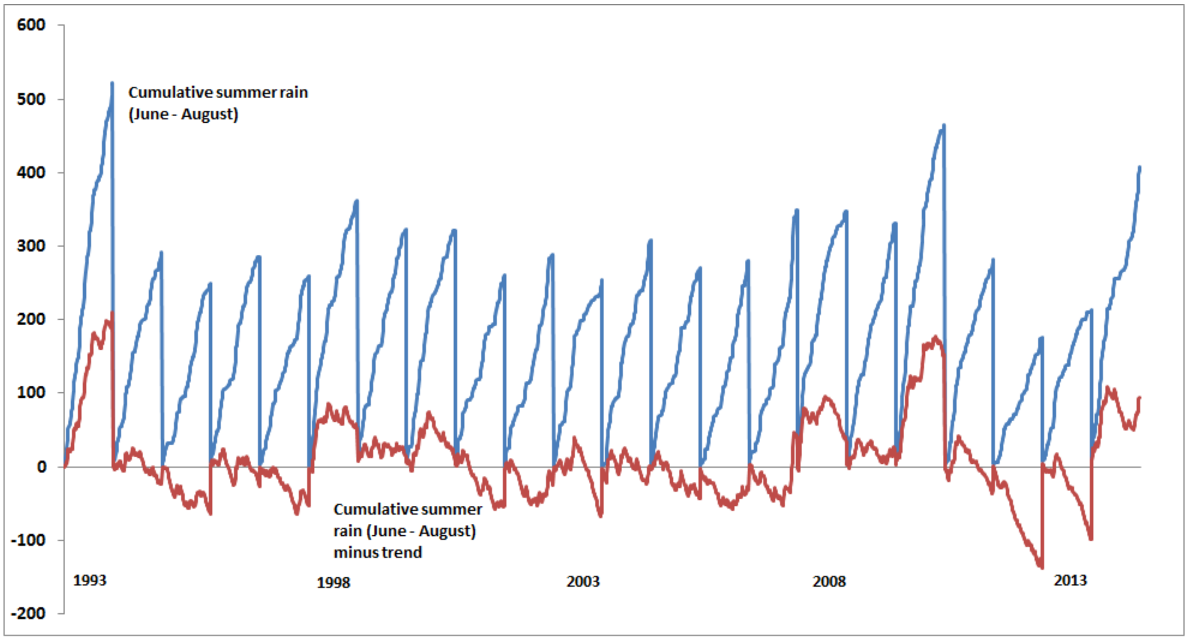

Figure 1: Daily accumulated rain averaged spatially over 41 weather stations in the US Midwest, between June 1st and August 31st of each year between 1993 and 2014. Also displayed, accumulated rain minus average daily rain over the same region and period.

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Tables

Table 2: Weekly time series regressions of corn returns on accumulated rain, VIX, Oil and momentum. June, July and August between 1993 and 2014.

$$ReturnDecCorn_t = \alpha + \beta_1 DiffAccRain_t + \beta_2 DiffVix_t + \beta_3 DiffOil_t + ReturnDecCorn_{t-1} + \epsilon_k$$

	Corn Unconditional	Corn Conditional on Rain Below Trend
Diff Acc. Rain	-0.00046*	-0.0013***
	(0.00025)	(0.0004)
Lag Diff Acc. Rain	-0.00005	-0.00003
	(0.00026)	(0.00045)
Diff Vix	0.00041	0.0001
	(0.0012)	(0.0012)
Lag Diff Vix	0.00042	-0.0010
	(0.00012)	(0.0016)
Return Oil	0.074	0.040
	(0.071)	(0.092)
Lag Return Oil	0.012	-0.013
	(0.057)	(0.092)
Lag Return Corn	0.051	-0.095
	(0.069)	(0.109)
Constant	-0.0024	-0.0011
	(0.0027)	(0.0044)
Sample size	268	125
R-squared	0.035	0.097

Table 3: Weekly time series regressions of changes in net positions on accumulated rain, VIX, Oil and momentum. Conditional on rain below trend. June, July and August between 1993 and 2014.

$$DiffCommNet_t = \alpha + \beta_1 DiffAccRain_t + \beta_2 DiffVix_t + \beta_3 DiffOil_t + ReturnDecCorn_{t-1} + \epsilon_k$$

$$DiffNonCommNet_t = \alpha + \beta_1 DiffAccRain_t + \beta_2 DiffVix_t + \beta_3 DiffOil_t + ReturnDecCorn_{t-1} + \epsilon_k$$

	Commercial Net	NonCommercial Net
Diff Acc. Rain	3,554***	-3,373***
	(785)	(685)
Lag Diff Acc. Rain	-11	-321
	(1,036)	(970)
Diff Vix	283	1,142
	(2,448)	(2,456)
Lag Diff Vix	2,468	-311
	(2,758)	(2,556)
Return Oil	146,333	-147,496
	(182,613)	(167,515)
Lag Return Oil	237,129	-118,640
	(195,560)	(185,193)
Lag Return Corn	-962,238***	955,482***
	(233,646)	(217,854)
Constant	-14,402	-20,493**
	(9,350)	(8,272)
Sample size	125	125
R-squared	0.285	0.307

Table 4: Weekly time series regressions of changes in commercial positions on accumulated rain, VIX, Oil and momentum for June, July and August between 1993 and 2014. Conditional on rain below trend.

$$DiffCommLong_t = \alpha + \beta_1 DiffAccRain_t + \beta_2 DiffVix_t + \beta_3 DiffOil_t + ReturnDecCorn_{t-1} + \epsilon_k$$

$$DiffCommShort_t = \alpha + \beta_1 DiffAccRain_t + \beta_2 DiffVix_t + \beta_3 DiffOil_t + ReturnDecCorn_{t-1} + \epsilon_k$$

	Commercial Long	Commercial Short
Diff Acc. Rain	1,290**	-2,264***
	(573)	(849)
Lag Diff Acc. Rain	-143	-132
	(638)	(864)
Diff Vix	1,172	889
	(1,775)	(2,651)
Lag Diff Vix	500	-1,967
	(1,747)	(2,771)
Return Oil	167,355	21,021
	(105,582)	(170,718)
Lag Return Oil	413,796***	-176,666
	(151,752)	(182,952)
Lag Return Corn	-121,781	840,457***
	(138,557)	(195,702)
Constant	-1,480	-15,883*
	(6,255)	(8,448)
Sample size	125	125
R-squared	0.106	0.236

Table 5: Weekly time series regressions of changes in noncommercial positions on accumulated rain, VIX, Oil and momentum for June, July and August between 1993 and 2014. Conditional on rain below trend.

$$DiffNonCommLong_t = \alpha+\beta_1 DiffAccRain_t+\beta_2 DiffVix_t+\beta_3 DiffOil_t+ReturnDecCorn_{t-1}+\epsilon_k$$

$$DiffNonCommShort_t = \alpha+\beta_1 DiffAccRain_t+\beta_2 DiffVix_t+\beta_3 DiffOil_t+ReturnDecCorn_{t-1}+\epsilon_k$$

	NonCommercial Long	NonCommercial Short
Diff Acc. Rain	-1,720***	1,653***
	(574)	(491)
Lag Diff Acc. Rain	-210	111
	(808)	(615)
Diff Vix	-2,141	-3,283*
	(2,180)	(1,738)
Lag Diff Vix	690	1,001
	(2,330)	(1,622)
Return Oil	-8,757	138,738
	(121,450)	(108,702)
Lag Return Oil	59,113	177,754
	(150,754)	(135,200)
Lag Return Corn	-209,065	-746,416***
	(134,237)	(155,094)
Constant	-6,975	13,518**
	(6,545)	(5,399)
Sample size	125	125
R-squared	0.100	0.320

Table 6: Weekly time series regression of December corn return on accumulated rain, VIX, Oil and momentum for June, July and August between 2006 and 2014. Conditional on rain below trend.

$$ReturnDecCorn_t = \alpha + \beta_1 DiffAccRain_t + \beta_2 DiffVix_t + \beta_3 DiffOil_t + ReturnDecCorn_{t-1} + \epsilon_k$$

	Corn Return
Diff Acc. Rain	-0.0017*
	(0.0009)
Lag Diff Acc. Rain	-0.0004
	(0.0011)
Diff Vix	-0.0016
	(0.0029)
Lag Diff Vix	-0.0033
	(0.0033)
Return Oil	0.003
	(0.210)
Lag Return Oil	-0.18
	(0.20)
Lag Return Corn	0.219
	(0.166)
Constant	-0.005
	(0.009)
Sample size	50
R-squared	0.203

Table 7: Weekly time series regressions of changes in Producers, Merchants and Processors positions on accumulated rain, VIX, Oil and momentum for June, July and August between 2006 and 2014. Conditional on rain below trend.

$$DiffProdMerc_t = \alpha + \beta_1 DiffAccRain_t + \beta_2 DiffVix_t + \beta_3 DiffOil_t + ReturnDecCorn_{t-1} + \epsilon_k$$

$$DiffProdMerc_t = \alpha + \beta_1 DiffAccRain_t + \beta_2 DiffVix_t + \beta_3 DiffOil_t + ReturnDecCorn_{t-1} + \epsilon_k$$

	Producers Long	Producers Short
Diff Acc. Rain	-1,306	-4,567***
	(1,233)	(1,550)
Lag Diff Acc. Rain	798	-2,229
	(1,521)	(1,881)
Diff Vix	-4,226	370
	(3,531)	(4,573)
Lag Diff Vix	1,099	-6,036
	(3,261)	(4,315)
Return Oil	-308,804	63,513
	(239,904)	(308,305)
Lag Return Oil	303,224	-368,301
	(278,119)	(305,566)
Lag Return Corn	-82,566	783,966***
	(181,376)	(261,412)
Constant	-5,881	-47,701***
	(15,111)	(14,517)
Sample size	49	49
R-squared	0.104	0.424

Table 8: Weekly time series regressions of changes in Managed Money positions on accumulated rain, VIX, Oil and momentum for June, July and August between 2006 and 2014. Conditional on rain below trend.

$$DiffMMoney_t = \alpha + \beta_1 DiffAccRain_t + \beta_2 DiffVix_t + \beta_3 DiffOil_t + ReturnDecCorn_{t-1} + \epsilon_k$$

$$DiffMMoney_t = \alpha + \beta_1 DiffAccRain_t + \beta_2 DiffVix_t + \beta_3 DiffOil_t + ReturnDecCorn_{t-1} + \epsilon_k$$

	Managed Money Long	Managed Money Short
Diff Acc. Rain	-954	1,649
	(1,211)	(1,148)
Lag Diff Acc. Rain	-2,054	1,020
	(1,233)	(1,486)
Diff Vix	-625	-8,371**
	(4,239)	(3,441)
Lag Diff Vix	-3,486	2,525
	(2,835)	(4,019)
Return Oil	319,001	-249,413
	(244,021)	(312,497)
Lag Return Oil	-130,877	468,749
	(211,557)	(292,367)
Lag Return Corn	313,637**	-1,045,368***
	(140,024)	(263,117)
Constant	-5,862	25,523*
	(13,228)	(14,814)
Sample size	49	49
R-squared	0.228	0.539