Fundamental Surprises, Market Structure, and Price Formation in Agricultural Commodity Futures Markets

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Abstract

Our study seeks to provide a better understanding of price formation process and determining factors of price volatility in agricultural commodity markets. We focus on corn and soybean futures traded in CBOT (Chicago Board of Trade). We innovatively construct two sets of variables to represent fundamental changes and market structure of the commodity markets. Fundamental changes are captured by the deviations of the supply and demand condition estimates released by USDA from the pre-announcement analysts' forecasts published by Bloomberg. We employ the transaction databases of CFTC (Commodity Futures Trading Commission) to construct the percentage shares of detailed participation group trading in the market. While fundamental changes are based on public observations and analysis, transaction percentage shares of trader groups are private information of individual traders. Both the fundamental surprises and the market structure related variables are found to have statistically significant effects on price and price volatility. Furthermore, the impacts vary across quantiles of the conditional distributions.

Keywords: log return, realized volatility, trader groups, WASDE report

JEL Codes: C22; G13; G14;

1. Introduction

How markets aggregate information is a central but unsettled question in the finance literature (see, e.g., Seasholes and Zhu 2010). The empirical evidence is sparse concerning what information is incorporated into prices by which agents and how quickly. Our study seeks to address the challenging questions by utilizing market level aggregate information and information about individual trades. We focus on commodity futures markets, whose dynamics are largely driven by changes of underlying supply demand fundamentals, market structure and other public and private information.

By partitioning individual transactions into various trader groups, market structure captures the roles of different participants on price formation in the market. Grossman and Miller (1988) argue that demand for liquidity of commodity futures contracts is typically high because futures contracts are commonly employed for hedging purpose. Furthermore, many participants use futures contracts to hedge price risk using spread across contracts with different maturities and/or commodities. Market makers or intermediaries, who assume the risk of waiting for ultimate buyers by continuously adjusting inventories, facilitate the provision of liquidity because demand from ultimate buyers and sellers is not in continuous equilibrium (Glosten and Milgrom 1985). The larger the group of market maker is, all else equal, the lower the cost of immediacy (Grossman and Miller 1988), and consequently the deeper and more resilient the market is (Kyle 1985). Market dynamics endogenously determine the size of the market maker group.

Public announcements via different channels regularly reveal supply and demand changes in commodity markets. The effect of private information is hard to quantify directly. We rely on the measurements of the market structure, which is represented by the shares of transactions conducted by various trader groups, to proxy for private information and other microstructure effects. Following the classical efficient market model, e.g., Madhavan, Richardson, and Roomans (1997), and using agricultural commodities of corn and soybean as examples, we hypothesize that commodity futures prices are driven by changes of publically available information and market structure, the latter of which conveys traders' private beliefs and expectation of the market. For example, a higher proportion of directional traders in both long and short transactions exert price pressure in the direction of their trades because their trades tend to change the amount of open interest, hence the amount of wealth subject to losses or gains, in a contract. While shocks of public information disclose fundamental changes of the underlying commodity, shifts between participation groups reflects trading frictions such as inventory and market-making costs (Roll 1984; Glosten and Harris 1988). The shifts also reflect private information as market participants learn from price dynamics, and engage in different market executions such as buy or sell, spread or outright, and aggressive or passive.[2]

Our study relates to several strands of the existing literature. The first is on the roles played by various parties in the market intermediation process, including, for example, institutional and individual traders. Anand et al. (2013) illustrates that institutional traders on the buy-side of the stock market, or liquidity providers in market downturns, may potentially ameliorate market illiquidity during a financial crisis as others withdraw from the market. Puckett and Yan (2011) find that institutional traders make significant and persistent abnormal trading returns within a trading quarter. A trading pattern is found to be consistent with the liquidity providing role of individual traders who buy after price falls in the previous month and sell following a price increase (Kaniel, Saar and Titman 2008).

[2] These terms will be defined and discussed in a later section.

The second strand of literature is related to the dynamics of market structure, liquidity and prices. For example, Grossman and Miller (1988) provides a general discussion of partitioning and shares of various market participants, especially market makers, which is closely related to market liquidity as discussed above, and their critical role in price formation. For the futures market, Grossman and Miller (1998) emphasize that the frequent adjustments of market makers influence the dynamic equilibriums for liquidity, which is in urgent and sustained demand for long and short contracts in the market. Kyle (1985) introduces a dynamic model with three types of traders (informed trader, noise trader and market maker) to explain the price formation process as the consequence of new information, market structure, and liquidity.

Lastly, our study is closely related to the literature of quantifying the announcement effects in various financial markets. For example, in the foreign exchange market, Andersen et al. (2003) quantifies the effects of macro announcements on the U.S. dollar spot exchange rate and finds that the information on fundamentals is important in explaining exchange rate dynamics. For agricultural commodity markets, there is an extensive literature examining the effects of publically announced information on market prices, for example, Adjemian (2012) on the reports of World Agricultural Supply Demand Estimates (WASDE) and Lehecka (2014) on crop progress and condition reports.

The objective of the current study is to quantify the impact of changes of fundamentals and market structure on the dynamics of the futures prices of agricultural commodities. Our contributions to the literature are three-fold: (1) we construct the so-called fundamental surprises, the different between actual announced values of market fundamentals and the pre-announcement forecasts published by Bloomberg. It makes intuitive sense that market responds to surprises beyond expectations, not the component of the announcement that the market has already anticipated. As we know, this is the first such effort in the agricultural commodity market literature.[3] (2) Utilizing the detailed intraday transaction data maintained by the Commodity Futures Trading Commission (CFTC), we construct a unique data set that contains the daily shares of a variety of trader groups to represent the market structure. And (3) in addition to quantifying the impact of fundamental surprises and market structure variables on the mean levels of log price differences and realized volatility, through quantile regression, we illustrate that the effects vary across the quantiles of the conditional price distributions.

The rest of paper is organized as follows. Section 2 introduces the institutional background of the agricultural commodity market and related data construction. Section 3 describes the empirical methods. The estimation results are discussed in Section 4. Section 5 concludes.

2. Institutional Background and Data

In this section, we start with the definition, construction and analysis of fundamental surprises, then elaborate the proxy of market structure in the agricultural commodity markets.

2.1 Fundamental Surprises

Corn and soybean futures contracts have unique features that are different than other financial assets. For example, there is a seasonal pattern as production takes place once a year in a specific region[4] and inventories are subsequently drawn down throughout the year. For example, in US crops are planted over the planting season in the spring, late March to early May, each year, grow and are managed over the growing season (May through November) and are harvested in

[3] Andersen et al. (2003) is the first that constructed fundamental surprises in the foreign exchange market. Examples related to other commodity markets can be found in Gay, Simkins and Turac (2009), Halova, Kurov and Kucher (2014), Roache and Rossi (2010).

[4] For corn, US is the main and largest production region with the harvest in December. For soybean, there are two main harvests, one in the US in November and the other around March in the southern hemisphere.

November to December. More importantly, over the planting, growing and harvest seasons in each year, estimates of supply and demand conditions are continuously released to the public through a series of USDA (US Department of Agriculture) and WASDE (World Agricultural Supply and Demand Estimates) reports on, for example, (i) crop progress and condition, (ii) prospective planting and planted acreage, and (iii) grain stock and crop production. WASDE reports contain information of not only the US domestic market but also the world market. The details of the reports are discussed below.

The USDA issues crop progress and condition reports each week in the growing season between April 1st and November 30th.[5] The estimates of overall status of crop progress and condition contained in the reports are collected by surveys in major producing states across the US. Based on the assessments of individual respondents, the USDA summarizes crop conditions by the shares of crop in excellent, good, fair, poor and very poor conditions. The USDA aggregates conditions at the county, state and national levels from individuals' responses.[6] These reports provide timely updates between other major monthly and quarterly reports on crop growth and development as well as potential market supply. Lehecka (2014) demonstrates that futures prices respond quickly to this valuable information.

The National Agricultural Statistical Service (NASS) of USDA releases annually the prospective plantings report on farmers' planting intentions by the end of March and the planted acreage reports in June on actual planted acreage based on the surveys it conducts. The number of acres farmers expect to plant and actually plant disclose relevant information for the potential size of the crop in the current crop year. Grain stocks reports are released in January, March, June, September for crop inventories and storage capacities. Monthly crop production and the

[5] All the reports can be found here: https://www.nass.usda.gov/Publications/.
[6] Interested readers are referred to Lehecka (2014) for more details of the crop progress and condition reports.

WASDE reports released also monthly contain information on crop production, consumption, and trade as well as stock and price forecasts for the U.S. domestic and international markets. These reports provide relevant information on market fundamentals and have significant impact on price changes of the corresponding markets (Adjemian 2012).

We expect that market prices respond to fundamental surprises, i.e., the deviation of newly arrived information from prevailing market expectation, not the announcement itself. Further away from market consensus the new information is, the larger the surprise and consequently the price changes. Although capturing announcement effect in this way has appeared in the literature (see Andersen et al. 2003 and references therein), for agricultural commodity markets, the existing studies tackle this issue in indirect ways. Some studies (e.g., Adjemian 2012) use the dummy variable to indicate the event of public announcement, while others use the changes of announcements in two consecutive periods to represent the information being announced. It is impossible to compare the corresponding market effects across different types of announcements using dummy variables because that typically one USDA or WASDE report contains information on several different market conditions. Given the mixed supply and demand information, dummies for the releasing time of individual reports are not sufficient or even misleading for distinguishing the exact sources of market responses. Using period-to-period changes ignores market expectation and consequently exaggerates the impact of announcement when markets are efficient and respond only to the "surprises".

Market expectations are typically measured by publically announced forecasts. We use the medians of the analysts' forecasts of market fundamental variables, which are collected by Bloomberg through surveys to commodity analysts and published a few days before the actual USDA and WASDE announcements. The number of analysts' estimates varies across reports and time ranging from 10 to 30 with large standard deviation compared to the mean sometimes. We manually collected all the pre-announcement forecasts from the Bloomberg's database by searching on its local terminal. The differences between the actual announced numbers in the USDA and WASDE reports and the median forecasts of Bloomberg's forecasts are then defined as fundamental surprises, which can be positive or negative.

We consider the following fundamental surprises of supply and demand conditions for corn and soybean, which are constructed from the USDA and WASDE reports, acreage planted, prospective planting acres, USDA quarterly grain stock, WASDE monthly stock estimate, and WASDE monthly production estimate. These are the key supply and demand estimates that Bloomberg consistently surveyed and published over the sample period. We do not account for other USDA announcements and WASDE estimates because Bloomberg did not collect and/or publish the corresponding analysts' forecasts. We anticipate that the constructed fundamental surprise variables capture major supply and demand factors affecting commodity futures prices given the frequency of the included reports.

The USDA releases the crop condition report weekly from the beginning of June to the end of October. Given that this is the USDA's only source of information available on market supply before harvest, it is interesting to see how market responds to the announcements. But there is not pre-announcement forecasts for crop conditions. It is reasonable to assume that market forms current expectations on crop conditions based on the conditions reported in the previous week and the weather conditions between the two reporting periods. Therefore, to generate the corresponding surprise variables, we regress the percentage shares of the crop conditions (excellent, good, fair, poor and very poor) on the percentage shares in the previous week, or lagged percentage shares, and three weather variables between the two reporting periods, growing degree days, overheating degree days, and precipitation. Growing degree days (GDDs) are commonly applied in the literature to measure the accumulated heat for crop growth. Specifically, it is calculated as the sum of temperature degrees within a certain range, which is $[8℃, 30℃]$ for corn and soybean over a certain period. On the other hand, overheating degree days (ODDs) are defined as the sum of degrees above a threshold ($32℃$ in our case), which is harmful to crop growth and yield. Precipitation is constructed as the total amount of rainfall over the specified period. All three weather variables are averaged over the sampled counties and calculated over the period of two consecutive crop condition reports.[7]

The crop conditions are regressed in a SUR (Seemingly Unrelated Regression) system in order to account for the potential correlations across individual equations. The regression residuals are taken as the surprises of crop conditions beyond market expectation.[8] The estimation results are reported in the Appendix. As expected, the crop conditions in the current week are largely explained by those of the previous week with the largest effect of the same condition. The weather variables between the two reporting periods also have significant effects on the current crop conditions. For example, growing degree days have a significant and positive impact on the shares of excellent and good conditions, while overheating degree days affect the shares negatively. The effect of precipitation is in general small but not consistent for corn and soybean. This is understandable given the short window of observation.

2.2 Market Structure

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[7] The daily temperature and precipitation data are downloaded from the US Historical Climatology Network (HSC). The original HSC data are for the 1218 weather stations across US. We generate corresponding county level weather variables based on those of the nearest weather stations.

[8] Because of collinearity, we can't run all five crop condition variables in one SUR system. So we run two SURs that include poor and very poor condition separately. The estimation results for the other 3 condition variables are exactly the same in two SURs. Therefore, the two sets of results are jointly reported in the Appendix.

As discussed above, our focus here is the corn and soybean futures traded in the Chicago Board of Trade (CBOT). The contracts are currently traded exclusively in Globex, an electronic trading platform maintained by the CME group (Chicago Mercantile Exchange), about 18 hours a day (8:30 am-1:20pm and 7pm-7:45pm), 6 days a week (except Saturday). The maturity months for corn are March, May, July, September, and December and January, March, May, July, August, September and November for soybean. Each contract is traded in the market for more than two years and has the highest trading activity when the maturity is approaching. These grain futures contracts are typically traded by crop producers and input buyers for hedging price risks. They may also serve as financial instruments for speculative purpose by certain players in the market. The contracts can be traded as standalone positions or legs of combined position, the latter of which is so-called spread positions and are typically taken for hedging across contract maturities or related commodities.

CME maintains the Central Limit Order book for each agricultural commodity market. For corn and soybean, 10 levels of the order book are disseminated and tagged at a nanosecond. Limit order feeds come to the market participants who pay to receive the data at a two nanosecond refresh rate. Filling of an order follows a certain matching algorithm defined by CME, for example, Split FIFO and Pro Rata for corn and soybean.[9] There are also daily price limits which are rarely breached when trading in the underlying futures contract month is halted until the trading day.

[9] More details of the algorithm can be found here: https://www.cmegroup.com/education/articles-and-reports/how-cme-group-agricultural-markets-operate.html. An exchange might want to deviate from a First-In First-Out (FIFO) limit order book. There are times during the day when there is lower trading volume and market depth at price ticks. A FIFO matching algorithm might not give sufficient incentive to place a limit order behind other market participants at the same price tick because the limit order is unlikely to be lifted and if it is lifted there may be increased adverse selection concerns (i.e., trading against a market participant with superior information to their disadvantage). Pro Rata sharing gives a market participant increased incentive to provide depth behind existing limit orders at the same price tick because these orders will be more likely to execute, at least partially.

Building upon the method commonly applied in the literature, we classify the traders of the interested futures into different groups. A relevant paper is Kirilenko et al. (2017; see related references therein) who classify a large number of stock trading accounts into intraday intermediaries, small traders, fundamental traders and opportunistic traders based daily trading volume, end-of-day position, and intraday minute-by-minute inventory patterns. Similarly, we classify the trading accounts in each trading day into four groups, market makers, directional traders, spread traders and others. The classifications are mutually exclusive: starting from market maker group, if a trader's transactions in a given day satisfy certain criteria, the account is classified as market maker; otherwise, moving down to directional trader, spread trader, and others.

To be classified as a market maker, the trades of a trading account in a given trading day should satisfy the following conditions: (i) over 90% of the trades are conducted as proprietary, i.e. designated as a Commodity Trader Indicator of 1 or 2, (ii) the ratio between net trade quantity (sum of buys and sells) and total quantity traded is less than 5%, (iii) its trades must be more than 0.1% of the total quantity traded in the market, and (iv) it must take positions on both sides of the market. For a directional trader, its net trade quantity over total quantity traded should be greater than 90%, i.e., trading predominantly in one direction. If a trading account is not being classified as a market maker or directional trader, and over 20% of its trades are spread trades, it is defined as spread trader. The traders who do not fit the classifications above are classified into the others group.

Traders get a classification for each trading day. We choose the classifications with the highest count in days for the trader over the year with ties going in the order (others, spread trader, directional trader, market maker). On a given trading day, we compute the proportion of trades in each classification with additional break outs for spread or outright, aggressive or passive, and buy or sell. A spread order is a limit order in at least two contracts with different maturities or commodities. It appears in the spread limit order book and is there implicitly in both the different maturities but does not show in the limit order book. The matching engine will match a spread order against an outright order if the implied price of the spread order is hit. An outright order is a limit order only in a single contract. So for each of the four trader groups, the subgroup of spread contains orders that are executing a spread transaction, the legs of which are in different maturities or commodities. “Outright” means that the side of the transaction is only in the maturity month (December for corn or November for soybean). An aggressive trade means that the corresponding order is the one that Globex engine matched with orders already populated in the limit order book, which are called resting or passive. In other words, the aggressive trades lift liquidity from the book instead of resting in the book and waiting to be hit. “Buy” means that the trader takes a long position in the futures contract. So in the regression of log price differences, we further break each trader group to 6 subgroups. Using the market makers (M) as an example, we include the shares of M-spread-aggressive-buy, M-spread-passive-buy, M-outright-buy, M-spread-aggressive-sell, M-spread-passive-sell, M-outright-sell as explanatory variables.

To classify the traders, we use the transaction database reported by Chicago Board of Trade (CBOT) to CFTC starting in late 2011 to the end of 2017.[10] We roll out of the contracts to avoid the spot month. The spot month is the first two week of trading in the contract month of the expiring contract when the underlying commodity may be delivered by the shorts to the

[10] We do not consider the 2018 data when the trade war between the US and China disrupted the soybean markets (and corn as an imperfect substitute to a lesser extent) that made futures prices responsive to trade negotiations between the two counties.

longest tenured long positions. For example, we use the December 2012 contract in corn starting in November of 2011 and roll out of the contract into the December 2013 contract at the end of November. This process is repeated through to the December 2017 contract. For soybean, the procedure is similar. Instead we use the November contract starting in October 2011 because there is no December soybean contract. We include only electronic transactions when Globex is open. Only outright verses outright and outright verses spread transactions are considered, not spread versus spread involving the contract month.

At a given moment in time, participants who are actively trading or holding open interest in a contract help to form the market consensus about the price. The relative influence of various participants is weighted by their wealth, confidence in their estimates, and their audacity (Beirwag and Grove 1965; Kane 1999). All else equal, someone with more wealth who is willing and able to trade a contract may have more influence on the price of the contract. Similarly, someone with more confidence in their estimates or more audacious may be more willing to place their wealth at stake to back their market views. We anticipate that a higher proportion of directional traders in both long and short transactions will exert price pressure because these trades tend to change the amount of open interest, hence their wealth at stake, in a contract. This should also be the case for the other traders because they need to absorb the change to open interest demanded by directional and spread traders as market makers have relatively small net change in open interest.

2.3 Price Volatility

Besides log price differences, we use a second dependent variable related to price volatility. Utilizing the detailed transaction level information available in the CFTC data, we construct the following realized volatility measure:

$$RV = \frac{1}{TV_d} \sum_{i=2}^{N_d} (P_i - P_{i-1})^2$$

where N_d denotes the total number of trades and TV_d is the total notional trade volume during the trading day d except for the first trade, i.e., $TV_d = \sum_{i=2}^{N_d} Q_i$. P_i is the price of trade i. It is well known that realized volatility is an asymptotically unbiased estimator of the expected volatility (Andersen, Bollerslev and Diebold 2008).

For interpreting daily price changes, we also compute negative and positive realized volatility, or downside and upside realized semi-variance (Barndorff-Nielsen, Kinnebrock and Shephard 2010) and include them as explanatory variables in the regression of log price differences:

$$RS_- = \frac{1}{TV_d} \sum_{i=2}^{N_d} \{Min[0, (P_i - P_{i-1})]\}^2$$

$$RS_+ = \frac{1}{TV_d} \sum_{i=2}^{N_d} \{Max[0, (P_i - P_{i-1})]\}^2$$

The negative realized semi-variance RS_- captures the downside risk, i.e., the risk of price falling. It is found to be negatively correlated with price changes and contains useful information that may not be captured by the measure of realized volatility (Barndorff-Nielsen, Kinnebrock and Shephard 2008). Similarly, we expect to see a positive effect of the upside movement of price variation on daily price changes.

3. Empirical Models

We conduct the time series analysis for the two dependent variables, log price difference and price volatility, both at the daily level. But the specific models vary given the different properties of individual time series.

For corn and soybean prices, we define the daily log price difference as the log difference between the last and the first transaction prices of each trading day over the sample period, which is December 1st, 2011-November 30th, 2017 for corn and December 1st, 2011-October 31, 2017 for soybean. The resulting time series of log price differences are stationary and have no remaining autocorrelation in the residuals, which is confirmed by the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. Also the Box-Pierce autocorrelation test fails to reject the null hypothesis of independent errors (Box and Pierce 1970). Therefore, a regular linear regression model is estimated using the Ordinary Least Square (OLS) method with a set of explanatory variables.

As discussed above, given the detailed transaction level information available, we construct the shares of various trader groups and subgroups: for each of the four major trader groups (market maker, directional trader, spread trader, and others), we further construct 6 subgroup shares, spread-aggressive-buy, spread-passive-buy, outright-buy, spread-aggressive-sell, spread-passive-sell, outright-sell. To capture the fundamental surprises, we construct 8 related variables, including, surprises of prospective planting, USDA quarterly stock, WASDE monthly stock, WASDE monthly production, crop condition-excellent, crop condition-fair, crop condition-good. Also, we include the positive and negative realized semi-variances (RS_+ and RS_-).

The time series of price volatility shows a slow decay of the sample ACFs suggesting a nonstationary process. So we apply the Autoregressive Integrated Moving Average model of order p (order of AR), d (order of differencing), q (order of MA), or $ARIMA(p, d, q)$, the general form of which is specified as follows (Wei 1990):[11]

[11] This is adopted from eqn. 4.2.1 on p. 71, Wei (1990).

$$\phi_p(B)(1-B)^d Y_t = X'\gamma + \theta_q(B)a_t \quad (1)$$

where B denotes the backshift operator, $\phi_p(B) \equiv 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ is the AR operator, and $\theta_q(B) \equiv 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_p B^q$ represents the MA operator. d is the order of differencing of Y_t. The orders p, d and q are determined by using the model selection criteria, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and AICC (AIC with small sample size correction).[12]

The effects of the right-hand-side explanatory variables included in the vector of X are captured by the coefficients of γ. Similar to the regression of the log price differences, two sets of explanatory variables are considered: fundamental surprises and shares of trader groups. Instead of 6 subgroups for each trader group, we aggregate the subgroups into market maker, directional trader, spread trader and others and include the shares of the first three groups in the regression. Also, we separately estimate the effect of aggressive traders (in shares) on price volatility. We make the changes because we anticipate that the impacts of the subgroups of each trader group on price volatility should be in the same direction. Instead of signed surprises used in the regression of log price differences, which are defined as actual announced numbers minus the median of pre-announcement forecasts, we use the absolute deviation of the announcements from the forecasts in the volatility regression. We expect that the size, not the direction, of the fundamental surprises affects the price variation.

For robustness check, we estimate the corresponding $ARMA(p', q')$ model without differencing after accounting for the embedded seasonality in order to make the series

[12] For the ARIMA model for price volatility and liquidity of corn and soybean, while the three model selection criteria all agree with the choice of d, for choosing the orders of p and q, the results of the three criteria don't agree with each other with small differences in some cases. But we find this doesn't affect the estimates of the coefficients γ, which is our focus in the current study.

stationary.[13] The orders for both AR and MA components are chosen by the AIC, BIC and AICC criteria, followed by the Box-Pierce test to confirm the independence of residuals. The results are similar to what we report in the next section.

It is reasonable to expect that the impact of the included influencing factors varies across the distribution quantiles of the dependent variables. Therefore, a linear quantile regression as specified as eqn. (2) is employed to quantify the impact of the explanatory variables X on the τth quantile of the conditional distribution of Y.

$$Q_Y(\tau|X) = X'\eta(\tau) \tag{2}$$

where $\eta(\tau)$ is the regression coefficients for the τth quantile. For log price differences, eqn. (2) is directly applied and estimated as the corresponding time series is stationary and the residuals are not autocorrelated. For price volatility, the dependent variable Y in eqn. (2) is replaced by the estimated residuals of the corresponding $ARIMA(p'', d'', q'')$ model, i.e., a''_t in eqn. (3) below, which is similar to a_t in eqn. (1) after removing the effects of the explanatory variables, $X\gamma$. Note that the orders of the ARIMA model (p'', d'', q'') are expected to be different from those in eqn. (1).

$$\phi_{p''}(B)(1-B)^{d''}Y_t = \theta_{q''}(B)a''_t \tag{3}$$

The standard errors of the parameter estimates are computed using the bootstrapping method.

4. Analysis of Results

4.1 Fundamental Surprises and Market Structure

To illustrate the effects of fundamental surprises on corn and soybean futures prices, Figures 1 and 2 plot the log price differences together with the surprises of “good” crop conditions, USDA

[13] The estimation results are available upon request.

quarterly stock and WASDE monthly stock for corn and soybean, respectively. In general, positive surprises or higher than expected fundamental announcements are associated with negative price changes, while the effects of negative surprises or lower than expected fundamental changes on prices are positive. Figure 3 zooms into a particular month,[14] July 2012 for corn and September 2012 for soybean, to show the impacts of certain fundamental surprises on prices. The dashed lines indicate the timings of the surprises. We see a relatively strong and negative relation between "good" crop conditions and log returns, but the linkage between WASDE stock reports and crop price changes is weak and inconsistent in the sample month.

To better understand the information content of the analysts' forecasts published by Bloomberg, following the literature (e.g., Andersen et al. 2003; Balduzzi, Elton and Green 2001), we regress the USDA announced fundamentals on the Bloomberg's forecasts and price changes between the publication of the forecast and the public announcement:

$$A_{it} = \beta_{0i} + \beta_{1i}F_{it} + \beta_{2i}\Delta p_{it} + e_{it} \tag{4}$$

where A_{it}, F_{it}, and Δp_{it} denote the announced fundamental, analysts' pre-announcement forecast, and price change for the announcement or report i at time t, respectively. The related hypotheses are: (i) a positive and statistically significant estimate of β_{1i} indicate that the analysts' forecast of announcement i is significantly associated with the announced fundamental value and therefore is informative, (ii) for the forecasts to be unbiased, we expect $\hat{\beta}_{0i}$, the estimate of β_{0i}, to be not significantly different from 0 and $\hat{\beta}_{1i}$, the estimate of β_{1i}, to be not significantly different from 1, and (iii) if the estimate of β_2 is significantly different from 0, it implies that the

[14] The two months are chosen mainly because of data availability after the crops are planted. We intentionally pick different months for the two crops.

market expectation on the corresponding fundamental condition is revised after the publication of the analysts' forecast. Table 1 reports the regression results.

The results indicate that in general, the analysts' forecasts of the five fundamentals, including, prospective planting, acreage planted, WASDE monthly stock and production, and USDA quarterly stocks, all provide unbiased estimates of the actual announced fundamental values. In other words, the estimates of β_{1i}'s ($i = 1, \cdots, 5$) are not significantly different from 1 for both corn and soybean and those of β_{0i}'s are not significantly different from 0 except that of WASDE monthly stock of soybean. But market expectation in the corn market did revise after the analysts' forecasts were published by Bloomberg for the WASDE stock and production as well as the USDA quarterly stock. The results for soybean are similar that the β_2 estimates on WASDE stock and production are significantly different from 0. It implies that price responded to other information beyond the analysts' forecasts before the WASDE reports were published. This is not surprising and indeed the price discovery function of the futures markets, which generates signals for storage and production of a commodity that ultimately leads to better resource allocation.

The shares of the three major trader groups (market maker, directional trader, and spread trader) for corn and soybean over the sample period are presented in Figure 4. For both crops, the market structure changes abruptly when switching to a new contract year as certain market participants, especially market makers, offset their positions in the maturing contract and directional traders put on the hedges with a longer time to maturity. This is consistent with the way the data is constructed. We switch out of each contract at the end of the month before its maturity (December for corn and November for soybean). The individual group shares exhibit distinct patterns over the contact year. The share of transactions conducted by spread traders tend to be stable in each period with slightly higher shares at the beginning and the end. During the same time, market makers trade increasing amount of contracts till maturity, while the share of directional traders' transactions gradually declines.

4.2 Regression of Log Price Differences

The OLS regression results of the log price differences for corn and soybean are reported in Table 2. In the corn market, the coefficients of the transaction share of the directional trader group sum to the largest magnitude of impact among the first three groups for both buy and sell transactions. But for soybean, the market maker group sums to the largest impact (in absolute value) followed by directional traders among the first three groups. At first blush this result seems counter intuitive because one would not suspect market makers to be the biggest influencer of price or to be trading aggressively. In particular, we observe large significant coefficients in aggressive spread trades from market makers. How do aggressive spread trades occur? They may occur when there is price movement in the spread contract or a contract month of another leg of the spread when the implied price of the outright contract month crosses with a spread trade. The Globex matching engine creates an aggressive order that executes against the passive outright. In this sense price discovery comes from spread trading to the outright market. Why would this occur for soybeans and not for corn? There are two major crop cycles for soybeans but only one for corn as South America has a large soybean crop. Further, there is less storage of soybeans than corn because soybeans are more expensive, hence more costly to finance the carry, and more likely to spoil. Second, with two crop cycles there is a shorter time needed for storage until the next corp. So, there is less soybeans in storage to smooth out the term structure. Thus, soybeans may be more sensitive to the term structure. Finally, the term structure is sensitive to information about the crop in Brazil as soybeans are exported to many locations around the globe.

Spread traders have a relatively smaller effect compared to market makers and directional traders. As expected, share of spread buys pushes up prices and that of spread sells depresses prices in both corn and soybean markets as these trades align the term structure between different contract months. It is worth noting that all estimated effects are relative to that of the "O-outright-sell" group, which is omitted from the regression to avoid the dummy variable trap.

Aggressive buys and sells tend to have larger price impacts (in absolute value) than the passive ones in general except for the spread traders (S) in both markets and the D-spread group of soybean. Compared with the subgroup of outright in each category, spread transactions have relatively larger and more significant impact. Surprisingly, the others group has the largest impact on corn prices and some significant impact on soybean prices as well. It is likely that traders in the others group are taking part of the other side of the positions of the directional and spread traders as the positions of the market makers are relatively flat. As such, these traders may require compensation in anticipated price returns to hold their positions, too. In summary, market structure proxyed by detailed shares of individual trader groups is one important driving force of price dynamics in both corn and soybean markets.

For the fundamental surprises, in the corn market, higher than expected quarterly stocks announced by USDA, monthly stocks reported by WASDE, and better than expected crop growing conditions all have significant and negative impacts on corn futures prices as all of them indicate larger potential supply to the market after harvest. For soybean, prospective planting and monthly stock announced in the WASDE report show significant and negative impact on soybean prices. The effect of the surprises of the planted acres is puzzling with positive price impact. As expected, positive semi-variance or upside price variation is positively related with daily returns, while the relation between price change and contemporaneous negative semi-variance is significant and negative.

The quantile regression results of log price differences are summarized in the figures included in the Appendix. In the corn market, for market structure related variables, we see the effects of individual variables vary across quantiles, in general smaller impact at the lower quantiles and relatively larger impact at the upper tail of the distribution. Majority of the impacts remain in the same direction, positive or negative, across the quantiles. A few of them flip signs when moving to the upper quantiles. For example, for the subgroup of spread-passive-buy of the market makers (M-spread-passive-buy), the impact on the quantiles below 0.5 is negative with a wide range between -0.4 and 0, but becomes positive for the quantiles above 0.5 ranging from 0 to 0.2. S-spread-aggressive-buy is another example with similar trend of impact across quantiles.

For the variables related to the fundamental surprises, all impacts are relatively small moving in a narrow range across quantiles except the three crop condition variables. For example, the “good” crop condition starts with a positive price impact, but the effect becomes negative when moving to the upper quantiles of the conditional distribution of log price differences. This indicates the heterogeneous impact of crop conditions for difference price scenarios. When price is low likely in the early growing season, good growing conditions provide confidence of adequate supply in the coming year and are treated as positive news to the market. Later in the season, when the potential supply becomes clear, good crop conditions are thought as signals of excess supply and thus induce negative price changes. For realized semi-variance, the effects are concentrated on the lower quantiles and become negligible in the upper quantiles for both positive and negative semi-variances.

For soybean, we see similar patterns of the price impacts. One notable difference is the impact of realized semi-variance. Although remaining positive across the whole distribution, the impact of positive semi-variance decreases from around 60 on the left tail to below 10 on the right tail of the distribution. The impact of negative semi-variance is negative across quantile but varies from -60 to close to 0 when moving from the left to right tail of the distribution.

4.3 Regressions of Realized Volatility

The regression results of the ARIMA model for daily realized volatility of corn and soybean are reported in Table 3. The selected model of realized volatility of corn is ARIMA(0,1,3), i.e., a first order differencing with a third order moving average, and ARIMA(3,0,1) for soybean, which are chosen based on AIC, BIC and AICC criteria. We estimate the impact of the shares of the three trader groups (market maker, directional trader and spread trader; the fourth group is omitted) and aggressive traders in two separate regressions. Here the three trader groups are aggregated over the related individual subgroups discussed in the previous section, and the aggressive trader group contains all transactions conducted by the subgroups of aggressive-buys and aggressive-sells in the four trader groups. Also different from the log price differences regression, the surprises are absolute, not signed, deviation from analysts' forecasts.

From the results of the corn market reported in Column I of Table 3, we see that larger shares of the transactions conducted by both market makers and spread traders have significant and negative impacts on price volatility, while the effect of directional traders is not significant. As shown in Column II, aggressive transactions have no significant impact on the price variation. Similar to the corn market, the results reported in Table 4 for soybean indicate a negative effect of the transaction share of market makers. Higher shares of directional trader are also found to lower price volatility, while the estimate of spread traders is not significant. It makes intuitive sense for market makers to reduce price volatility because they provide immediacy when parties want to trade and the other side of the trade is not available to trade at the prevailing price. A priori, there is no expected for directional traders or spread traders. At first blush, the shares of aggressive traders would appear to have an incorrect sign. The result indicates, however, that aggressive traders are not trading through into the next price tick very often when they lift an order. For instance, this might be accomplished by aggressive traders shredding their trades or by using mostly marketable limit orders instead of market orders.[15]

For the fundamental surprises related variables, the USDA quarterly stock and WASDE monthly production and stock all have positive and significant impact on price volatility of corn. And the surprises (in absolute value) related to all the USDA and WASDE reports except crop conditions push up price variation in the soybean market. This implies that when fundamental surprise arrive, markets adjust quickly to the newly arrived information on crop production and inventory and consequently induces large price variations. This is consistent with the findings in the literature that the intraday and daily price volatility patterns can be largely explained by scheduled news announcements in various financial markets (see, e.g., Ederington and Lee 1993; Harvey and Huang 1991).

The corresponding quantile regression results are reported in the Appendix, in which the standard errors are calculated based on 1,000 bootstrapped samples. Across the quantiles of the conditional distribution of price volatility, all market structure related variables, including, shares of market maker, directional trader, spread traders and aggressive trader, exhibit a similar pattern

[15] A market order executes immediately and for the full quantity of an order at the best price(s) available in the limit order book. A marketable limit order is an order that is submitted at the prevailing best offer on the other side of the transaction. Assuming no other limit orders, the order will execute against all the liquidity at the prevailing best offer and if unsatisfied will become a limit order for the residual amount of the order and become a resting order at the new best offer on the other side of the contract, i.e., the order will not trade through to the next price tick as a market order would do.

that the impact on price volatility increases from negative at lower quantiles to positive at upper quantiles. All surprise variables are not statistically important at all quantiles, so we didn't report the results.[16]

Conclusion

Our study seeks to provide a better understanding on how participants process new information, the determinants of price volatility in corn and soybeans futures markets. The constructed variables of fundamental surprises, which is defined as the deviations of actual announced fundamentals from pre-announcement analysts' forecast, enable us to quantify the impact of public information on price formation in the corn and soybean markets. We employ unique transaction level data to proxy for market structure, which is represented by shares of transactions of various trader groups. In particular, we find a higher proportion of directional traders in both long and short transactions exert price pressure in the direction of their trades. Also, both the fundamental surprises and other market structure related variables have statistically significant effects on logs price differences and price volatility. Furthermore, the impacts vary across quantiles of the conditional distributions.

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[16] The quantile regression results are available upon request.

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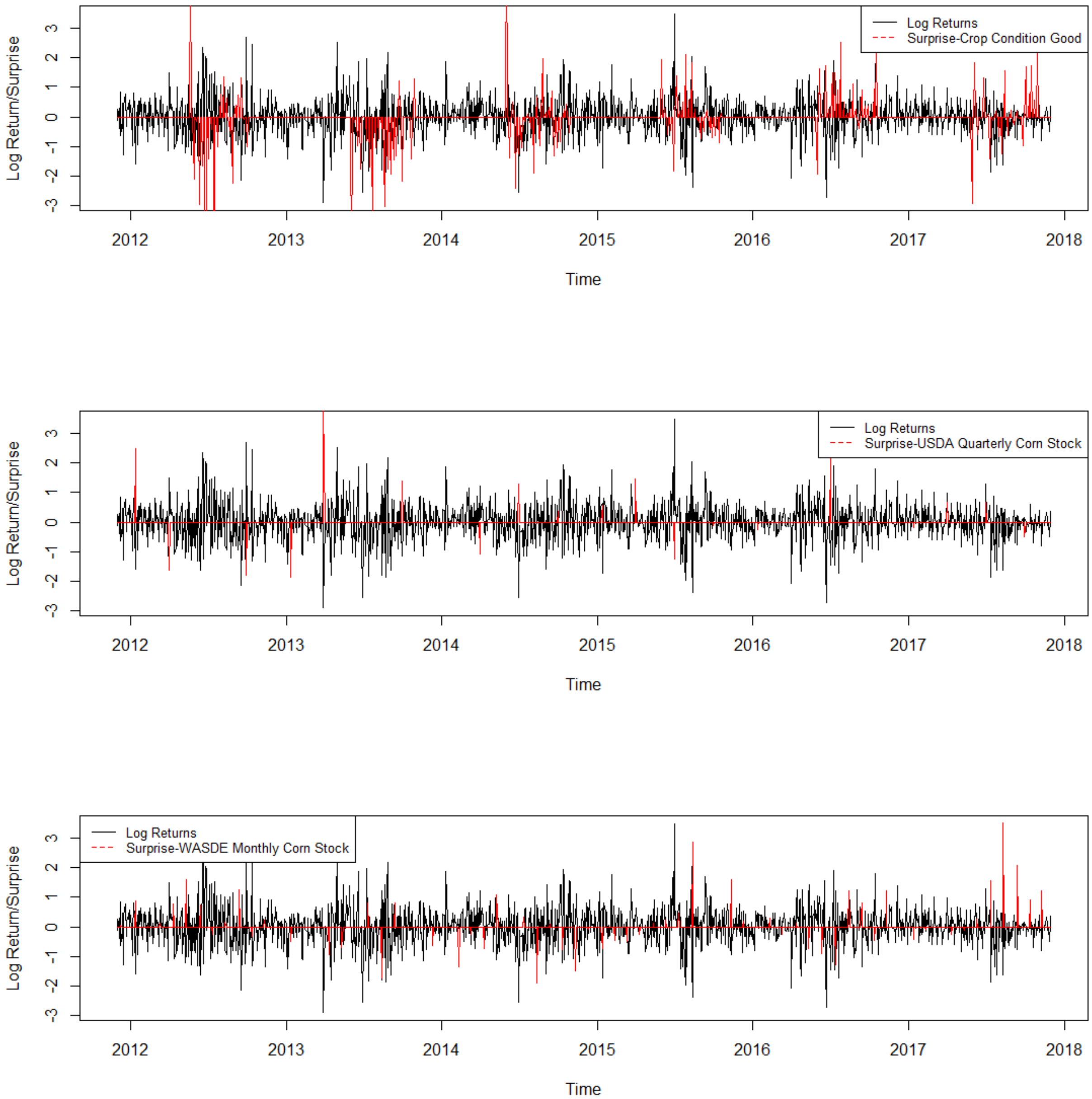


Figure 1. Log price differences of corn (in black) and fundamental surprises (in red), 12/1/2011-11/30/2017.

Log price differences graphed against time. The surprise crop condition, surprise USDA Quarterly stock, and surprise WASDE monthly stock for corn, on the announcement days are superimposed in red reported as a percentage.

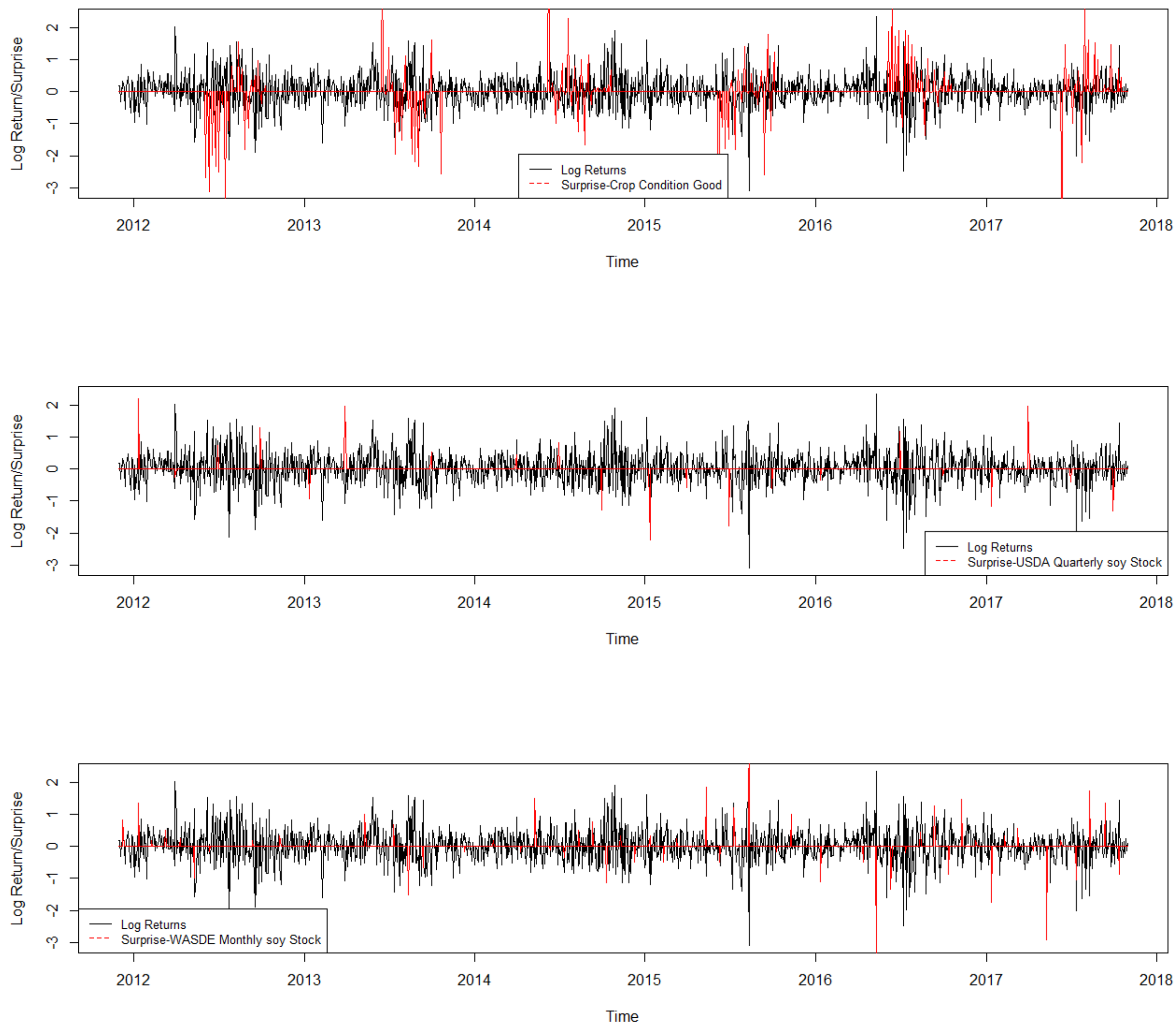
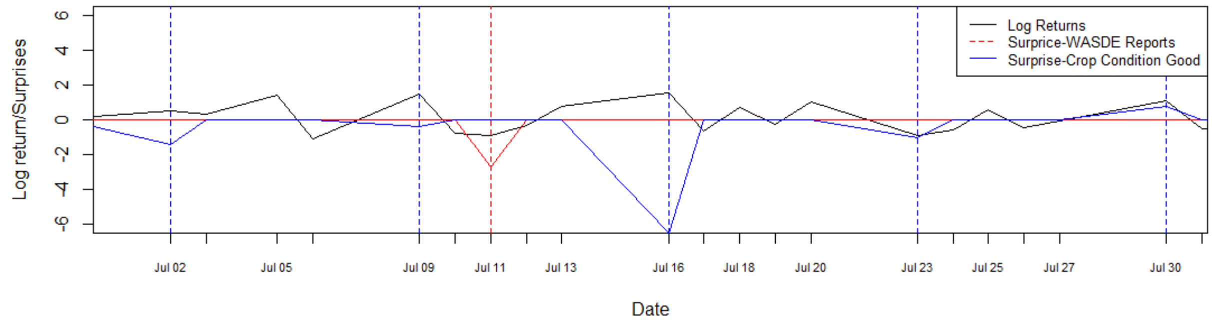
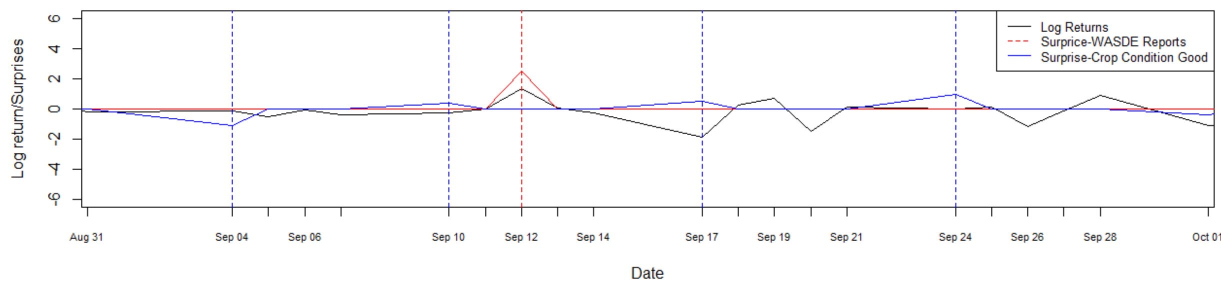


Figure 2. Log price differences of soybean (in black) and fundamental surprises (in red), 12/1/2011-10/31/2017.

Log price differences graphed against time. The surprise crop condition, surprise USDA Quarterly stock, and surprise WASDE monthly stock for soybean, on the announcement days are superimposed in red reported as a percentage.



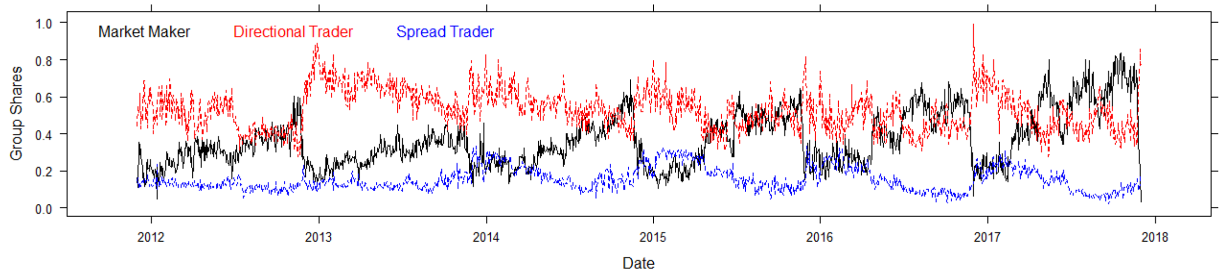
(a) Corn, July 2012



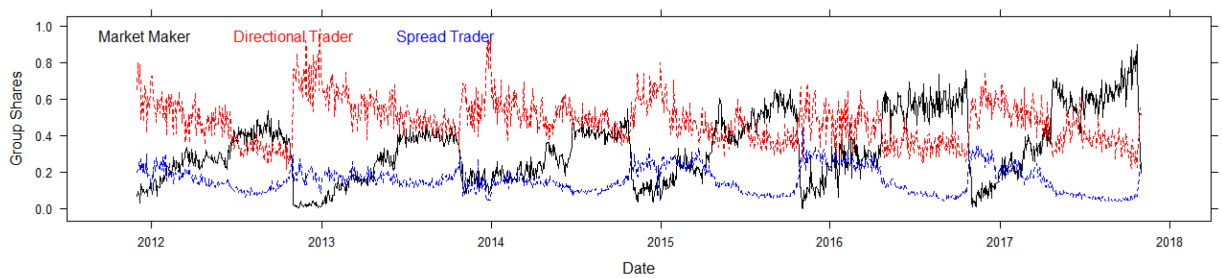
(b) Soybean, September 2012.

Figure 3. Log price differences of corn (a) (soybean b) and fundamental surprises of WASDE monthly stock and “good” crop conditions, July 2012 (September 2012).

A close up of log price differences, fundamental surprises for WASDE stock, and “good” crop conditions for July 2012 for corn and September 2012 for soybean where the surprises are reported on a percentage basis.



(a) Corn



(b) Soybean

Figure 4. Shares of trader groups (market maker, directional trader and spread trader).

Percentage of traders involving market makers, directional traders, and spread traders for both corn and soybean graphed against time. Note the seasonality as well as the discontinuity when we roll out of the expiring contract into the next year's contract just before the contract goes to delivery in the trader composition. The percentages add to 200% as there are two sides to every trade. The other trader group is not displayed.

Table 1. Regression of information content of the analysts' forecasts (Standard errors are in the parentheses)

Corn	Forecasts	Price Changes	Constant	R^2
Prospective Planting	0.74* (0.23)	-7992.09 (4631.24)	24013.89 (20878.62)	0.97
Acreage Planted	1.06** (0.18)	-666.4 (1166.59)	-4869.46 (16383.68)	0.95
WASDE Monthly Stock	1.00*** (0.02)	-414.98*** (135.18)	3.33 (37.29)	0.97
WASDE Monthly Production	0.99*** (0.02)	-914.53** (339.07)	164.45 (323.19)	0.98
USDA Quarterly Stock	1.00*** (0.01)	-315.40** (139.70)	44.50 (57.27)	0.99
Soybean	Forecasts	Price Changes	Constant	R^2
Prospective Planting	1.11** (0.15)	-1301.02 (3724.81)	-9718.06 (12175.86)	0.96
Acreage Planted	0.85** (0.13)	-3391.47 (2871.97)	14152.88 (11533.05)	0.92
WASDE Monthly Stock	0.95*** (0.03)	-87.73*** (19.54)	21.89** (10.92)	0.94
WASDE Monthly Production	1.00*** (0.02)	-156.86*** (42.88)	12.88 (74.13)	0.99
USDA Quarterly Stock	1.00*** (0.01)	-9.07 (34.08)	6.08 (13.80)	0.99

Table 2. OLS estimation results of log price differences (Standard errors are in the parenthesis)

	Corn	Soybean
Constant	-0.01 (0.03)	-0.03* (0.02)
M-spread-aggressive-buy	0.08 (0.07)	0.38*** (0.08)
M-spread-passive-buy	0.03 (0.15)	0.24** (0.10)
M-outright-buy	0.21 (0.14)	0.26*** (0.10)
M-spread-aggressive-sell	-0.15** (0.07)	-0.50*** (0.08)
M-spread-passive-sell	-0.11 (0.14)	-0.22** (0.09)
M-outright-sell	-0.16 (0.12)	-0.14 (0.10)
D-spread-aggressive-buy	0.19*** (0.02)	0.12*** (0.02)
D-spread-passive-buy	0.16** (0.07)	0.22*** (0.04)
D-outright-buy	0.07 (0.06)	0.18*** (0.03)
D-spread-aggressive-sell	-0.18*** (0.02)	-0.14*** (0.02)
D-spread-passive-sell	-0.15*** (0.03)	-0.16*** (0.02)
D-outright-sell	-0.06** (0.02)	-0.09*** (0.02)
S-spread-aggressive-buy	-0.03 (0.11)	-0.10 (0.08)
S-spread-passive-buy	0.21*** (0.06)	0.24*** (0.03)
S-outright-buy	0.14* (0.07)	0.26*** (0.05)
S-spread-aggressive-sell	0.27** (0.11)	0.06 (0.08)
S-spread-passive-sell	-0.19*** (0.02)	-0.19*** (0.02)
S-outright-sell	-0.14** (0.06)	-0.14*** (0.05)
O-spread-aggressive-buy	0.24*** (0.03)	0.18*** (0.03)
O-spread-passive-buy	0.20** (0.08)	0.18*** (0.04)
O-outright-buy	0.05 (0.06)	0.10*** (0.04)
O-spread-aggressive-sell	-0.30*** (0.03)	-0.26*** (0.03)
O-spread-passive-sell	-0.16** (0.08)	-0.16*** (0.04)

Surprise-acreage planted	0.01** (0.003)	0.01* (0.005)
Surprise-USDA prospective planting	-0.002 (0.003)	-0.005* (0.003)
Surprise-USDA quarterly stock	-0.02*** (0.002)	0.001 (0.001)
Surprise-WASDE monthly stock	-0.01*** (0.001)	-0.01*** (0.001)
Surprise-WASDE monthly production	0.0006 (0.001)	-0.0009 (0.002)
Surprise-crop condition excellent	0.0003 (0.001)	0.00001 (0.001)
Surprise-crop condition good	-0.002** (0.001)	0.0002 (0.001)
Surprise-crop condition fair	-0.0009 (0.002)	0.0005 (0.001)
Realized semivariance-positive	138.40** (65.26)	20.17*** (6.76)
Realized semivariance-negative	-133.50** (56.56)	-18.84*** (6.34)
R^2	0.40	0.32

Note: ***, ** and * denote the 1%, 5% and 10% significance level, respectively. “m-” indicates the group market makers, “d-” directional traders, “s-” spread traders, and “o-” the group of others.

Table 3. ARIMA estimation results of realized volatility of corn (standard errors are in the parenthesis)

	Corn		Soybean	
	I	II	I	II
Share of market maker	-2.24***		-1.95***	
	(0.56)		(0.31)	
Share of directional trader	-0.49		-0.81***	
	(0.48)		(0.25)	
Share of spread trader	-3.41**		0.03	
	(0.97)		(0.55)	
Share of aggressive traders		1.72		-3.15***
		(1.09)		(0.54)
Surprise-acreage planted	-0.22	-0.19	0.90***	0.91***
	(0.25)	(0.25)	(0.25)	(0.25)
Surprise-USDA prospective planting	0.15	0,.22	1.09***	1.10***
	(0.23)	(0.23)	(0.16)	(0.16)
Surprise-USDA quarterly stock	3.43***	3.39***	0.70***	0.73***
	(0.15)	(0.16)	(0.06)	(0.06)
Surprise-WASDE monthly stock	1.17***	1.20***	0.49***	0.51***
	(0.13)	(0.13)	(0.06)	(0.06)
Surprise-WASDE monthly production	0.46***	0.48***	0.39***	0.41***
	(0.12)	(0.11)	(0.08)	(0.08)
Surprise-crop condition excellent	0.10	0.11	0.02	0.03
	(0.08)	(0.08)	(0.03)	(0.03)
Surprise-crop condition good	-0.01	-0.04	0.02	0.02
	(0.13)	(0.13)	(0.06)	(0.06)
Surprise-crop condition fair	0.02	0.03	-0.01	-0.01
	(0.08)	(0.08)	(0.05)	(0.05)

Note: ***, ** and * denote the 1%, 5% and 10% significance level, respectively. Estimates for constants are not reported.