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Ran Xie, Olga Isengildina-Massa, Julia L. Sharp, and Gerald P. Dwyer

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Ran Xie,

Olga Isengildina-Massa,

Julia L. Sharp,

and

Gerald P. Dwyer[*]

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[*] Ran Xie is a PhD student in the John E. Walker Department of Economics, Clemson University, Olga Isengildina-Massa is an Associate Clinical Professor at the University of Texas at Arlington, Julia L. Sharp is an Associate Professor in the Department of Mathematical Sciences, Clemson University, and Gerald P. Dwyer is a Visiting Professor and BB&T Scholar at Clemson University. Any opinions, findings, conclusions, or recommendations expressed in this publication are those of the authors and do not necessarily reflect the view of the U.S. Department of Agriculture or the Economic Research Service.

Quantifying Public and Private Information Effects on the Cotton Market

The study evaluates the impact of four public reports and one private report on the cotton market: Export Sales, Crop Progress, World Agricultural Supply and Demand Estimates (WASDE), Perspective Planting, and Cotton This Month. The best fitting GARCH models are selected separately for the daily cotton futures close-to-close, close-to-open, and open-to-close returns from January 1995 through January 2012. In measuring the report effects, we control for the day-of-week, seasonality, stock level, and weekend-holiday effects on cotton futures returns. We find statistically significant impact of the WASDE and Perspective Planting reports on cotton returns. Furthermore, results indicate that the progression of market reaction varied across reports.

Key words: Cotton This Month, Crop Progress, Event Study, Export Sales, GARCH Model, Information Effects, Perspective Planting, WASDE,

Introduction

In volatile agricultural markets, most public information is provided by the U.S. Department of Agriculture (USDA), which historically devoted substantial resources to their agricultural forecasting program (Offutt, 2002). Information in the USDA forecast reports is widely used by farmers, agribusiness firms, other commercial decision makers, speculators, as well as secondary information producers, such as universities, and consulting and market advisory firms. Moreover, the importance of public information on agricultural markets has been debated since the early 80s, given the emergence of private agricultural analysis and the gradual reduction in governmental spending for statistical reporting services. In comparison to public expenditure in 1980, 1983 federal budget request for USDA was reduced by 20%. More recently, the USDA cut 12 statistical and commodity reports in response to budgetary constraints in 2011 (NASS news, October 17, 2011), and in early 2013 USDA suspended a number of statistical surveys and reports due to reduced funding (NASS news, March 12, 2013). Thus, the issue of the value of public information sources has become particularly urgent.

Most previous studies evaluating public information effects focused on a single report and provided mixed evidence. Sumner and Mueller (1989) found significant announcement effect on corn and soybean market price movements using USDA harvest forecast reports. McNew and Espinosa (1994) and Fortenbery and Sumner (1993) used USDA Crop Production Report and reached a consistent conclusion that there is no strong evidence indicating a significant influence USDA corn and soybean production forecasts on the level of futures prices after 1985. In contrast, Garcia et al. (1997) and Mckenzie (2008) analyzed the same USDA reports and suggested that corn and soybean forecasts still provide valuable information on commodity futures markets, even though there has been a reduction in the information effects after the mid-1980s. Colling and Irwin (1990) and Mann and Dowen (1997) examined the effect of USDA Hogs and Pigs

Report and they found the ability of the futures market of hogs to incorporate unanticipated information. Grunewald, McNulty, and Biere (1993) and Schaefer, Myers, and Koontz (2004) discovered that live cattle futures prices respond to information contained in the Cattle on Feed Report.

The information in World Agricultural Supply and Demand Estimates (WASDE), one of the most influential public sources of commodity forecasts, has also been analyzed by several previous studies. Isengildina-Massa, Irwin, and Good (2008a, 2008b) respectively investigated the impact of WASDE on the options and futures price for corn and soybean. Both studies confirmed a significant price reaction to the WASDE reports. More recently, Adjemian (2012) conducted a comprehensive study by quantifing the WASDE information effect for multiple crop markets, and he found significant impact. Dorfman and Karali (2013) analyzed multiple USDA reports (Acreage & Prospective Plantings; Cattle; Cattle on Feed; Crop Progress; Feed Outlook; Grain Stocks; Hogs and Pigs; Livestock, Dairy, and Poultry Outlook; Oil Crops Outlook; and WASDE) within one study, but they examined these reports separately using parametric and nonparametric approaches. Report-by-report analysis does not allow the measurement of the overall impact of a group of similar reports. More importantly, evaluating a single report is likely to overestimate its effect since several public reports could be simultaneously published within the same reaction window.

Isengildina, Irwin, and Good (2006) addressed the "clustering reports problem" by simultaneously analyzing six USDA reports using a GARCH-type model. They focused on the most influential reports in live hog and cattle returns. Later, Karali (2012) evaluated the impact of multiple USDA reports on the conditional variances and covariances of returns on 5 related futures contract.

As the above literature indicates most research has focused on the corn, soybean, cattle, and hog markets, leaving the effect of public information on other commodity markets unclear. The objective of this study is to estimate the impact of all major public reports and one private report on the cotton market from 1995 through 2012. The cotton market was chosen because (a) the cotton industry has undergone substantial changes over the last fifteen years (Isengildina and MacDonald, 2013); (b) cotton prices have become particularly volatile in recent years (Robinson, 2009); (c) USDA forecasts of cotton prices were prohibited from 1929 to 2008; and (d) relatively little is known about the effect of information on cotton markets.

Cotton returns of nearby daily futures contracts from January 1995 through January 2012 are used in the analysis. The reports identified as main sources of public information for the cotton market include *Crop Progress*, *Export Sales*, *Perspective Plantings*, and *WASDE* reports released by the USDA. This study also includes the most commonly used private report: the *Cotton This Month* report from the International Cotton Advisory

Committee.[1] Having both public and private reports allows us to compare the impact of public and private information on the cotton market.

This study uses the standard event study approach, which has been widely used in analyzing information effects (e.g. Dorfman and Karali, 2013; Isengildina-Massa, Irwin, and Good, 2006). Within this framework, information is considered valuable to market participants if prices respond to the information release (the event). Evaluation of the effect of multiple reports is then conducted using a GARCH-type model similar to the one outlined in Isengildina-Massa, Irwin, and Good (2006). The model controls for other potential determinants of abnormal price movements, such as stock levels, day of the week, seasonality, and weekend-holiday effects. This approach allows for valuation of relative importance of the five main reports in the cotton futures market. The methods reveal the announcement effects on both the mean and the variance of returns.

Data

Public and Private Reports

The USDA, as the main public information provider, releases over 20 different reports related to cotton industry each year. Moreover, other government-funded organizations, such as International Cotton Advisory Committee (ICAC), National Cotton Council (NCC), World Bank, and International Monetary Fund (IMF) publish various cotton reports. The reports usded in this study as main information sources for the cotton market are *Export Sales*, *Crop Progress*, *WASDE*, *Perspective Plantings* from USDA and *Cotton This Month* from ICAC. Other reports such as *Cotton and Wool Outlook* and *Weekly Cotton Market Review* contain mostly secondary information and analysis and are not expected to move the markets.

Export Sales is published by the USDA through its export sales reporting system. The reports are part of the USDA's Export Sales Reporting Program, which monitors U.S. agricultural exports on a daily and weekly basis. Only the weekly *Export Sales* reports are included in this study; these reports are published every Thursday at 8:30 AM ET and contain the weekly summary of export activity for all major commodities. The historical reports are available since November 1, 1990. *Crop Progress* reports list planting, fruiting, and harvesting progress and overall condition of crops in major producing states. The National Agricultural Statistics Service (NASS) issues weekly *Crop Progress* reports during the growing season (early April through the end of November or the beginning of December) of selected crops, including cotton, after 4:00 PM ET on the first business day of the week. The *WASDE* reports are released monthly by the World Agricultural

[1] The selection of main public reports on cotton has been discussed with Steven MacDonald, a senior economist in USDA, and John R. C. Robinson, professor and extension economist in Texas A&M University.

Outlook Board. They provide the USDA's comprehensive estimates and forecasts of supply and demand for major U.S. and global crops and U.S. livestock. The purpose of the WASDE reports is to advise market participants about the current and expected market conditions. Historically *WASDE* was published about one hour after the close of trading of cotton futures. Starting in May 1994, the USDA changed the release time to 8:30 AM ET. *Prospective Plantings* reports are published at the end of March by the NASS every year and concentrate on the expected plantings as of March 1st for various crops. Similar to *WASDE*, *Prospective Planting* were released after the market is close before 1996 and the publishing time was switched to before market opening since then. ICAC issues *Cotton This Month* reports at 3:00 pm ET of the first working day of each month in five languages. These reports present estimates and projections of world supply and demand and assessments of supply and demand by country. In contrast to other reports included in this study, *Cotton this Month* is released to subscribers only.

The release of these five major reports in the cotton market represents "events" in this study and is used to capture the effect of public reports on cotton futures prices. The trading days immediately following reports release are considered event days. Thus, for reports that are released after the cotton futures market close, the event day is the day following the release. On the other hand, the event day is the same as the release date if a report is issued before trading hours. The event days for *Cotton This Month*, the only private report included in this study, are the second day after the release of each month's report. The reason for using the second day[2] instead of the first day is that the private report releases to subscriber first and the new information takes longer to reach the market.

Because the *Crop Progress* reports are available only since 1995, the sample period for this study is chosen from January 1995 through January 2012. During the sample period, weekly *Export Sales* and *Crop Progress* were published 893 and 598 times, respectively. Monthly *WASDE* reports were published 205 times and yearly *Prospective Plantings* reports were published 17 times. ICAC released its first *Cotton This Month* on November 1, 1995 and has published 194 reports since then. In total, 1907 public reports were included in this study. None of the five reports was scheduled to be released on the same day as another report, but reports are issued on the same day occasionally. Out of 1759 event days, 146 days have two reports and one day has three reports. This indicates the need to consider the effect of "report clustering".

Cotton Futures Returns

During the period of study, Cotton No. 2 futures contracts were traded on the New York Board of Trade (NYBOT) operated under the CME Group. Cotton No. 2 has contract months of March, May, July, October, and December and the contract size is 50,000

[2] This study also used the third days, forth days, and fifth days after the reports release as event days and the results are available upon requests.

pounds. To obtain a spliced, continuous price series for cotton, the closest to delivery contract is used until the third Tuesday of the month prior to delivery, after which the series switch to the next nearby contract. In this way, expiration effects on prices and on the level of trading activity are avoided. Table 1 presents the matching futures contracts with each report release month.

The information effect in cotton futures market is measured in terms of returns. Following previous studies by Yang and Brorsen (1993) and Isengildina-Massa, Irwin, and Good (2006) returns are calculated as log percentage changes in the nearby futures contract prices for cotton from January 3, 1995 through January 31, 2012. Accordingly, the equation we use to calculate returns is:

(1) $R_t = 100* (lnP_t - lnP_{t-1})$,

where lnP_t is the natural logarithm of the settlement price of cotton's futures contract on day t (event day), while P_{t-1} is the settlement price on the previous day. This calculation is also called the Close-to-Close (CTC) approach as the settlement prices are used in two consecutive days. Karali (2012) stated "the advantage of using the CTC approach, as it is more conservative if the impact is disseminated into prices instantaneously in the opening". However, Isengildina-Massa, Irwin and Good (2006) argued that CTC measurement may mask the markets' reaction to USDA reports as other information becomes available to the market during the event day. Based on the efficient market theory, which suggests the impact of new information should be reflected almost instantaneously in futures prices right after a trading session begins, Isengildina-Massa, Irwin and Good (2006) suggested using Close-to-Open (CTO) returns, and they also mentioned it is necessary to use all three measures of returns--CTC, CTO, and open-to-close (OTC)--to completely understand the dynamics of market reaction to USDA reports when the reaction speed is unknown. Therefore, this study also calculates the returns in two other ways: a) CTO returns, when P_t is the open price on the event day and P_{t-1} is the settlement price on the previous day; b) OTC returns (intra-daily returns), where P_t and P_{t-1} are the event day's settlement and open price, respectively.

The cotton futures contract is subject to a daily price limit, which restricts potential large price movements. Following previous studies (Park, 2000; Isengildina-Massa, Irwin, and Good, 2006; Karali, 2012), this research does not adjust returns data for price limit moves. Thus, the estimates of announcement effects may be underestimated because of the lack of ability to detect large market reactions to new information in days with price limit moves.

Descriptive Analysis

CTC, CTO, and OTC returns of cotton futures are respectively plotted in Panel 1-3 of figure 1. Spikes can be seen in all three plots and they are presumably related to the arrival of news. This study evaluates if the five reports (*Exports Sales*, *Crop Progress*, *WASDE*, *Perspective Plantings*, and *Cotton This Month*) can be used to explain some of the volatility in returns. The volatilities of returns in cotton futures are plotted in figure 2 in terms of squared returns (a common measure of volatility). The plots in Panels A and C show that CTC and OTC measurements share a similar volatility pattern, with the returns most volatile in the year of 2001 and 2009. The plot of the CTO return indicates that the CTO returns were most volatile around year 2005.[3] All three plots in figure 2 suggest heteroskedasticity in variance over time and they show evidence of volatility clustering, indicating that low volatility was normally followed by low volatility and vice versa.

Descriptive statistics for cotton futures returns are presented in table 2. The average magnitude of returns is -0.03, -0.06, and 0.03 percentage points for CTC, CTO, and OTC respectively. The skewness for all three measurements are small (between -0.5 and 0.5), suggesting the distribution of returns is approximately symmetric. The assumption of normality is rejected in all three cases based on the Jarque-Bera test, and the rejection is likely to be explained by the large value for kurtosis. Although the values of kurtosis for CTC and OTC returns are about half of the size for CTO, the kurtosis value for all is larger than 3, indicating the distribution of returns has a fatter tail than a normal distribution.

Methods

Traditional Ordinary Least Squares (OLS) method is not suitable to analyze cotton's daily futures returns because the distribution of returns is non-normal with time-varying volatility as discussed in the previous section. GARCH models have been widely used in commodity futures studies and they have been shown to be informative about the distribution of daily futures returns (e.g. Yang and Brorsen, 1993; Yang and Brorsen, 1994; etc.). Selection of an appropriate GARCH model has always been a great challenge, and there is no single GARCH-type model claimed as the best fit for various commodities. Yang and Brorsen (1993) applied the GARCH(1,1) to capture the nonlinear dynamics of 15 commodities' daily futures price. One year later, they compared three different models and concluded the GARCH(1,1)-t (GARCH with t-distribution) fits their data the best. Isengildina-Massa, Irwin, and Good (2006) used a TARCH-in-mean (the threshold GARCH model with the volatility in the mean equation) model to measure live/lean hog and live cattle futures returns as they found evidence that the markets react asymmetrically to "good" and "bad" news. Instead of directly selecting a GARCH-type model from previous literature, this study strives to select a GARCH model that best fits the characteristics of the cotton futures daily returns. We first present the steps for choosing an optimal GARCH model that fits the returns without any external effects. The external effects, including public reports, are then added to build the full model.

[3] Panel A, B, C in figure 2 have different scales. The largest volatility in Panel A is two times larger than the largest one in Panel B.

Model with No External Effects
Basic GARCH model

Prior to determining the order for the GARCH terms, it is necessary to know if the daily cotton futures returns imply the existence of ARCH effect. So, the first step is to estimate the daily cotton futures returns using the "best fitting" ARMA model.[4] Then, the ARCH disturbances can be tested using the Lagrange multiplier test (LM) proposed by Engle (1982). If the null hypothesis of no ARCH effect has been rejected, the GARCH model should be considered.

The GARCH model is an extension of the ARCH model developed by Engle (1982), and the basic GARCH(p,q) model developed by Bollerslev (1986) and Taylor is:

(2) $R_t = g(x;\theta) + \varepsilon_t$

(3) $\varepsilon_t = z_t h_t, z_t \sim iidN(0,1),$

(4) $h_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}^2 .$

The function $g(x_t;\theta)$ is the mean equation (2) determined by the "best fitting" ARMA model. The constant term in the ARMA model is interpreted as the price of risk. Isengildina-Massa, Irwin, and Good (2006) argued that the price of risk might be associated with the volatility of returns and GARCH with mean model can capture the association by adding the conditional standard deviation (h_t) into the mean equation.The error term ε_t is assumed to have the decomposition of $z_t h_t$, where h_t^2 is the conditional variance, representing the forecast variance based on past information. The conditional variance is presented as a function of a constant term (α_0), the new information measured as the sum of squared previous days' returns, and the previous forecast variances. The coefficients of the GARCH model are usually estimated by maximum likelihood estimation (MLE) method using a nonlinear maximization algorithm, such as the one developed by Marquardt (1963).

As noted by Teräsvirta, Tjøstheim and Granger (2011), the overwhelmingly most popular GARCH model in applications has been the GARCH(1,1) model, where p=q=1 in equation (4). In addition, Hansen and Lunde (2005) compared 330 different volatility models using daily exchange rate data (DM/$) and IBM stock prices and they concluded that the GARCH(1,1) was not significantly outperformed by any complicated GARCH models. Therefore, GARCH(1,1) is a good starting point to fit the daily cotton futures returns data. The LM test can be applied again for testing the existence of left over ARCH effects and higher order GARCH model will be considered if the null hypothesis is rejected.

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[4] More detail on how to find the "best fitting" model is given in Brockwell and Davis (2009).

Extensions of the basic GARCH model have been developed to deal with "stylized facts", including asymmetric, non-gaussian error distribution, and long memory, in financial and agricultural commodity time series data. Our approach to incorporating these additional factors in the daily cotton futures returns is described in the following sections.

GARCH Model with Non-Gaussian Error Distribution

In the basic GARCH model, the error term follows a normal distribution (see equation 3). Even though the distribution of financial and commodity returns have fatter tail than a normal distribution, He and Teräsvirta (1999) argue that a GARCH model with normal errors (GARCH-normal) can replicate some fat-tailed behavior. However, due to the high kurtosis values (4.50, 10.03, and 5.24 for CTC, CTO and OTC returns, respectively), it is important to consider distributions with fatter tails than the normal distribution. Zivot (2009) notes that the commonly used fat-tailed distributions for fitting GARCH models include the Student's t distribution, the double exponential distribution, and the generalized error distribution.

The GARCH model with Student's t distribution (GARCH-t) is considered in this study. Bollerslev (1987) first developed the GARCH-t, and the GARCH-t model is useful in modeling leptokurtosis as it features both conditional heteroskedasticity and conditional leptokurtosis (Yang and Brorsen, 1994). For a GARCH-t model, the error term ε_t in the GARCH model follows a Student's t distribution with v degrees of freedom (Bollerslev, 1987). After the GARCH-t model has been fit to the data, the adequacy of assuming Student's t distribution can be tested graphically by plotting the quantile-quantile plot (QQ plot) with the standardized residuals because the distribution of the standardized residuals should match the specified error distribution used in the estimation (Zivot, 2009).

Asymmetric GARCH Model

In the basic GARCH model, the signs of the residuals (ε_t) have no effect on the conditional variance (h_t^2) because only squared residuals are included in equation (4). However, previous literature suggests that "bad" news (when previous returns are negative) has a larger effect on volatility than "good" news (when previous returns are positive) (e.g. Engle, 2004; Isengildina-Massa, Irwin, and Good, 2006). In other words, the reaction of volatility toward different types of news is asymmetric. Therefore, it is interesting to examine whether such asymmetric reactions exist in the daily cotton futures returns.

Asymmetry can be tested by calculating the correlation between the squared return R_t^2 and lagged return R_{t-1}. Negative correlation suggests the existence of asymmetry (Zivot, 2009). If asymmetry in the daily cotton futures returns has been identified, an asymmetric volatility model such as EGARCH (Nelson, 1991), TGARCH (Zakoian, 1994), and GJR-GARCH (Glosten, Jaggnnathan, and Runkle, 1993) may be preferred to the basic

GARCH model. Using TGARCH as an example, equation (4) will be adjusted as:

$$(5) \qquad h_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \gamma_j I_{t-j} \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}^2,$$

where $I_{t-j} = 1$ if $\varepsilon_{t-j}^2 < 0$ or $I_{t-j} = 0$ if $\varepsilon_{t-j} \geq 0$. Therefore, for "bad" news, the total effect of ε_{t-j}^2 is given by $(\alpha_j + \gamma_j)\varepsilon_{t-j}^2$, while for "good" news, the total effect of ε_{t-j}^2 is given solely by $\alpha_j \varepsilon_{t-j}^2$.

Long Memory GARCH Model

For many financial and agricultural commodity time series, the β_1 for the previous period's volatility h_{t-1}^2 in equation (4) is very close to 0.9 (e.g. Yang and Brorsen, 1994; Hansen and Lunde 2001), indicating a high volatility tends to be followed by a high volatility, and low volatility tends to be followed by low volatility. This feature is identified as volatility persistence or volatility clustering. The basic GARCH model captures this feature with an exponential decay in the autocorrelation of conditional variance. However, it has been noticed that the squared and absolute returns of financial assets have serial correlations that decay much slower than exponentially. To the best of our knowledge, previous studies in agricultural commodity futures returns have not paid particular attention to this long memory phenomenon.

In this study, plotting the autocorrelation function for the squared daily cotton futures returns is used to check for the presence of the long memory behavior. If such behavior exists, the Integrated GARCH (IGARCH) model will be used. IGARCH eliminates the intercept coefficient α_0 in equation (4) and restricts the sum of all other α_j and β_j coefficients to be one (Engle and Bollerslev, 1986).[5]

Full Model with External Effects

Although the objective of this study is to identify the information effect on cotton futures market, it is necessary to account for other potential determinants of market volatility while considering the effect of public and private reports. Well-documented external factors include day-of-the-week effects (e.g. Yang and Brorsen, 1994; Isengildina-Massa, Irwin, and Good, 2006) and seasonality in variance (e.g. Hennessy and Wahl, 1996; Isengildina, Irwin, and Good, 2006). In addition, Williams and Wright (1991) made a theoretical argument that market conditions affect the reaction of a storable commodity's

[5] The IGARCH process is not weekly stationary as the unconditional variance does not exist. Nelson (1990) showed that the IGARCH(1,1) process is strongly stationary if $E\ln(\alpha_1 + \beta_1 z_t^2) < 0$. Therefore, the parameters of the model can still be consistently estimated by MLE.

price to announcements. "Market conditions" have latter been interpreted as commodity stock levels or inventory conditions (Good and Irwin, 2006; Colling, Irwin, and Zulauf, 1996; Adjemian, 2012).

The effect of external factors is commonly estimated by adding dummy variables into the mean/or variance equations. In this study, the dummy variables for each day of the week, including D_T, D_w, D_H and D_F, with D_M treated as the base category, are included in both the mean equation (2) and the variance equation (4). Using D_T as an example, D_T equals one if Tuesday and zero otherwise. Outlined in Isengildina-Massa, Irwin, and Good (2006) and Karali (2012), seasonality is introduced into the variance equation as 11 monthly dummy variables (D_{JAN} for January, D_{FEB} for February, D_{MAR} for March, D_{APR} for April, D_{MAY} for May, D_{JUN} for June, D_{JUL} for July, D_{AUG} for August, D_{SEP} for September, D_{OCT} for October, D_{NOV} for November) with D_{DEC} for December as the base categories. Monthly cotton stocks data (value of ending stocks, which is recorded on the last day of the month) are drawn from the USDA Economic Research Service's Cotton and Wool Situation and Outlook Yearbook. The procedure to generate the inventory level for each day is described in Adjemian (2012). He defined the stock level on the report day of the first month (C) is S_C and the stock on the report day of the next month (N) is S_N. Then the stock level for any day t between report days C and N is calculated by linear interpolation as:

$$(6) \qquad \hat{S}_t = \begin{cases} S_C & \text{if } t=C \\ \hat{S}_{t-1} + \dfrac{S_N - S_C}{N - C} & \text{if } C<t<N \end{cases} .$$

The calculated daily stock levels can be then ordered by their magnitudes and the lowest $1/5^{th}$ are recorded as low stock levels. The stock level effect is tested by adding a dummy variable D_{LOW} into the variance equation (4) directly. D_{LOW} equals one if the daily stock level is low and zero otherwise.

Following Isengildina-Massa, Irwin, and Good (2006) and Karali (2012), the effect of reports on cotton daily futures returns is measured only in the variance equation because the positive effect of reports canceled out with the negative effect of reports in the mean equation. D_{ES} for *Export Sales*, D_{CP} for *Crop Progress*, D_{WASDE} for *WASDE*, D_{PP} for *Perspective Plantings* and D_{CTM} for *Cotton This Month* reports are introduced as dummy variables with the value of one on the event day and zero otherwise. We also include a weekend-holiday factor, which we define as a report release after the futures market closes on Friday or the day before a holiday. Because the futures market closes on weekends and holidays, the markets have more time to react to the new information. We anticipate that the effect of reports would be influenced by this weekend-holiday effect. Two dummies D_{HWCP} and D_{HWCTM}[6] are generated and added into the variance equation. These dummy variables equal one on the first day after the weekends or holidays if the

[6] D_{HWES}, $D_{HWWASDE}$, and D_{HWPP} are not included because the holiday-weekend effect does not apply to the *Export Sales*, *WASDE*, and *Perspective Plantings* reports.

corresponding report releases after the futures market closes on the previous Fridays or the day before holidays, and zero otherwise.

Results

Model Selection[7]

Although previous studies normally included ten lagged values in the mean equation (Yang and Brorsen, 1994; Isengildina-Massa, Irwin, and Good, 2006), the best fitting ARMA model to estimate the daily cotton futures CTC returns was an autoregressive process with four lags.[8] Additionally, the null hypothesis of no ARCH effect with lag of five[9] was rejected at the 1% significance level, indicating the need for using a GARCH model of some sort.

The GARCH(1,1)-normal model was estimated first and the test statistics are presented in the first column of table 3. No higher order of GARCH model is needed as the LM test indicates there is no ARCH effect left after fitting the GARCH(1,1)-normal. If the residuals are normally distributed, the standardized residuals in the QQ plot should lie alongside a straight 45-degree line. However, the QQ plot in figure 3a of the standardized residuals calculated based on the GARCH(1,1)-normal model indicates a departure from normality as the points are off the straight line at both ends. This finding suggests using a distribution with fatter tails.

The GARCH(1,1)-t was then estimated and the test statistics can be found in the second column of table 3. The LM test result is consistent with the one for GARCH(1,1)-normal. The Akaike Information Criterion (AIC) and the Schwartz Bayesian Criterion (SBC) for GARCH(1,1)-t are smaller than the ones for GARCH(1,1)-normal, consistent with the GARCH(1,1)-t being better. The standardized residuals computed after fitting the GARCH(1,1)-t more closely follow the straight line in the QQ plot in figure 3b, suggesting that the GARCH(1,1)-t is a better fit for cotton daily futures returns.

As described in the methodology section, asymmetry can be tested by examining the correlation between the squared returns and lagged returns. The correlation between these two variables is -0.02, which suggests no asymmetry. Furthermore, the insignificant asymmetric coefficient γ in equation (5) of the TGARCH-normal model leads to the same conclusion.

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[7] Due to space limitation, the model selecting process is only explained in detail for the CTC returns.

[8] Details on the selection of AR(4) is available upon request.

[9] The null hypothesis of the Lagrange multiplier test with other lag values were also rejected.

Figure 4 shows the autocorrelations (ACF) and partial autocorrelations (PACF) plots of the squared CTC returns. Starting from lag one, the autocorrelations decay much slower than an exponentially decay expected for a GARCH model. In addition, the sum of the GARCH coefficients α_1 and β_1 for GARCH(1,1)-t is very close to one. Both findings suggest that the daily cotton futures returns have long memory behavior. Therefore, the IGARCH(1,1)-t was fitted next to capture the strong persistence in the returns' variance and the test statistics are reported in the third column of table 3. Due to this change, that the intercept in the variance equation is eliminated while the other GARCH coefficients were forced to add up to one. Although the log-likelihood was reduced from -8063.34 (from GARCH(1,1)-t) to -8071.01, which implies a log-likelihood ratio test statistic of 15.34 with two degree of freedom, Engle and Bollerslev (1986) argued that this reduction is mainly due to the restriction of setting the intercept to be zero. The QQ plot for IGARCH(1,1)-t in Figure 3 demonstrates that IGARCH(1,1)-t is preferred to GARCH(1,1)-t as the standard residuals follows the straight line in figure 3c closer than in 3b.

GARCH(1,1)-t with mean was also tested and the results are reported in the last column of table 3. Neither the coefficient for h_t nor the log-likelihood ratio statistic was significant, indicating little support for including the conditional standard deviation in the mean equation (2).

Based on the results in table 3, the best fitting model for daily cotton futures CTC, CTO, OTC returns were AR(4)-IGARCH(1,1)-t, AR(4)-GARCH(1,1)-t with mean, and AR(7)-IGARCH(1,1)-t, respectively.

Full Model for CTC Returns[10]

The first column in table 4 presents the results for CTC returns including all external factors (the day-of-week effect both in the mean and variance equation, the seasonality effect, reports effect, stock level effect, and weekend-holiday effect in the variance equation). Autocorrelation was significant in the second and the fourth lags. Because the external effects were introduced through a series of dummy variables, the estimates need to be interpreted relative to the base alternative of a no-report Monday in December with a high stock level. Wednesday returns appeared to be 0.144 percentage points higher than Monday returns and cotton futures were less volatile on Wednesdays and Fridays. Seasonality can be found in May and September where cotton futures were significantly more volatile in these two months than in December. The stock level effect and weekend-holiday effect were both insignificant. The GARCH coefficients in the variance equation suggest that the conditional variance of cotton futures placed a weight of about 95.3% on

[10] Because of the space limitation, the impacts of external effects, especially the information effect, were explained focusing on the CTC returns.

the prior day's conditional variance estimate and a weight of 4.7% on the previous day's information about returns.

Effects of Public and Private Reports

According to the results in the column 1 of table 4, the coefficients of the dummy variables are positive for most reports except *Crop Progress*. Positive signs indicate USDA reports increase the conditional variance of returns on the event day, and under market efficiency, provide new information to the market. Among the five reports, *WASDE* and *Perspective Planting* reports had a significant impact on cotton futures CTC returns. The release of *WASDE* and *Perspective Planting* report increased the conditional variance by a factor of 0.5827 and 0.8468, respectively. The only private report included in the study, *Cotton This Month*, did not significantly affect the cotton market.

Since return volatility in an agricultural market is often perceived in terms of standard deviation, Isengildina-Massa, Irwin and Good (2006) suggested interpreting the effect of reports relative to the estimated average standard deviation of the daily futures returns. Therefore, the coefficients in table 4 can be translated to changes in standard deviation of the underlying futures returns using the comparative statistic equation:

(7) $$\frac{\partial h_t}{\partial D_i} = \frac{\partial h_t}{\partial h_t^2} \times \frac{\partial h_t^2}{\partial D_i} = \frac{1}{2h_t} \times \delta_i = \frac{\delta_i}{2h_t},$$

where δ_i is the estimated coefficient for each report and h_t is the estimated mean conditional standard deviation from the IGARCH(1,1)-t model. In table 5, the mean estimated conditional standard deviation is 1.75%, calculated as the average across all observations. The coefficients in table 5 were drawn from the first column of table 4 and the partial derivative $\partial \hat{h}_t / \partial D_i$ can be interpreted as the increase in the conditional standard deviation of cotton futures CTC returns associated with the release of a report, given all other external factors constant. For example, the partial derivative for *Perspective Planting* is 0.248 (calculated by $\frac{0.8648}{2 \times 1.705}$), indicates that the conditional standard deviation of cotton futures returns increased by 0.248 percentage points on average because of the release of a *Perspective Planting* report. The proportion of the mean $\hat{h}_t$ in table 5 represents the increase in conditional standard deviation due to report release expressed as a proportion of the mean conditional standard deviation. For example, the conditional standard deviation of cotton futures returns was 14.6 percent (0.248/1.705) greater on the release days of *Perspective Planting* reports. The release of *WASDE* also significantly increased the mean conditional standard deviation by about 10 percent.

Following Adjemian (2012), the impact of information can be explained one step further, in the context of a holder of cotton futures contract, measured against the size of the maintenance margin. The maintenance margin is the minimum amount of collateral that has to be posted in an account for a futures position to remain open. Currently, IntercontinentalExchange requires \$1,750 for a speculative or hedge trader and the size of the cotton futures contract is 50,000 pounds. Results in table 6 illustrate the impact of report release on market participants. At the mean settle price of \$0.673 per pound during our sample period, *WASDE* reports moved cotton prices by an average of \$0.0012 (0.673*0.171) per pound. In terms of the futures contract, the *WASDE* shifted the value of each contract (up or down) by an average of \$57.5 (\$0.0012*50,000 pounds), which represents 3.29% (\$57.5/\$1,750) of collateral tied up in a position. On the other hand, the release of *Perspective Planting* report resulted in 4.77% change in the collateral. Similar interpretation using the maximum settle price of cotton \$2.14 per pound showed that the release of *WASDE* and *Perspective Planting* reports could change the value of a cotton futures contract by as much as \$182.8 and \$265.7—10.45% and 15.18% on collateral, respectively.

WASDE is considered one of the most valuable forecasting reports for agricultural commodities and its value has been analyzed by multiple studies. It is useful to find out if prices react differently to *WASDE* reports released at various times within a year. Therefore, the interaction terms for Monthly effects with *WASDE* dummies are included in the full model and the results are reported in the column 2 of table 4. The monthly effects of *WASDE* reports are also plotted in figure 5. Based on the results, the September *WASDE* report had the largest significant impact on price volatility as it increased the conditional variance of the CTC returns by 1.74 percentage point comparing with a non-*WASDE* event day in December, given other external factors constant.

Column 3 of table 4 presents the results with only *WASDE* in the model. The significant coefficient for the *WASDE* report is 0.6501, which is higher than the coefficient in the column 1 of that table, suggesting that evaluating *WASDE* reports separately overestimates their effects due to "clustering". The extent of clustering in our sample is 67 out of 205 *WASDE* event days, with one or two other reports also published in 67 days.

Comparison of results for CTC, CTO, and OTC returns

While table 4 presents the results of the full model with all external effects (day-of-week, seasonality, stock level, weekend-holiday, and reports effect) for CTC returns, table 7 reports the model with selective external factors for CTC, CTO, and OTC returns. The external factors are included if they improved the fit of the model significantly using a series of log-likelihood ratio tests. Different "best fitting" models were applied for various returns as described in a previous section. According to the results, the day-of-week effect was included both in the mean and variance equations for CTC and OTC returns, while it was only added in the variance equation for CTO returns. The weekend-holiday effect for *Crop Progress* report was included only in CTO and OTC returns.

All CTC, CTO, and OTC returns were used in the study to examine the progression of market reaction to new information. Isengildina-Massa, Irwin, and Good (2006) discussed the three different patterns of market reaction. First, under market efficiency, the futures price may reach its new equilibrium shortly after the release of new information between trading sessions. In this case, CTO returns would reflect the full impact of the new information while the OTC returns would reflect no impact and the CTC returns would reflect the impact dampened by additional information arriving in the market during the trading day. The second scenario is when the market is not efficient and tends to over-react to new information, and the third scenario is when the market reacts to new information but not instantaneously. If the market reaction follows the second or third scenarios, the initial reaction (open price of the event day) should not be used, and the CTC returns would reflect the true equilibrium.

The coefficient results in table 7 show that the *WASDE* effect was significant using the CTO and CTC returns while the impact of Perspective Planting was significant using the CTC and OTC returns. Interestingly, the impact of the only private report, *Cotton this Month*, was also significant in the OTC returns.

Notice that the magnitudes of coefficients can be only compared within one type of returns. At a minimum, the comparisons among different returns should be conducted by using the ratios of coefficients of the reports relative to the corresponding mean of estimated conditional variance. Figure 6 presents the market reaction to *WASDE*, *Prospective Planting*, and *Cotton This Month* using different returns. The values above each bar represent the increase in conditional standard deviation associated with each report. For example, given other external effects constant, the conditional standard deviation of cotton future returns was 11.9%, 7.5%, and 4.1% greater on the release days of *WASDE* reports using the CTC, CTO, and OTC returns, respectively.

Graph 1 in figure 6 indicates that the cotton futures price responded to the *WASDE* report immediately (CTO with the change of 7.5%) and continuously absorbed the new information through the trading day (OTC with the change of 4.1%, insignificant). Although the reaction during the trading day was not significant, the impact of *WASDE* using the CTC returns was significant. Therefore, the CTC returns was preferred since using CTO apparently under-estimates the impact of *WASDE* reports. On the other hand, graph 2 shows that the cotton market reacted to the *Perspective Planning* report slowly during the trading session since no impact was observed in CTO returns (0%), but a significant effect was detected in OTC (15.2%) and CTC (14.8%) returns. A similar pattern, but even more pronounced is observed in market reaction to the release of *Cotton This Month* reports. As shown in in graph 3, almost no reaction is observed in the opening prices (CTO with the change of 0.8%, insignificant) but a small reaction is observed during the event day[11] (OTC with the change of 3%, significant). This reaction

[11] Note the event days for *Cotton This Month* were considered as the second days after the release of every month's report.

is not strong enough to be statistically significant relative to higher volatility of the CTC returns (1%).

Summary and Conclusions

This study estimated the effect of all major public and private reports on the cotton futures market from 1995 through 2012. The estimation was based on the event study approach with the events measured by the release of 5 major reports: *Export Sales*, *Crop Progress*, *WASDE*, and *Perspective Plantings* (public reports from USDA) and *Cotton This Month* (private report from ICAC). In measuring the report effects, we controlled for the day-of-week, seasonality, and stock level effects on cotton futures returns.

A best fitting GARCH-type model was carefully selected to model cotton futures returns, characterized by non-normal, time-varying volatility.

Instead of investigating the information effect of a single report, this study analyzes the effects of five reports simultaneously, which avoid the issue of overestimation due to "clustering of reports". In fact, the results indicate the existence of the "clustering reports" problem as the coefficient of the *WASDE* report is smaller as expected when we included all 5 reports instead of having only the *WASDE* report. Having all five reports also allow us to judge the relative importance of different reports. Results indicate the *Perspective Planting* has the largest effect on the cotton market, followed by the *WASDE* reports. Specifically, information contains in the average *Perspective Planting* report is estimated to affect the price of cotton futures contracts by more than $83.6/contract at the mean settle price during the sample period, equivalent to 4.7% of collateral for a trader in a single day, and the release of the *WASDE* report brings more than 3.3% gain or loss of collateral. By further investigating the price reaction to *WASDE* report over time, we find that September *WASDE* report has the largest effect on price volatility. The effects of the other two public reports *Export Sales* and *Crop Progress* are not significant. The impact of the only private report included in this study, *Cotton this Month*, is much smaller and delay as detected in Open-to-Close results.

The analysis of this study was also carried out using the Close-to-Close, Close-to-Open, and Open-to-Close returns to investigate the progression of market reaction to new information. This analysis demonstrates that although most of the reaction to *WASDE* reports happened immediately after the report release, the cotton market continuously absorbed the new information throughout the trading day. This finding is slightly different from Adjemian (2012) where market reaction to *WASDE* reports was concentrated in the opening futures prices following the report's announcement. We also discover that the cotton market reacts to the *Perspective Planning* report not immediately but slowly during the trading session. Similar results are found in the reaction to the *Cotton This Month* report but with a much smaller magnitude.

This study contributes to the literature on the value of information by simultaneously evaluating the impact of five public and private reports on the cotton futures market. The findings can assist market participants, who are exposed to announcement shocks, to build expectations concerning the main information resource. This study reflects only one aspect (moves in the price in the futures market) of the use of USDA reports. Other purposes such as the use of data for policy analysis or research are not covered. Future studies are necessary to generate a complete benefit-and-cost analysis of the value of USDA reports, which would further help USDA officials to efficiently allocate public funds to their best uses.

References

Adjemian, M. K. “Quantifying the WASDE announcement effect.” American Journal of Agricultural Economics 94(2012):238-256.

Bollerslev, T. “Generalized Autoregressive Conditional Heteroskedasticity.” Journal of econometrics 31(1986):307-327.

Bollerslev, T. “A Conditionally Heteroskedastic Time Series Model for Speculative Prices and Rates of Return.” The review of economics and statistics (1987):542-547.

Brockwell, P. J., and R. A. Davis. Time series: theory and methods. Springer, 2009.

Colling, P. L., and S. H. Irwin. “The Reaction of Live Hog Futures Prices to USDA ‘Hogs and Pigs Reports’.” American Journal of Agricultural Economics 72(1990):84-94.

Colling,P. L., S. H. Irwin, and C. R. Zulauf. “Reaction of Wheat, Corn and Soybean Futures Prices to USDA ‘Export Inspections’ Reports.” Review of Agricultural Economics 18(1996):127-136.

Dorfman, J. H., and B. Karali. “A Nonparametric Search for Information Effects from USDA Reports.” Paper presented at the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, St. Louis, Missouri, April 22-23, 2013.

Engle, R. F. “Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation.” Econometrica: Journal of the Econometric Society (1982):987-1007.

Engle, R. F. “Risk and Volatility: Econometric Models and Financial Practice.” American Economics Review 94(2004):405-420.

Engle, R. F., and T. Bollerslev. “Modelling the Persistence of Conditional Variances.” Econometric reviews 5(1986):1-50.

Fortenbery, T. R., and D. A. Summer. “The Effects of USDA Reports in Futures and Options Markets.” The Journal of Futures Markets 13(1993):157-173.

Garcia, P., J. S. Roh, and R. M. Leuthold. “Simultaneously Determined, Time-Varying Hedge Ratios in the Soybean Complex.” Applied Economics 27(1995):1127-1134.

Glosten, L. R., R. Jagannathan, and D. E. Runkle. “On the Relation Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks.” Journal of Finance 48(1993):1779-1801.

Good, D. L., and S. H. Irwin. "Understanding USDA Corn and Soybean Production Forecasts: An Overview of Methods, Performance and Market Impact over 1970–2005." Department of Agriculture and Consumer Economics, University of Illinois Urbana-Champaign, 2006.

Grunewald, O., M. S. McNulty, and A. W. Biere. "Live cattle futures response to cattle on feed reports." American Journal of Agricultural Economics 75(1993):131-137.

Hansen, P. R., and A. Lunde. "A Forecast Comparison of Volatility Models: Does Anything Beat a GARCH (1, 1)?" Journal of applied econometrics 20(2005):873-889.

He, C., and T. Teräsvirta. "Properties of Moments of a Family of GARCH Processes. Journal of Econometrics 92(1999):173-192.

Hennessy, D. A. and T. I. Wahl. "The Effects of Decision Making on Futures Price Volatility." American Journal of Agricultural Economics 78(1996):591-603.

Isengildina, O., H. I. Scott, and D. L. Good. "The Value of USDA Situation and Outlook Information in Hog and Cattle Markets." Journal of Agricultural and Resource Economics (2006): 262-282.

Isengildina-Massa, O., S. H. Irwin, D. L. Good, and J. K. Gomez. "The Impact of Situation and Outlook Information in Corn and Soybean Futures Markets: Evidence from WASDE Reports." Journal of Agricultural and Applied Economics 40(2008):89-103.

Isengildina-Massa, O., S. H. Irwin, D. L. Good, and J. K. Gomez. "Impact of WASDE reports on implied volatility in corn and soybean markets." Agribusiness 24(2008):473-490.

Isengildina-Massa, O., and S. MacDonald. "Forecasting U.S. Cotton Prices in a Changing Market." Advances in Business and Management Forecasting 9(2013):91-113.

Karali, B. "Do USDA Announcements Affect Comovements Across Commodity Futures Returns?" Journal of Agricultural & Resource Economics 37(2012):77-97.

Mann, T. L. and R. J. Dowen. "Are Hog and Pig Reports Informative?" The Journal of Futures Markets 16(1996):273-287.

Marquardt, D. W. "An Algorithm for Least-Squares Estimation of Nonlinear Parameters." Journal of the Society for Industrial & Applied Mathematics 11(1963):431-441.

McNew, K. P., and J. A. Espinosa. “The Informational Content of USDA Crop Reports: Impacts on Uncertainty and Expectations in Grain Futures Markets.” Journal of Futures Markets 14(1994):475-492.

McKenzie, A. M. “Pre-Harvest Price Expectations for Corn: The Information Content of USDA Reports and New Crop Futures.” American Journal of Agricultural Economics 90(2008):351-366.

Nelson, D. B. “Stationarity and Persistence in the GARCH (1, 1) Model.” Econometric theory 6(1990):318-334.

Nelson, D. B. “Conditional Heteroskedasticity in Asset Returns: a New Approach.” Econometrica 59(1991):347-370.

Offutt, S. “Finding the Keys to Federal Statistical Programs.” The Exchange: The Newsletter of the American Agricultural Economics Association (2002):1.

Park, C. W. “Examining Futures Price Changes and Volatility on the Trading Day after a Limit-Lock Day.” The Journal of Futures Markets 20(2000):445-466.

Robinson, J. R. C. 2009. “Weekly Net Speculative Position from CFTC's Commitment of Traders”. The Cotton Marketing Planner Newsletter. Texas AgriLife Extension Service. http://agecon2.tamu.edu/people/faculty/robinson-john/commitmentoftraders.html. Accessed April 27, 2009.

Schaefer, M. P., R. J. Myers, and S. R. Koontz. “Rational Expectations and Market Efficiency in the U.S. Live Cattle Futures Market: The Role of Proprietary Information.” The Journal of Futures Markets 24(2004):429-451.

Sumner, D. A., and R. Mueller. “Are Harvest Forecasts News? USDA Announcements and Futures Market Reactions.” American Journal of Agricultural Economics 71(1989):1-8.

Taylor, S. J. Modelling Financial Time Series. John Wiley and Sons, 1986.

Terasvirta, T., D. Tjostheim, and C. W. J. Granger. Modelling nonlinear economic time series. OUP Catalogue, 2010.

United States Department of Agriculture. National Agricultural Statistics Service. “NASS Suspends Certain Statistical Estimates and Reports Due to Sequestration”. http://www.nass.usda.gov/Newsroom/Notices/02_12_2013.asp. Accessed March 12, 2013.

United States Department of Agriculture. National Agricultural Statistics Service. "NASS Reduces Agricultural Estimation Programs". http://www.nass.usda.gov/Newsroom/Notices/10_17_2011.asp. Accessed October 17, 2011.

Williams, J. C., and B. D. Wright. Storage and Commodity Markets. Cambridge: Cambridge University Press, 1991.

Yang, S. R., and B. W. Brorsen. "Nonlinear Dynamics of Daily Futures Prices: Conditional Heteroskedasticity or Chaos?" The Journal of Futures Markets 13(1993):175-191.

Yang, S. R., and B. W. Brorsen. "Daily Futures Price Changes and Non-Linear Dynamics." Structural Change and Economic Dynamics 5(1994):111-132.

Zakoian, M. "Threshold Heteroscedastic Models." Journal of Economic Dynamics and Control 18(1994): 931-955.

Zivot, E. "Practical Issues in the Analysis of Univariate GARCH Models." Handbook of financial time series. T. G. Andersen, R. A. Davis, J. Kreiß, and T. Mikosch, eds. Berlin Heidelberg: Springer, 2009.

Table 1. New York Board of Trade (NYBOT) Cotton No. 2 Futures Contracts with Each Report Release Month

Month of Report Release	Cotton No. 2 Futures Contract
January	March
February	March
March	May
April	May
May	July
June	July
July	October
August	October
September	October
October	December
November	December
December	March

Table 2. Descriptive Statistics for Cotton Daily Futures Returns, January 1995-January 2012

	Close-to-Close Returns	Close-to-Open Returns	Open-to-Close Returns
Mean	-0.03	-0.06	0.03
Variance	3.03	0.59	2.52
Skewness	0.03	-0.28	-0.09
Kurtosis	4.50	10.03	5.24
Jarque.test	401.57***	8854.05***	898.32***

Note: Single, double, and triple asterisks (*, **, ***) denote statistical significance at 10%, 5%, and 1%.

Table 3. Test Statistics of Model Selection for Cotton Daily Futures Returns, January 1995-January 2012

	GARCH(1,1) -normal		GARCH(1,1) -t		IGARCH(1,1) -t		GARCH(1,1) -t with MEAN	
Close-to-Close Returns								
LM p-value with lags=10	0.8601		0.9103		0.7283		0.9085	
Mean Equation								
Intercept	-0.0401	*	-0.0368	*	-0.0371	*	-0.0784	
h_t							0.5730	
y_{t-1}	0.0323	**	0.0159		0.0147		0.0158	
y_{t-2}	-0.0377	**	-0.0392	**	-0.0382	**	-0.0392	**
y_{t-3}	0.0069		0.0090		0.0091		0.0090	
y_{t-4}	0.0340	**	0.0307	**	0.0299	**	0.0306	**
Variance Equation								
Intercept	0.0169	***	0.0135	***			0.0136	***
ε_{t-1}^2	0.0474	***	0.0495	***	0.0424	***	0.0497	***
h_{t-1}^2	0.9477	***	0.9474	***	0.9576	***	0.9472	***
Degree of Freedom			10.3655	***	10.8451	***	10.3718	***
Log-likelihood	-8096.24		-8063.34		-8071.01		-8063.17	
AIC	3.7968		3.7818		3.7850		3.7822	
SBC	3.8087		3.7952		3.7882		3.7971	
Close-to-Open Returns								
LM p-value with lags=10	0.9068		0.9489		0.9609		0.9554	
Mean Equation								
Intercept	-0.0381	***	-0.0113	*	-0.0113	*	0.0373	**
h_t							-0.0983	***
y_{t-1}	0.1364	***	0.0851	***	0.0865	***	0.0817	***
y_{t-2}	-0.0004		0.0198		0.0199		0.0150	
y_{t-3}	0.0395	**	0.0440	***	0.0451	***	0.0396	***
y_{t-4}	0.0228		0.0306	**	0.0312	**	0.0262	*
Variance Equation								
Intercept	0.0059	***	0.0014	**			0.0014	**
ε_{t-1}^2	0.0590	***	0.0894	***	0.0578	***	0.0899	***

Table 3. Continued

	GARCH(1,1) -normal		GARCH(1,1) -t		IGARCH(1,1) -t		GARCH(1,1) -t with MEAN	
h_{t-1}^2	0.9337	***	0.9272	***	0.9422	***	0.9266	***
Degree of Freedom			3.3257	***	4.0535	***	3.3460	***
Log-likelihood	-4416.01		-3956.43		-3970.89		-3948.76	
AIC	2.0726		1.8578		1.8636		1.8547	
SBC	2.0845		1.8719		1.8740		1.8696	
Open-to-Close Returns								
LM p-value with lags=10	0.4460		0.3583				0.3588	
Mean Equation								
Intercept	0.0288		0.0348	*	0.0343	*	-0.0331	
h_t							0.0543	
y_{t-1}	-0.0370	**	-0.0447	***	-0.0448	***	-0.0452	***
y_{t-2}	-0.0220		-0.0149		-0.0146		-0.0150	
y_{t-3}	0.0306	*	0.0293	*	0.0294	**	0.0291	*
y_{t-4}	0.0405	**	0.0394	***	0.0392	***	0.0392	**
y_{t-5}	-0.0046		0.0077		0.0076		0.0076	
y_{t-6}	0.0244		0.0177		0.0176		0.0174	
y_{t-7}	0.0194		0.0273	*	0.0277	*	0.0273	*
Variance Equation								
Intercept	0.0091	***	0.0060	**			0.0060	**
ε_{t-1}^2	0.0431	***	0.0397	***	0.0336	***	0.0399	***
h_{t-1}^2	0.9542	***	0.9595	***	0.9664	***	0.9593	***
Degree of Freedom			6.4919	***	7.0274	***	6.4649	***
Log-likelihood	-7640.76		-7563.76		-7568.96		-7563.04	
AIC	3.5873		3.5517		3.5532		3.5518	
SBC	3.6037		3.5696		3.5681		3.5712	

Note: Single, double, and triple asterisks (*, **, ***) denote statistical significance at 10%, 5%, and 1%.

Table 4. Results for Cotton Daily Futures Close-to-Close Returns, January 1995-January 2012

	Full Model with Five Reports		Full Model with Interaction (Monthly Effect and WASDE)		Full Model with WASDE Report Only	
Model			IGARCH(1,1)-t			
Mean Equation						
Intercept	-0.0831	*	-0.0823	*	-0.0882	*
y_{t-1}	0.0163		0.0153		0.0177	
y_{t-2}	-0.0399	**	-0.0373	**	-0.0378	**
y_{t-3}	0.0083		0.0065		0.0104	
y_{t-4}	0.0270	*	0.0254		0.0256	*
D_T (Tuesday)	0.0022		-0.0013		0.0017	
D_W (Wednesday)	0.1440	**	0.1330	**	0.1476	**
D_H (Thursday)	-0.0107		-0.0069		-0.0101	
D_F (Friday)	0.1008		0.0695		0.0816	
Variance Equation						
ε_{t-1}^2	0.0472	***	0.0446	***	0.0476	***
h_{t-1}^2	0.9528	***	0.9554	***	0.9524	***
D_{ES} (*Export Sales*)	0.2451		0.1424			
D_{CP} (*Crop Progress*)	-0.1675		-0.1314			
D_{WASDE} (*WASDE*)	0.5827	***	0.5658		0.6501	***
D_{PP} (*Perspective Planting*)	0.8468	**	0.8547	**		
D_{CTM} (*Cotton This Month*)	0.0385		0.0378			
D_T (Tuesday)	0.0444		-0.1252		0.0575	
D_W (Wednesday)	-0.1819	*	0.1118		-0.0837	
D_H (Thursday)	0.0471		-0.3281		0.1587	*
D_F (Friday)	-0.3295	***	0.0613	***	-0.2665	***
D_{JAN} (January)	0.0277		0.0126		0.0229	
D_{FEB} (February)	0.0235		-0.0121		0.0098	
D_{MAR} (March)	-0.0221		0.0201		-0.0003	
D_{APR} (April)	0.0101		0.0683		-0.0073	
D_{MAY} (May)	0.0784	**	0.0706		0.0312	
D_{JUN} (June)	0.0439		-0.0068		0.0114	
D_{JUL} (July)	0.0024		0.0301		-0.0305	
D_{AUG} (August)	0.0428		-0.0084		0.0045	
D_{SEP} (September)	0.0651	*	0.0026		0.0198	
D_{OCT} (October)	0.0128		-0.0124		-0.0250	*

Table 4. Continued

	Full Model with Five Reports		Full Model with Interaction (Monthly Effect and WASDE)		Full Model with WASDE Report Only	
D_{NOV} (November)	0.0377		-0.0014		-0.0103	
$D_{JANWASDE}$			-0.6650			
$D_{FEBWASDE}$			0.1005			
$D_{MARWASDE}$			-0.2427			
$D_{APRWASDE}$			-0.4181			
$D_{MAYWASDE}$			-0.0901			
$D_{JUNWASDE}$			-0.7562			
$D_{JULWASDE}$			0.0423			
$D_{AUGWASDE}$			0.1665			
$D_{SEPWASDE}$			1.1725	*		
$D_{OCTWASDE}$			0.2194			
$D_{NOVWASDE}$			0.7999			
D_{HWCP}	0.8031		0.6086			
D_{HWCTM}	0.1777		0.1443			
$D_{STOCKLEVEL}$	0.0092		0.0061		0.0056	
Degree of Freedom	11.5938	***	11.7269	***	10.7897	***
R^2	0.0044		0.0044		0.0044	
Log-Likelihood	-8033.86		-8027.80		-8040.01	

Note: Single, double, and triple asterisks (*, **, ***) denote statistical significance at 10%, 5%, and 1%.

Table 5. Impact of Reports on Conditional Standard Deviation of the Daily Cotton Futures Close-to-Close Returns, January 1995-January 2012

Close-to-Close Returns				
Mean Estimated Conditional Standard Deviation $\hat{h}_t$ =1.705%				
Reports	Coefficients		$\partial\hat{h}_t / \partial D_i$	Proportion of Mean $\hat{h}_t$
D_{ES} (*Export Sales*)	0.2451		0.072	4.2%
D_{CP} (*Crop Progress*)	-0.1675		-0.049	-2.9%
D_{WASDE} (*WASDE*)	0.5827	***	0.171	10.0%
D_{PP} (*Perspective Planting*)	0.8468	**	0.248	14.6%
D_{CTM} (*Cotton This Month*)	0.0385		0.011	0.7%

Note: Single, double, and triple asterisks (*, **, ***) denote statistical significance at 10%, 5%, and 1%.

Table 6. *WASDE* and *Prospective Planting* Reports Effect in Context

	Effect on Returns ($/lb)	**Effect per Contract ($/Contract)**	**Return on Collateral**
	Mean Price (0.673$/lb)		
WASDE	0.0012	57.5001	3.29%
Prospective Planting	0.0017	83.5612	4.77%
	Maximum Price (2.140$/lb)		
WASDE	0.0037	182.8385	10.45%
Prospective Planting	0.0053	265.7073	15.18%

Table 7. Final Results for Cotton Daily Futures Returns, January 1995-January 2012

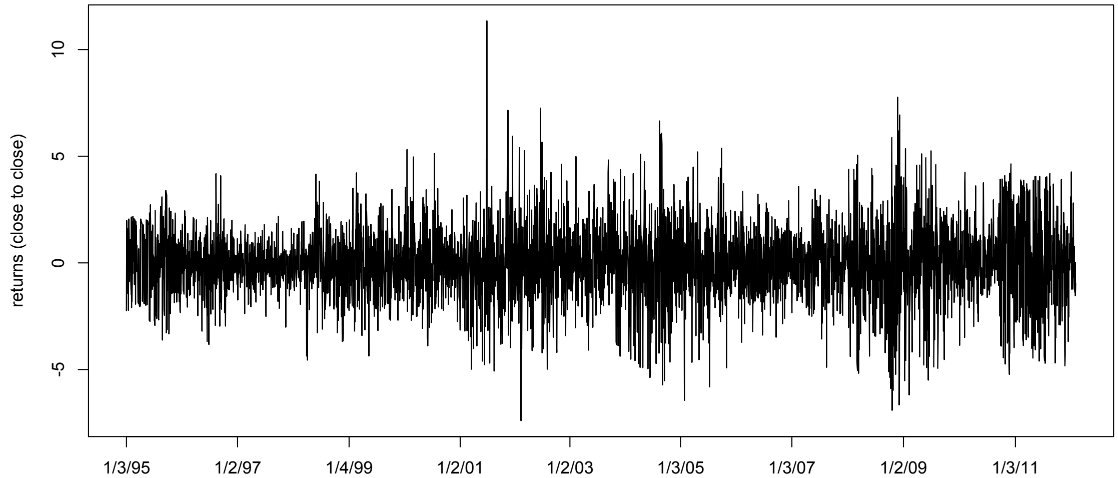
	Close-to-Close Returns		Close-to-Open Returns		Open-to-Close Returns	
	IGARCH(1,1)-t		GARCH(1,1)-t with Mean		IGARCH(1,1)-t	
Mean Equation						
Intercept	-0.0740		0.0398	***	0.0083	
h_t			-0.1066	***		
y_{t-1}	0.0166		0.0844	***	-0.0444	***
y_{t-2}	-0.0374	**	0.0130		-0.0141	
y_{t-3}	0.0083		0.0421	***	0.0248	
y_{t-4}	0.0272	*	0.0243	*	0.0386	**
y_{t-5}					0.0072	
y_{t-6}					0.0208	
y_{t-7}					0.0287	*
D_T (Tuesday)	-0.0201				-0.0190	
D_W (Wednesday)	0.1307	**			0.1060	*
D_H (Thursday)	-0.0240				-0.0348	
D_F (Friday)	0.0760				0.0785	
Variance Equation						
Intercept			-0.0083			
ε_{t-1}^2	0.0466	***	0.0784	***	0.0378	***
h_{t-1}^2	0.9534	***	0.9306	***	0.9622	***
D_{ES} (*Export Sales*)	0.2024		-0.0075		0.0673	
D_{CP} (*Crop Progress*)	-0.1097		0.0022		-0.0822	
D_{WASDE} (*WASDE*)	0.6896	***	0.0773	***	0.1945	
D_{PP} (*Perspective Planting*)	0.8622	**	0.0005		0.7228	**
D_{CTM1} (*Cotton This Month*)	0.0475		0.0102		0.1415	*
D_T (Tuesday)	-0.1025		-0.0144		0.1228	
D_W (Wednesday)	0.0151		-0.0087		-0.0736	
D_H (Thursday)	-0.3391		0.0428		0.1303	
D_F (Friday)	0.0475	***	0.0143		-0.3101	***
D_{JAN} (January)	0.0204		0.0004		0.0023	
D_{FEB} (February)	0.0289		0.0022		0.0185	
D_{MAR} (March)	-0.0267		-0.0010		-0.0308	*
D_{APR} (April)	-0.0033		0.0005		-0.0138	

Table 7. Continued

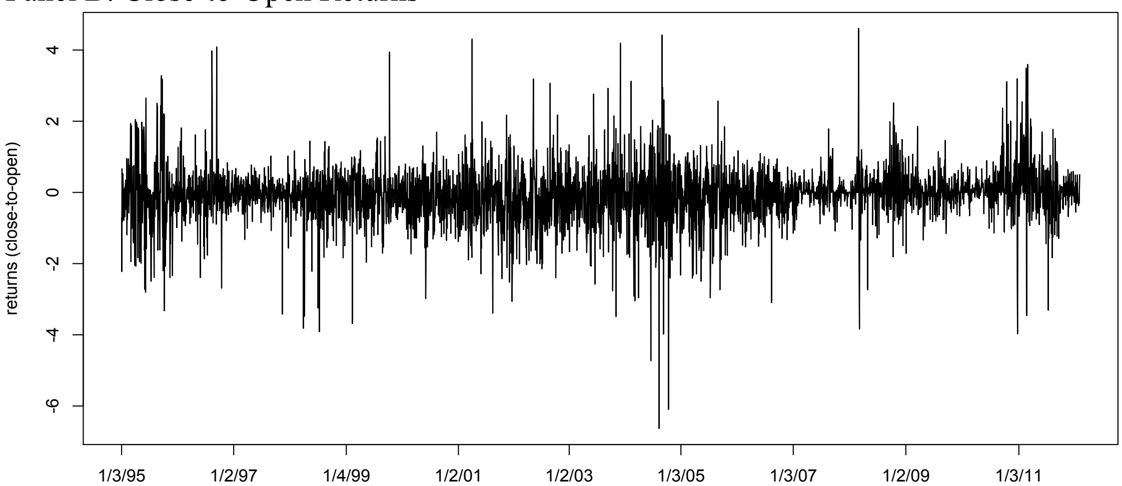
	Close-to-Close Returns		Close-to-Open Returns		Open-to-Close Returns	
D_{MAY} (May)	0.0639	*	-0.0026		0.0417	
D_{JUN} (June)	0.0381		0.0114	**	0.0328	
D_{JULY} (July)	0.0022		-0.0018		-0.0304	
D_{AUG} (August)	0.0343		0.0124	*	0.0236	
D_{SEP} (September)	0.0549		-0.0071		0.0438	
D_{OCT} (October)	0.0058		-0.0029		-0.0033	
D_{NOV} (November)	0.0150		0.0021		0.0101	
D_{HWCP}			0.2762		0.8405	
Degree of Freedom	11.4465	***	3.4535	***	6.7348	***
Diagnostics						
R^2	0.0044		0.0181		0.0062	
Log-Likelihood	-8035.29		-3920.13		-7538.56	

Note: Single, double, and triple asterisks (*, **, ***) denote statistical significance at 10%, 5%, and 1%.

Panel A: Close-to-Close Returns



Panel B: Close-to-Open Returns



Panel C: Open-to-Close Returns

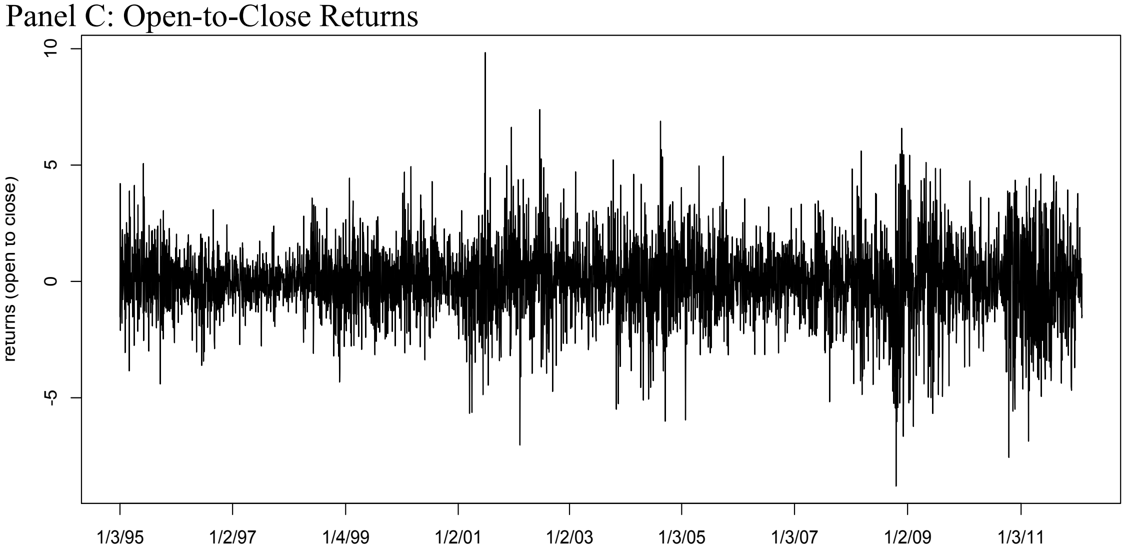
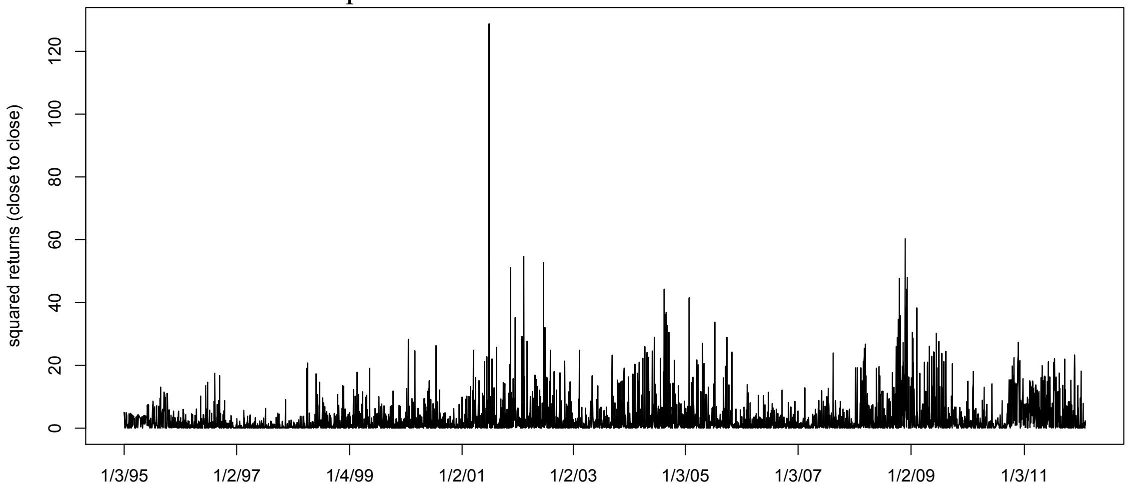
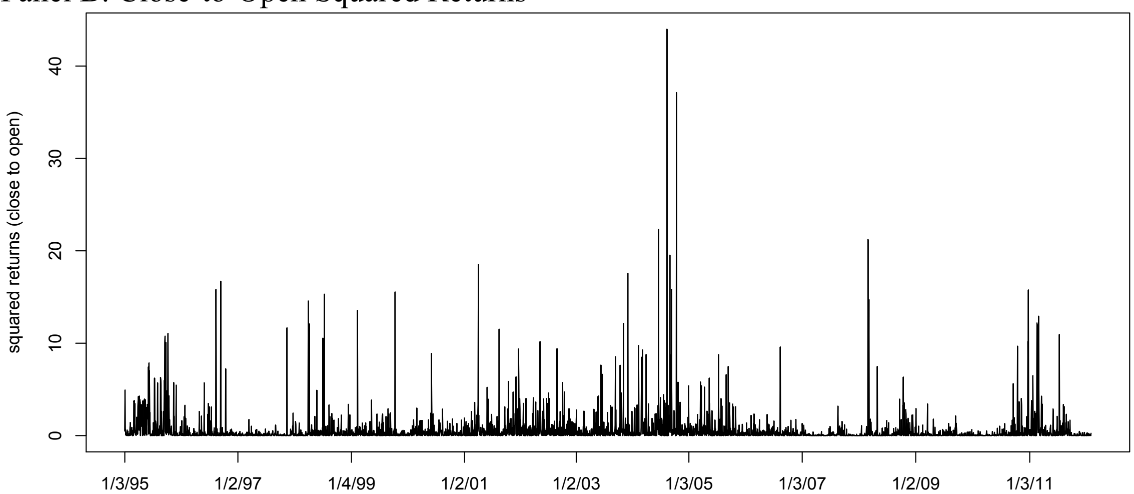


Figure 1. Cotton Daily Futures Returns, January 1995-Janaury 2012

Panel A: Close-to-Close Squared Returns



Panel B: Close-to-Open Squared Returns



Panel C: Open-to-Close Squared Returns

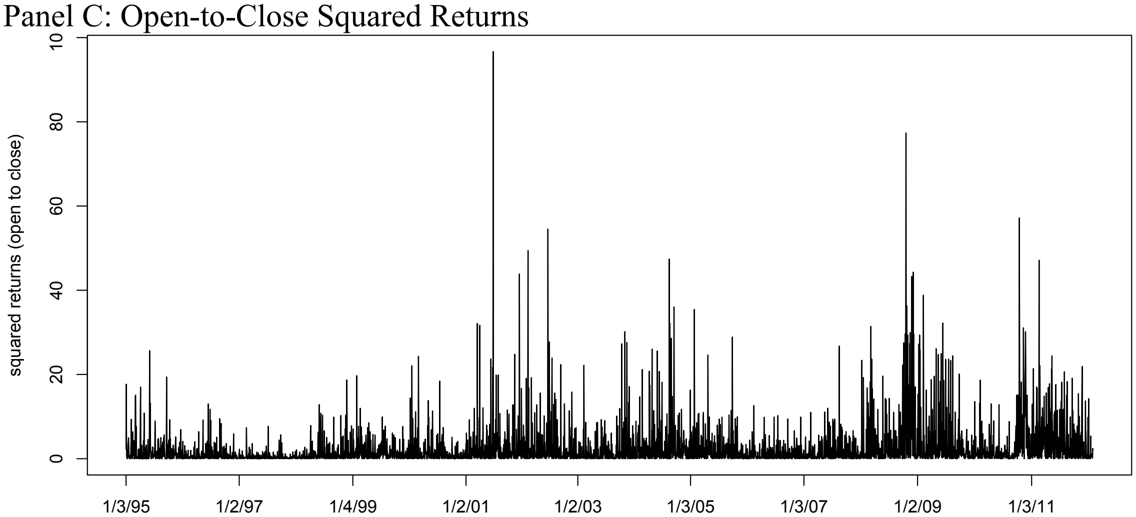
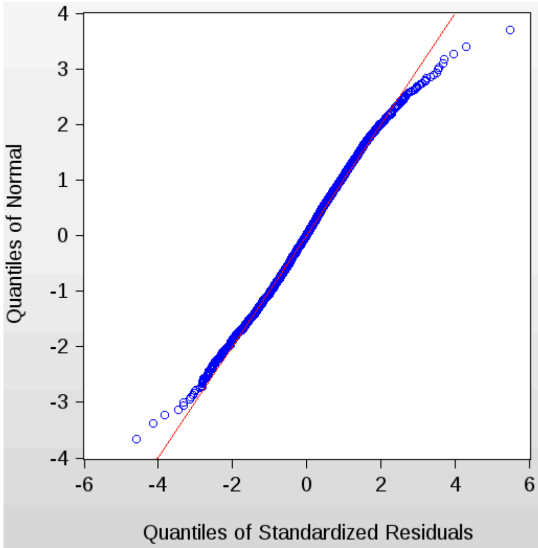
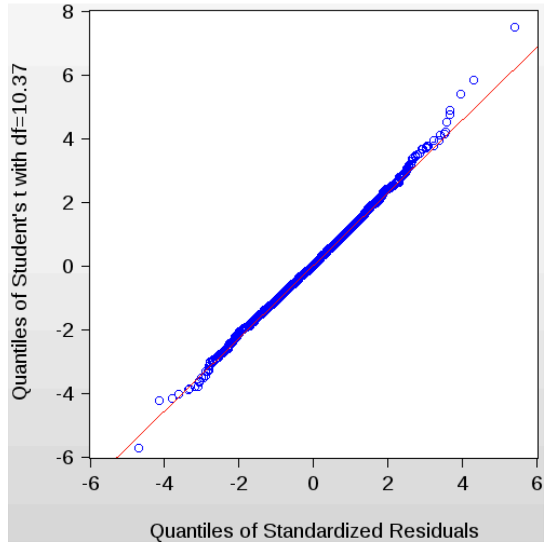


Figure 2. Cotton Daily Futures Squared Returns, January 1995-Janaury 2012

3a. QQ Plot for GARCH(1,1)-normal



3b. QQ Plot for GARCH(1,1)-t



3c. QQ Plot for IGARCH(1,1)-t

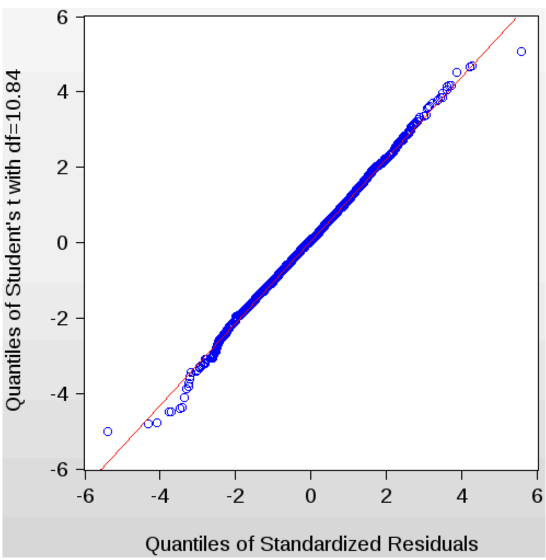


Figure 3. Quantile and Quantile Plot of GARCH(1,1)-normal, GARCH(1,1)-t, and IGARCH(1,1)-t models for Cotton Daily Futures Close-to-Close Returns, January 1995-Janaury 2012

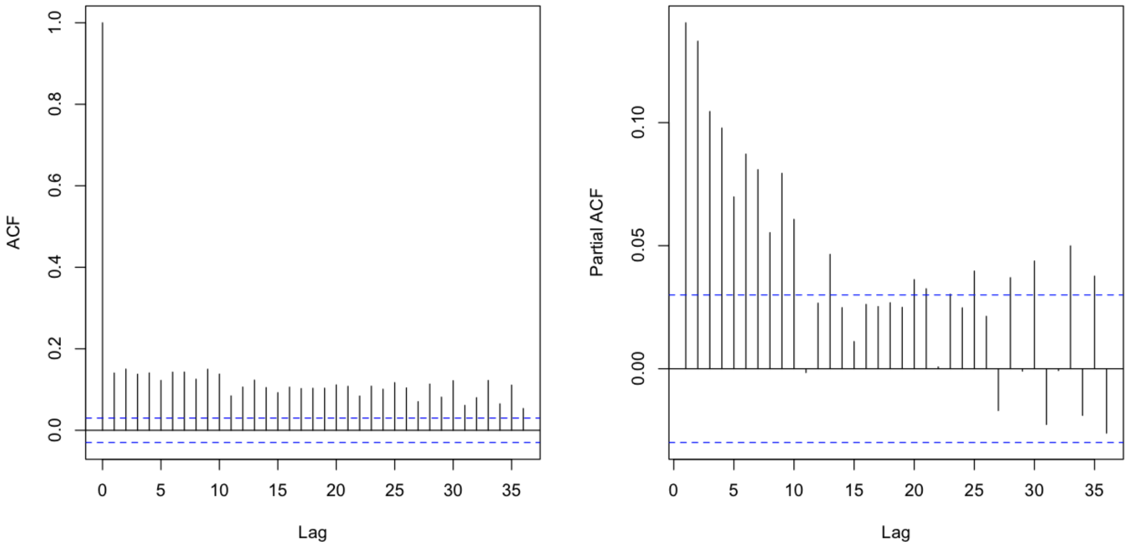


Figure 4. The Autocorrelations (ACF) and Partial Autocorrelations (PACF) Plots of the Squared Close-to-Close Returns, January 1995-Janaury 2012

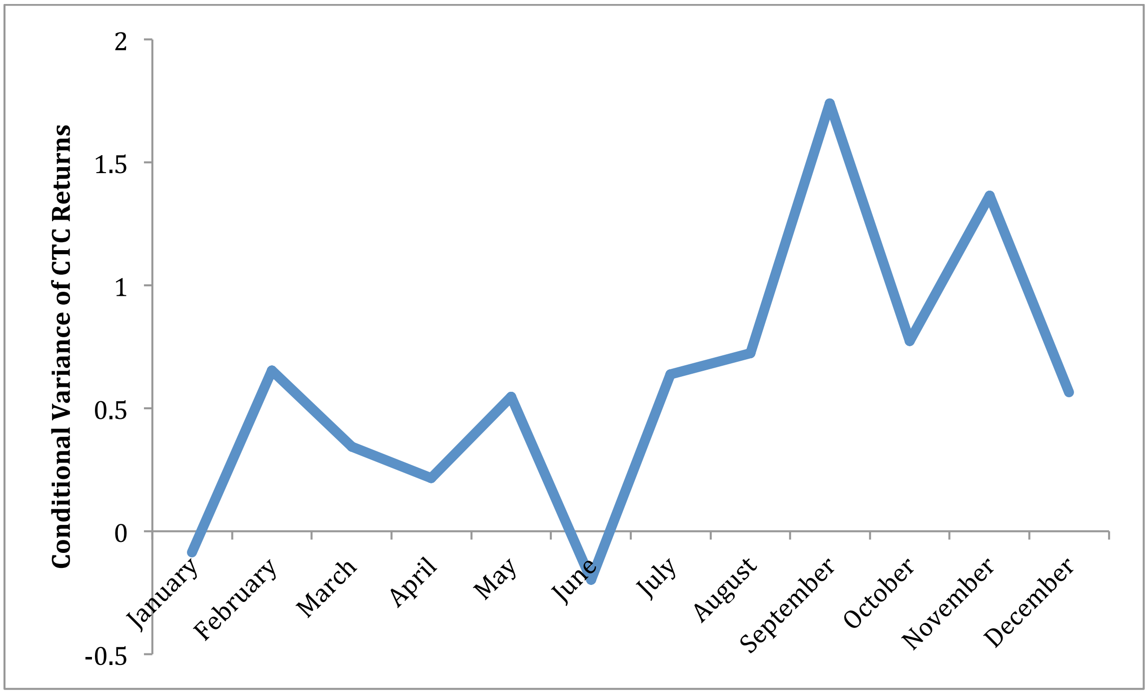


Figure 5. Monthly Effects of *WASDE* Reports on Cotton Daily Futures Close-to-Close Returns, January 1995-Janaury 2012

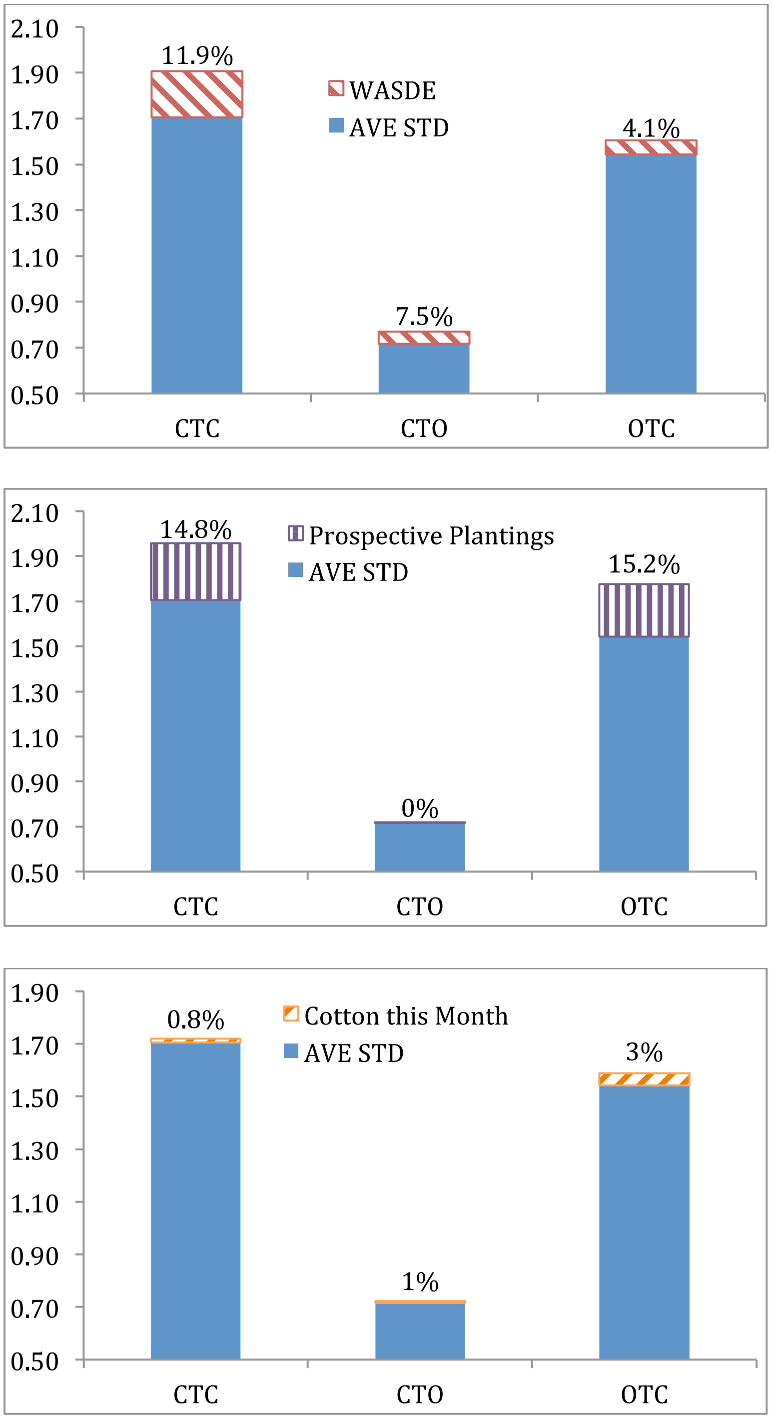


Figure 6. Progression of Market Reaction to *WASDE*, *Prospective Planting*, *Cotton This Month* Reports in Cotton Daily Futures Close-to-Close, Close-to-Open, and Open-to-Close Returns, January 1995-Janaury 2012