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APPLICATION OF MODERN STATISTICAL TOOLS TO SOLVING CONTEMPORARY ECONOMIC PROBLEMS: EVALUATION OF THE REGIONAL AGRICULTURAL CAMPAIGN IMPACT AND THE USDA FORECASTING EFFORTS

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APPLICATION OF MODERN STATISTICAL TOOLS TO SOLVING CONTEMPORARY ECONOMIC PROBLEMS: EVALUATION OF THE REGIONAL AGRICULTURAL CAMPAIGN IMPACT AND THE USDA FORECASTING EFFORTS

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Applied Economics

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by
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Accepted by:
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ABSTRACT

The research is comprised with three studies to implement statistical tools for examining two economic issues: the impact of a regional agricultural campaign on participating restaurants and efforts of U.S. Department of Agriculture (USDA) forecasting reports in agricultural commodity markets.

The first study examined how various components of the *Certified South Carolina* campaign are valued by participating restaurants. A choice experiment was conducted to estimate the average willingness to pay (WTP) for each campaign component using a mixed logit model. Three existing campaign components—Labeling, Multimedia Advertising, and the "Fresh on the Menu" program were found to have a significant positive economic value. Results also revealed that the type of restaurant, the level of satisfaction with the campaign, and the factors motivating participation significantly affected restaurants' WTP for the campaign components.

The second study evaluated the revision inefficiencies of all supply, demand, and price categories of World Agricultural Supply and Demand Estimates (WASDE) forecasts for U.S. corn, soybeans, wheat, and cotton. Significant correlations between consecutive forecast revisions were found in all crops, all categories except for the seed category in wheat forecasts. This study also developed a statistical procedure for correction of inefficiencies. The procedure took into account the issue of outliers, the impact of forecasts size and direction, and the stability of revision inefficiency. Findings suggested that the adjustment procedure has the highest potential for improving accuracy in corn, wheat, and cotton production forecasts.

The third study evaluated the impact of four public reports and one private report on the cotton market: *Export Sales*, *Crop Processing*, *World Agricultural Supply and Demand Estimates* (*WASDE*), *Perspective Planting*, and *Cotton This Month*. The "best fitting" GARCH-type models were 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 controlled for the day-of-week, seasonality, stock level, and weekend-holiday effects on cotton futures returns. We found statistically significant impacts of the *WASDE* and *Perspective Planting* reports on cotton returns. Furthermore, results indicated that the progression of market reaction varied across reports.

DEDICATION

This work is dedicated to the most important people in my life.

God: thank you for your unreserved love and thank you for the wisdom you provide me to accomplish this work.

My parents: thank you for your unconditional support with my studies. Thank you for your understanding and encouragement.

My husband: thank you for your endurance and your constant love. Because of you, my life at Clemson is full of laughs!

My church friends: I am so thankful for having you as my sisters and brothers. Thank you for your affirmation and prayers.

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CHAPTER ONE

INTRODUCTION

Overview and Objective

The current research aims to implement statistical tools for examining two economic issues: the impact of a regional agricultural campaign on participating restaurants and efforts of U.S. Department of Agriculture (USDA) forecasting reports in agricultural commodity markets. Both the campaign and the forecasts are supported by governmental funding. Given the current market environment that federal and state budgets have been gradually pruned, addressing these two issues will help government officials to justify the expenditure of public funds. This research comprises three manuscripts including 1) the examination of the *Certified South Carolina* campaign, 2) the evaluation of accuracy and efficiency of the World Agricultural Supply and Demand Estimates (WASDE), a forecasting report by the U.S. Department of Agriculture (USDA), and 3) the assessment of public and private information effects on the cotton market.

In the United States, regional agricultural campaigns, which promote locally grown products, have grown rapidly since the mid-1990s; by 2010, all 50 states had such campaigns in place (Onkenand Bernard, 2010). The *Certified South Carolina* campaign was launched on May 22, 2007. The “Fresh on the Menu” component, which promotes local restaurants preparing dishes with “Certified South Carolina” products, was added in February 2008. Most previous studies (e.g. Carpio and Isengildina-Massa, 2010; Patterson et al., 1999) analyzed the impact of locally grown campaigns focusing exclusively on the benefits received by farmers, while the impact of such campaigns on local restaurants had been neglected. The objective of the first study is to examine the perceived economic value of various components of the *Certified South Carolina* campaign by the generally overlooked segment of participating restaurants and to explore the relationship between campaign valuation and characteristics of participating restaurants. This study is described in Chapter 2.

Industry participants have relied on USDA forecasts to make production, marketing processing, and retailing decisions for many years. Recently, there have been concerns about the accuracy of USDA estimates. Releasing an incorrect forecast will mislead the markets and cause unnecessary price movements. In addition, errors in USDA price estimates may result in large changes in the payments to agricultural producers since some government payments are computed using these estimates (Isengildina-Massa, Karali, and Irwin, 2013). The USDA actually warns readers that its estimates are subject to revisions and sampling errors. The objective of the second study is to evaluate the monthly revision efficiency of all supply, demand, and price categories for U.S. corn, soybean, wheat, and cotton forecasts, published in the monthly WASDE reports, which are viewed as some of the most influential public reports. In addition, a statistical model is developed in this study, which takes into account outlier adjustment, the impact of other variables on inefficiency, and structural changes to correct for inefficiency and therefore improve the accuracy of WASDE forecasts. This study is described in Chapter 3.

The National Agricultural Statistics Service, part of the USDA, has a $156.8m budget for approximately 500 reports each year and 1,050 employees (Meyer, 2011). There is no doubt that releases of USDA reports move the markets. However, most previous studies evaluating the impact of USDA forecasting reports concentrated on one report at a time. In addition, while the USDA *Crop Production*, *the World Agricultural Supply and Demand Estimates* (*WASDE*), and other reports have been evaluated, the influences of many other reports, such as the *Crop Process* and *Perspective Plantings*, have been neglected. Furthermore, while we know which reports affect corn, soybean, wheat, livestock and hog markets, other commodities have been overlooked. Therefore, the objective of the third study is to estimate the impact of all major public and private reports on the cotton market. In measuring the report effects, we control for the day-of-week, seasonality, stock level, and weekend-holiday effects on cotton futures returns. This study is described in Chapter 4.

Chapter 5 summarizes the results from all three studies.

References

Carpio, C.E., and O. Isengildina-Massa. “To Fund or Not to Fund: Assessment of the Potential Impact of a Regional Promotion Campaign.” *Journal of Agricultural and Resource Economics* 35(August 2010):245-60.

Isengildina, O., B. Karali, S.H. Irwin. “When do the USDA forecasters make mistakes?” *Applied Economics* 45(2013):5086-5103.

Meyer, G. Reliability of US Crop Reports Questioned. *Financial Times*, July 12, 2011.

Onken, K.A., and J.C. Bernard. “Catching the ‘Local’ Bug: A Look at State Agricultural Marketing Programs.” *Choices* 25(2010):1-7.

Patterson, P.M., H. Olofsson, T.J. Richards, and S. Sass. “An Empirical Analysis of State Agricultural Product Promotions: A Case Study on Arizona Grown.” *Agribusiness* 15(1999):179-96.

CHAPTER TWO

VALUATION OF VARIOUS COMPONENTS OF A REGIONAL PROMOTION CAMPAIGN BY PARTICIPATING RESTAURANTS

Introduction

Government funded advertising campaigns play an important role in agricultural and food policy around the world. In the United States, regional promotion programs have grown rapidly since the mid-1990s. The number of states conducting such programs increased from 23 to 43 between 1995 and 2006 (Patterson, 2006), and by 2010 all 50 states had such programs in place (Onken and Bernard, 2010). Previous studies evaluating regional promotion campaigns showed mixed evidence regarding campaign effectiveness (e.g. Carpio and Isengildina-Massa, 2010; Govindasamy et al., 2003; Patterson et al., 1999). Govindasamy et al. (2003) found that the *Jersey Fresh* program generated about $32 of returns for fruit and vegetable growers for every dollar invested. In other words, the $1.16 million campaign generated $36.6 million in sales for New Jersey produce growers and a total economic impact for the state economy of $63.2 million in 2000. Carpio and Isengildina-Massa (2010) concluded that the *Certified South Carolina* campaign generated a return on investment of 618% or a benefit-cost (producers benefit / state government expenses) ratio of 6.18 in 2007. In contrast, Patterson (1999) found little evidence of an increase in local product sales due to the *Arizona Grown* campaign.

Most previous studies analyze the impact of the locally grown campaigns focusing exclusively on benefits received by farmers (e.g., Carpio and Isengildina-Massa, 2010; Patterson et al., 1999). While farmers tend to be the primary beneficiaries of such campaigns, their benefits extend far beyond and include consumers, restaurants and farmers' markets as well as the secondary effects on the rest of the economy (Govindasamy et al., 2003; Carpio and Isengildina-Massa, 2013). To the best of our knowledge, no studies of the impact of such campaigns on local restaurants have been conducted to date. Ignoring these additional effects of locally grown campaigns would lead to an underestimation of their impact, especially in cases where some of the campaign components focus exclusively on restaurants. Additionally, regional promotion campaigns have typically been analyzed as a whole, providing little guidance to policy makers about the value of separate campaign components. Given these limitations, the goals of the current study are twofold: 1) to examine the perceived economic value of various components of the *Certified South Carolina* campaign by the generally overlooked segment of participating restaurants, and 2) to explore the relationship between campaign valuation and characteristics of participating restaurants.

The *Certified South Carolina* campaign was launched on May 22, 2007 and was financed by special appropriations from the state legislature. The goal of the campaign was to increase consumer demand for the state produced food products and increase agribusiness profitability. Annual campaign expenditures averaged about $1.3 million during 2007-2010. Original campaign components included the design and distribution of labels and signage for "Certified South Carolina" products and advertisement of South Carolina food products on television, radio, magazines, newspapers and billboards. The "Fresh on the Menu" component, which promotes local restaurants preparing dishes with

“Certified South Carolina” products, was added in February 2008. In order to enroll into this free program, restaurants needed to complete an application form, pledging to offer a menu that includes at least twenty-five percent “Certified South Carolina” products such as fresh fruits, vegetables, meats and seafood as available in season. Participating restaurants take advantage of the South Carolina Department of Agriculture’s (SCDA) multimedia advertising and branding efforts, including kits and artwork for logos and online, radio, magazine, newspaper, and billboard advertisement promotions. When it was first introduced in 2008, 180 restaurants signed up for the “Fresh on the Menu” program. By July 2010, when the data for this study was collected, the campaign membership had increased to 288 restaurants.

Since restaurants are not required to pay a participation fee for the campaign, this study used a choice-based conjoint analysis method to determine the perceived economic value that participating restaurants place on each campaign component. The data generated from a discrete choice experiment were analyzed using a mixed logit model, allowing us to estimate participating restaurants’ average willingness to pay (WTP) for each of the campaign components, which represents their respective economic values (Holmes and Adamowicz, 2003). In addition to the average WTP estimates for each campaign component, we estimated individual level WTP values which are in turn used as dependent variables in linear regression models to uncover how individual WTP for each component is affected by participating restaurants’ characteristics. The findings of this study could help policy makers and marketers determine which campaign components are more effective and could be used to guide future campaign fund allocations. In an environment of decreasing state and federal funding it becomes increasingly important to have specific estimates of the effectiveness of alternative campaign investments.

Data and Methods

Survey Approach

The data used for estimation in this study were collected via a survey of the managers of 288 restaurants that participated in the South Carolina "Fresh on the Menu" in July 2010. The survey was administered through a combination of internet (Qualtrics) and mail[1] and included the entire population of participating restaurants. Every effort was made to obtain the highest possible response rate including the use of economic incentives, an invitation letter, the shortest possible survey instruments pre-tested using focus groups; the use of the Dillman survey method (with two reminders after the first (e-)mailing); and the use of a mail survey to complement online surveys. The survey generated 71 usable observations for a response rate of about 25%, which is relatively high compared to a 13.4% average response rate in a study of 199 online surveys conducted by Hamilton (2003)[2]. In order to assess the representativeness of our sample, we compared the location of the restaurants in the population with that of the sample (location was the only known characteristic of the population). The proportion of

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[1] The results of this study were not statistically different across the two survey formats.

[2] Although the relationship between low response rates and low survey accuracy has been
[2] Although the relationship between low response rates and low survey accuracy has been
academically debated for a long time, several recent studies suggest a very weak or non-existent relation between the two (Keeter et al., 2000; Curtin et al., 2000; Brick et al., 2003; Keeter et al., 2006; Holbrook et al., 2008).

restaurants from each region in the sample generally followed the corresponding proportion in the population except for one of ten regions considered: the Berkerly-Charleston-Dorchester whose proportion in the sample (16.4%) was lower than the proportion in the population (30.9%).[3]

Choice Experiment

Various methods are available to elicit and estimate preferences for products or services or the value of changes in the qualities of existing products. These methods include choice experiments (e.g., Adamowicz et al., 1998; Louviere, Hensher, and Swait, 2000), dichotomous choice questions (e.g., Hanemann, Loomis, and Kanninen, 1991; Ready, Buzby, and Hu, 1996), and experimental auctions (e.g., Lusk et al., 2001; List and Shogren, 1998). Choice-based conjoint analysis or choice experiments (CE) have the advantage of closely mirroring typical choice experience--making one decision over several options--and allowing a researcher to estimate the trade-offs between several competing product attributes (Lusk and Hudson, 2004). Additionally, CE are easier to organize with no requirement for laboratory sessions and the need of an actual product (which is not realistic in the context of this project). Several studies also prove that hypothetical responses to CE are very consistent with revealed preferences (e.g., Carlsson and Martinsson, 2001; Adamowicz et al., 1997).

CE are firmly rooted in the economic theory that the decision making process can

[3] A weighted maximum likelihood estimator was also used to explore the robustness of the results to the difference between the sampling and population proportions (Cameron and Trivedi, 2005). All the estimated coefficients were similar and had overlapping 95% confidence intervals except for the mean coefficient for SIGNAGE. This coefficient was significant in the model using weights.

be viewed as a comparison of indirect utility functions and analyzed within the random utility framework (McFadden, 1974). The data obtained from CE can then be analyzed using discrete choice models and the results can be used to estimate WTP values for the various attributes of the good or product under study (Alfnes et al., 2006; Holmes and Adamowicz, 2003; Revelt and Train, 1998). In this study we use CE to examine restaurant managers' preferences for each of the attributes (components) of the *Certified South Carolina* campaign. Thus restaurant managers are considered the consumers of the regional promotion campaign and choose the campaign profile (combination of various components) that allows them to reach the highest level of utility. Accordingly, the value of the campaign can be measured as the maximum amount of money restaurants would be willing to pay for a certain campaign profile. This approach allows us to estimate the economic value of the campaign, which is currently offered to participants free of charge.

In order to determine the perceived economic value of each component of the *Certified South Carolina* campaign, the CE design incorporated four attributes corresponding to the components of the existing campaign: (1) Labeling (LABEL) which provides labels for "Certified South Carolina" products; (2) Point of Purchase Signage (SIGNAGE) which provides "Certified South Carolina" signs at food buying locations, such as supermarkets, farmers markets, and roadside stands; (3) Multimedia Advertising (MULTI), which funds television, radio, magazine, newspaper, and billboard advertisements promoting "Certified South Carolina" products; and (4) the "Fresh on the Menu" component (FOTM) which promotes local restaurants preparing and selling menu items that include "Certified South Carolina" products in season. Each choice was associated with one of two payment methods (METHOD): membership fee or donation. These two options were selected because they are the most widely used methods for funding public and private programs that promote locally grown products. The payment amount was also added so that the WTP for each campaign component could be calculated. A pilot study of four randomly selected restaurants in the upstate region of South Carolina was conducted to determine the appropriate bid vector (following Ratcliffe, 2000). The payment levels (PAY) were identified as $20, $50, $100, $150, and $200. The combination of all the attributes and levels resulted in a total of 160 (2*2*2*2*2*5) possible campaign profiles and a full factorial design consisting of 12,720 (C^2_{160}) possible choices. However, it was not feasible to include such a large number of scenarios in a CE. Hence, a fractional factorial design was applied to choose 18 scenarios by comparing the D-Efficiency of each combination. Having 18 scenarios within a single survey was still considered excessive. Therefore, the design was blocked into three versions of the questionnaire where each respondent was offered 6 scenarios with trinary choices. A series of SAS Macro programs were used to first generate the campaign profiles and then to construct the CE used in this study. Figure 2.1 provides an example of one of the 18 scenarios. In each case, the manager of the restaurant was asked to choose from campaign A, B, or no campaign at all with two types of funding and 5 different funding levels. Having these options allowed the experimental design to fit an actual market situation without “forcing” a choice (Louviere, Hensher, and Swait, 2000).

Average WTP Estimation, Mixed Logit Model

The econometric choice model used in this study is the random parameter/mixed logit model[4] developed by Revelt and Train (1998). The mixed logit model was chosen because it allows efficient estimation of repeated choices by the same respondent within choice-based conjoint experiments. Moreover, this model relaxes the restrictive assumptions of the conditional logit model (Revelt and Train, 1998).

Following Revelt and Train (1998), the random utility function of restaurant managers (U_{ni}) is assumed to be comprised of a systematic (v_{ni}) and a random (ε_{ni}) component:

(2.1) $U_{ni} = v_{ni} + \varepsilon_{ni}$, *i=1,...,I,* $i \in C$, *and n=1,...,N,*

where U_{ni} is the true but unobservable indirect utility of restaurant *n* associated with campaign profile *i*. A restaurant chooses alternative *i* from choice set *C* only if $U_{ni} > U_{nj}$, where *n=1,..., N*, alternative $i, j \in C$ and $i \neq j$. Accordingly, choices are made based on utility differences across alternatives and the probability of choosing *i* can be expressed as:

$$\begin{aligned} (2.2) \quad & P(i \mid C) = P(U_{ni} > U_{nj}) = P(v_{ni} + \varepsilon_{ni} > v_{nj} + \varepsilon_{nj}) = P(v_{ni} - v_{nj} > \varepsilon_{nj} - \varepsilon_{ni}) \\ & \forall i, j \in C, i \neq j, n = 1, \ldots, N \end{aligned}$$

In this study, restaurant managers need to make six choices in a row, so choice situations are defined using the index *t (t=1, ..., 6)*. Moreover, the indirect utility that restaurant manager *n* expects to obtain from alternative *i* in choice situation *t* is assumed to be linear-in-parameters (Revelt and Train, 1998):

(2.3) $U_{nit} = \beta_n' x_{nit} + \varepsilon_{nit}$,

where coefficient vector β_n is the unobserved preference parameter associated with

[4] The results generated by applying a conditional logit model are available upon request.

attribute x_{nit} for each n and varies in the population with density $f(\beta_n|\theta)$, in which θ are the true parameters of the distribution of β_n; and ε_{nit} is an unobserved random term that is independent and identically distributed extreme value, independent of β_n and x_{nit}.. Conditional on β_n, the probability that restaurant manager n chooses alternative i in period t is:

$$(2.4) \quad L_{nit} = \frac{e^{\beta_n' x_{nit}}}{\sum_j e^{\beta_n' x_{njt}}}.$$

Denote $i_{(n,t)}$ as the campaign profile that restaurant manager n has chosen in period t, and let $i_n=(i_{(n,1)}, \ldots, i_{(n,T)})$ be restaurant manager n's sequence of choices. Conditional on β_n, the probability of respondent n's observed sequence of choices is:

$$(2.5) \quad P_n(i_n \mid \beta_n) = \prod_t L_{ni_{(n,t)}t}(\beta_n).$$

Because the β_n's are not observable, these conditional probabilities are integrated over all possible values of β as:

$$(2.6) \quad Q_n(i_n \mid \theta) = \int P_n(i_n \mid \beta) f(\beta \mid \theta) d\beta,$$

where $Q_n(i_n \mid \theta)$ is the probability of restaurant n's sequences of choices conditional on the parameters of the population distribution, $f(\beta \mid \theta)$.

The parameter vector θ is estimated using the log-likelihood function:

$$(2.7) \quad \ln L(\theta) = \sum_{n=1}^{N} \ln Q_n(i_n \mid \theta).$$

Log-likelihood estimation procedures are used to estimate the parameters of the distribution of β_n. Since the integral in equation (2.6) cannot be calculated analytically, estimation of the population level parameters is carried out by using simulated maximum likelihood procedure following Revelt and Train (1998). The models were estimated using modified versions of Kenneth Train's Matlab programs, which are available online at http://elsa.berkeley.edu/~train/software.html. The estimation was carried out using one thousand random draws for each sampled respondent.

Individual Restaurant Managers' WTP Estimation

In order to estimate the relationship between campaign components and participating restaurants' characteristics, individual restaurant managers' WTP for each campaign component had to be recovered, which required knowledge of the individual β_n parameters. Train (2003) showed that using Bayes' rule, the density of each β_n conditional on the individual's sequence (i_n) of choices and the population parameters (θ) is given by:

$$(2.8)\qquad h(\beta_n \mid i_n, \theta) = \frac{P_n(i_n \mid \beta) * f(\beta \mid \theta)}{Q_n(i_n \mid \theta)},$$

and the simulated approximation to the individual's expected preference is:

$$(2.9)\qquad \tilde{E}(\beta_n \mid i_n, \theta) = \frac{\sum_r \beta^r * P_n(i_n \mid \beta^r)}{\sum_r P_n(i_n \mid \beta^r)},$$

where β^r is the r-th draw from the population distribution $f(\beta \mid \theta)$, which is assumed as given and $P_n(i_n \mid \beta^r)$ is the probability of restaurant mangers n's sequence of choices conditional on the r-th draw. Individual restaurant managers' WTP values were calculated using estimates of β_n. The estimated parameters $\hat{\theta}$ were used instead of the population parameters θ.

Factors affecting individual WTP, OLS method

Four linear regression models estimated using the Ordinary Least Squares (OLS) method[5] were used to explore how the individual WTP for each component is affected by participating restaurants' characteristics. Hence, the dependent variables in the regression models were the individual restaurant managers' WTP_{LABEL}, $WTP_{SIGNAGE}$, WTP_{MULTI}, and WTP_{FOTM}. The same set of explanatory variables was used in the four models and included: restaurant image (IMAGE), size of the restaurant (SIZE), motivation to join the *Certified South Carolina* campaign (MOTIVATION), and satisfaction with the campaign (SATISFACTION) (as described in table 2.1). Because both the IMAGE, and MOTIVATION variables had several categories, they were included into the models as a set of dummy variables with MOTIVATION Category 4 (supporting South Carolina economy) and IMAGE category 6 (American cuisine) treated as base categories. The variable SIZE was recoded as small or big (base category) dummy variable by using \$500,000 as the cutoff point since more than half of all restaurant sales exceeded \$500,000. The following specification was used for the linear regressions:

(2.10)
$$WTP_k = \alpha_k + \sum_{i=1}^{4} \beta_{k,i} MOTIVATION + \beta_{k,5} SATISFACTION + \sum_{i=6}^{12} \beta_{k,i} IMAGE + \beta_{k,13} SIZE + \varepsilon_k$$
$$k = LABEL, SIGNAGE, MULTI, FOTM$$

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[5] Results of using OLS method is equivalent to the ones generated by Seemingly Unrelated Regression because the regressors on the right-hand-side are exactly the same for all four equations.

Results

Descriptive Analysis

Table 2.2 presents selected descriptive statistics of the participating restaurants. Almost all (94%) participating restaurants were locally owned. The largest response category for the image of participating restaurants was fine dining (30%), followed by American cuisine (23%). The average annual sales for year 2009 across all respondents was $385,080[6] with about half of the restaurants having sales over $500,000. The average participating restaurant manager was 47 years old, male, with a college degree. The most commonly mentioned motivation to participate in the campaign was to support the South Carolina economy (35%) (similar to the findings for consumers reported by Carpio and Isengildina-Massa, 2009), followed by a desire to increase sales by attracting customers interested in South Carolina products (26%), and to improve the quality of ingredients (since South Carolina products are believed to be of better quality) (21%). The most frequent way respondents learned about the *Certified South Carolina* campaign "Fresh on the Menu" program was through a direct contact from the SCDA (27%), followed by the "Fresh on the Menu" website (16%), and food service shows (14%).

Perceived impacts of restaurant participation in the *Certified South Carolina* campaign "Fresh on the Menu" program are described in table 2.3. About 38.1% of respondents reported that their sales increased during the last year due to the campaign, and the estimated average reported increase for this group was 16.2%. About 31.7% of

[6] Since responses were given in the form of intervals, the means were calculated by applying a parametric approach following Bhat (1994) and Zapata et al. (2011).

respondents indicated that the number of clientele visiting their restaurant increased by an average of 16.4%. Approximately 55.7% of the restaurants reported that the cost of participation was less than $50. The cost was low because the restaurants were provided with promotional materials free of charge by the SCDA. About 36.5% of respondents believed that participating in the campaign had increased their ingredient costs by an average of 18%. On the other hand, around 11.1% of restaurants indicated that their ingredient costs had decreased by 9.6%. While about 23% of the restaurants indicated their profitability increased by about 15.2%, only 3.28% of the restaurants reported an average of 5% decrease.[7]

Average Value of Campaign Components

In this study, the variables included in the vector x_{nit} of equation (2.3) were the campaign component variables, the method of payment, and the cost of the campaign. The campaign component variables LABEL, SIGNAGE, MULTI, and FOTM were introduced as dummy variables with the value of one if the component was included in the campaign, and zero otherwise. The two methods of payment were also treated as dummy variables, where the payment through membership took the value of zero, and the method donation was coded as one. The estimation of the mixed logit model required assumptions for the distributions of the parameters corresponding to LABEL, SIGNAGE, MULTI, FOTM, METHOD and PAY. The PAY coefficient was specified to be fixed to facilitate the estimation of the distribution of WTP (Revelt and Train, 1998; Train, 2003;

[7] Results of three Chi-square tests indicate the perceived changes in profit and costs are independent, while the perceived changes in profit are related with the perceived changes in sales and clientele.

Hensher, Shore and Train, 2005) while the other coefficients were allowed to vary in the mixed logit model. Some authors (e.g. Hasing et al., 2012; Revelt, 1999) have argued that a truncated normal distribution is a better assumption for dummy variable parameters, which also can be used to restrict the sign of the marginal effects in the model. However, this specification resulted in convergence difficulties and/or unreasonably high estimates for the standard deviations of the distributions; therefore, in the final specification of the mixed logit model, the normal distribution assumption was used for all coefficients related to non-cost attributes.

Results of the mixed logit estimation shown in table 2.4 indicate that the estimated mean coefficients of LABEL, MULTI, and FOTM are positive and significantly different from zero at the significance level of 0.05, suggesting that these campaign components are positively valued by participating restaurants. The economic value of each component is measured as the average WTP for all participating restaurants which is computed by dividing the coefficient of the component of interest by the negative of the coefficient of the PAY attribute. For example, the average value of LABEL in the *Certified South Carolina* campaign is obtained as $-\hat{\bar{\theta}}_{LABEL} / \hat{\bar{\theta}}_{PAY}$, where $\hat{\bar{\theta}}_{LABEL}$ is the estimated average scaled effect of LABEL on utility and -$\hat{\bar{\theta}}_{PAY}$ is the estimated marginal utility of money. The results reveal that the FOTM component has an average WTP across restaurants of $217.14/year. This finding is not surprising given that restaurants are the most direct beneficiaries of this campaign component. The availability of multimedia advertising is also highly valued with an average WTP of $198.44/year. Multimedia advertising sends positive messages about locally grown products to consumers with the goal of increasing consumer demand that would benefit all campaign participants. The relatively high WTP by restaurants for this campaign component supports the current campaign design where the majority of expenses is devoted to multimedia advertising.[8] On the other hand, restaurants usually do not benefit directly from the point of purchase signage, which explains why the mean coefficient for this variable is not statistically significant. The significant positive coefficient for METHOD indicates that restaurants prefer to participate in the *Certified South Carolina* campaign by donating annually instead of paying a membership fee.[9] Following Holmes and Adamowicz's (2003) approach to calculating the compensating variation, our findings suggest that participating restaurants would be willing to pay an average annual membership fee of \$532.82 or a donation of \$613.43 to support a campaign that includes LABEL, MULTI, and FOTM components.

The standard deviation coefficients for LABEL, MULTI, and FOTM are significantly different from zero at the 0.05 significance level. These coefficients allow us to calculate the population shares that place either a positive or negative value on each attribute. For instance, the distribution of the coefficient of FOTM component has an

[8] Another mixed logit model was tested by adding the interaction effect between MULTI and FOTM. Results indicate restaurants' WTP for having both the FOTM and MULTI components is \$374.6 (\$98.03+\$116.81+\$159.82), which is similar to the result of \$415.58 (\$198.44+\$217.14) obtained in the model without the interaction effect.

[9] We checked the robustness of the mixed logit results by estimating models excluding, from one group at a time, individuals who responded "unsure" to question 2, 3, 4, and 5 in table 2.3. The sign, magnitude and statistical significance of the mean coefficients were generally consistent across specifications except for the statistical significance of the mean coefficients corresponding to the METHOD attribute. This coefficient was only significant in one of the three alternative specifications. However, the samples used in the alternative specifications were significantly smaller than the original sample size.

estimated mean of 1.70 and an estimated standard deviation of 2.57, suggesting that 75% of respondents positively value this component within the *Certified South Carolina* campaign. Based on this interpretation, 76% of respondents have a positive WTP for the MULTI component, and 70% of respondents have a positive WTP for the LABEL component of the *Certified South Carolina* campaign.

Factors Affecting Campaign Valuation

Table 2.5 reports the mean values of the individual level preference parameters (β_n) estimated using equation (2.9). As shown in the table, the mean values of individual parameters are very similar to those found for population parameters.[10] As in the case of the population mean WTP, the individual restaurant WTP values for LABEL, SIGNAGE, MULTI, and FOTM were calculated dividing the estimated individual level parameters for each component by the negative of the coefficient estimate for PAY. The boxplots shown in figure 2.2 provide information about the distributional characteristics of these WTP values. Restaurant managers' WTP for signage was estimated in a very narrow range, between \$30.5 and \$54.3, while the WTP for the FOTM component had the largest dispersion, between \$-313.1 and \$687.3. Half of the observations fell into the range of \$28.7 to \$213.2 for Labeling, \$16.2 to \$390.4 for Multimedia Advertising and \$32.6 to \$380.1 for the FOTM component. In all cases, more than 75% of restaurants were willing to pay a positive amount of money for having these campaign components. The numbers

[10] This finding is consistent with Train's (2003) suggestion that the mean of individual-specific parameters derived from a correctly specified model should mirror closely the population parameters.

inside the boxplots are the mean values of individual WTP for each variable; these values are close to the median of WTP estimates (the vertical line inside the box), suggesting that distributions are fairly symmetric. Furthermore, the mean values are consistent with the population mean WTP estimates (reported in a previous section).

The effects of participating restaurant characteristics on their individual WTP for campaign components reveal no significant difference in WTP for any component between big and small restaurants (SIZE) (table 2.6). Restaurants' WTP for the LABEL component of the campaign is driven by their motivations and image. The coefficients of MOTIVATION2 (strong South Carolina pride) and MOTIVATION3 (increase the sales of my restaurant) are significant in the WTP_{LABEL} equation, suggesting that, *ceteris paribus,* these motivations induce restaurants to pay more for the LABEL component of the campaign. Fast-food restaurants and bars-and-restaurants are willing to pay $124 and $24 less, respectively, for the LABEL component relative to American cuisine restaurants.

Motivations also affect restaurants' WTP for the SIGNAGE component of the campaign, with restaurants that are trying to improve the quality of their ingredients or increase sales willing to pay about $6 more than the ones that joined the campaign to support the South Carolina economy. Fast-food restaurants, fine-dining restaurants and health-conscious restaurants are willing to pay $12, $4 and $3 more, respectively for the SIGNAGE component relative to American cuisine restaurants.

Participating restaurants' WTP for the FOTM component is significantly affected by their motivations, satisfaction with the campaign and image. For example, restaurants are willing to pay $217 and $204 more for the FOTM campaign if their motivations are to improve the quality of their ingredients and increase sales, respectively. The coefficient of the SATISFACTION variable suggests that restaurants are willing to pay $71 more for having the FOTM component when their satisfaction increases by one unit (on a five point scale shown in table 2.1). At the same time, fine-dining, family-oriented and bar-and-restaurant types of restaurants are willing to pay $262, $299, and $364 more, respectively, for this campaign component compared to American cuisine restaurants, holding everything else constant. This finding likely reflects differences in the preferences of restaurants' clientele[11] and the extent to which different types of restaurants use locally grown ingredients. Finally, none of the variables affect restaurant WTP for the MULTI component of the campaign. This result is not surprising given the very general nature of this component.

The intercepts in the linear models are the WTP values for a large American cuisine restaurant, which is motivated to participate in the campaign mainly to support the South Carolina economy, but which is also dissatisfied with the campaign. Two of the intercepts are statistically different from zero ($WTP_{SIGNAGE}$ and WTP_{FOTM} models). The estimated intercept value in the WTP_{FOTM} model of -$267 provides another indication of the importance of this component since the "baseline" restaurant captured in the intercept has the lowest possible level of satisfaction.

Overall, these findings can help SCDA market the campaign to potential participants. For example, WTP for both FOTM and SIGNAGE components is

[11] For example, Carpio and Isengildina-Massa (2009) showed that consumer preferences for locally grown foods are affected by their age, income, and gender.

significantly positively affected by the motivation to increase sales. Our finding showing that the sales of the participating restaurants were believed to increase by 16% due to campaign participation can serve as a strong marketing tool for campaign promotion.

Summary and Conclusions

The first objective of this study was to estimate the perceived economic value of each of the four components of the *Certified South Carolina* campaign from the viewpoint of participating restaurants. A choice experiment was conducted as part of a restaurant manager survey to estimate average WTP for each campaign component using a mixed logit model. The four existing campaign components were treated as attributes in mixed logit model estimation, which also included the method of payment and the amount of payment for the campaign. Findings indicate that three existing campaign components--Labeling, Multimedia Advertising, and "Fresh on the Menu" have a significant positive economic value for restaurants participating in the program. The estimated mean WTP for the components are $117.24, $198.44, and $217.14 per year, respectively. These estimated WTP values could be used as a guide if a participation fee is imposed in the future.

The results suggest that restaurants prefer to participate in the *Certified South Carolina* campaign by donating annually instead of paying a membership fee. Nevertheless participating restaurants are willing to pay an average membership fee of $532.82 annually to support the campaign that includes Labeling, Multimedia Advertising, and "Fresh on the Menu" components.

This study also sheds light on determinants of restaurants' WTP for the campaign. We found that restaurants' image, satisfaction with the campaign, and motivation for participation significantly affect their WTP for the "Fresh on the Menu", Signage and Labeling campaign components. However, restaurants' size does not affect WTP for any component. These findings can help the South Carolina Department of Agriculture marketing the campaign to potential participants.

Currently, the *Certified South Carolina* campaign is entirely funded by special appropriations from the state legislature. The economic value of the campaign demonstrated in this study may help government officials justify the expenditure of public funds on the operational costs associated with the campaign. Furthermore, our estimates of the economic value of each of the campaign components allow comparison of their relative benefits and provides information needed for possible re-allocation of funds towards the most valued uses. Although our results reflect the view of participating restaurants only, the framework and survey instruments developed in this study can be applied to other program participants and beneficiaries (e.g. farmers, farmer's market vendors, grocery stores) to draw more general conclusions.

References

Adamowicz, W., P. Boxall, M. Williams, and J.J. Louviere. "Stated Preference Approaches for Measuring Passive Use Values: Choice Experiments and Contingent Valuation." *American Journal of Agricultural Economics* 80(Feburary 1998):64-75.

Adamowicz, W., J. Swait, R. Boxall, J. Louviere, and M. Williams. "Perception versus Objective Measures of Environmental Quality in Combined Revealed and Stated Prefernce Models of Environmental Valuation." Journal of Environmental Economics and Management 32(1997):65-84.

Alfnes, F., A. Guttormsen, G. Steine, and K. Kolstad. "Consumers' Willingness to Pay for the Color of Salmon: a Choice Experiment with Real Economic Incentives." American Journal of Agricultural Economics 88(November 2006):1050-61.

Bhat, C.R. "Imputing a Continuous Income Variable from Grouped and Missing Income Observations." Economics Letters 46(December 1994):311-19.

Brick, J.M., D. Martin, P. Warren, and J. Wivagg. "Increased Efforts in RDD Surveys." 2003 Proceedings of the Section on Survey Research Methods (2003):26-31.

Cameron, A.C., and P.K. Trivedi. Microeconometrics: Methods and Applications. Cambridge, U.K.: Cambridge University Press, 2005.

Carlsson, E, and P. Martinsson. "Do Hypothetical and Actual Marginal Willingness to Pay Differ in Choice Experiments?" Journal of Environmental Economics and Management 41(2001):179-92.

Carpio, C.E., and O. Isengildina-Massa. "Does Government Sponsored Advertising Increase Social Welfare? A Theoretical and Empirical Investigation." Paper presented at the Agricultural and Applied Economics Association's 2013 AAEA and CAES Joint Annual Meeting, Washington, DC, August 4-6, 2013.

Carpio, C.E., and O. Isengildina-Massa. "To Fund or Not to Fund: Assessment of the Potential Impact of a Regional Promotion Campaign." Journal of Agricultural and Resource Economics 35(August 2010):245-60.

Carpio, C.E. and O. Isengildina-Massa. "Consumer Willingness to Pay for Locally Grown Products: the Case of South Carolina." Agribusiness 25(2009):412-26.

Curtin, R., E. Presser, and E. Singer. "The Effects of Response Rate Changes on the Index of Consumer Sentiment." Public Opinion Quarterly 64(2000):413-28.

Govindasamy, R., B. Schilling, K. Sullivan, C. Turvey, L. Brown, and V.S. Puduri. "Returns to the Jersey Fresh Promotional Program: the Impacts of Promotional Expenditures on Farm Cash Receipts in New Jersey." Working Paper, Department of Agricultural, Food and Resource Economics and the Food Policy Institute, Rutgers, The State University of New Jersey, 2003.

Hamilton, M.B. "Online Survey Response Rates and Times: Background and Guidance for Industry." Ipathia, Inc./SuperSurvey (2003). Internet site: http://www.supersurvey.com/papers/supersurvey_white_paper_response_rates.pdf (Accessed June 1, 2013)

Hanemann, M., J. Loomis, and B. Kanninen. "Statistical Efficiency of Double-Bounded Dichotomous Choice Contingent Valuation." American Journal of Agricultural Economics 73(November 1991):1255-63.

Hasing, T., C.E. Carpio, D.B. Willis, O. Sydorovych, and M. Marra. "The Effect of Label Information on U.S. Farmers' Herbicide Choices." Agricultural and Resource Economics Review 41(August 2012):200-14.

Hensher, D., N. Shore, and K. Train. "Households Willingness to Pay for Water Service Attributes." Environmental and Resource Economics 32(2005):509-31.

Holbrook, A., J. Krosnick, A. Pfent. "The Causes and Consequences of Response Rates in Surveys by the News Media and Government Contractor Survey Research Firms." Advances in telephone survey methodology. J.M. Lepkowski, C. Tucker, J.M. Brick, E.D. de Leeuw, L. Japec, P.J. Lavrakas, M.W. Link, and R.L. Sangster, eds. New York: Wiley, 2007.

Holmes, T. P. and W. L. Adamowicz. "Attribute-based methods." A Primer on Nonmarket Valuation. P.A. Champ, K.J. Boyle, and T.C. Brown, eds. Dordrecht, Netherlands: Springer, 2003.

Keeter, S., C. Kennedy, M. Dimock, J. Best, P. Craighill. "Gauging the Impact of Growing Nonresponse on Estimates from a National RDD Telephone Survey." Public Opinion Quarterly 70(2006):759-79.

Keeter, S., C. Miller, A. Kohut, R. Groves, and S. Presser. "Consequences of Reducing Nonresponse in a Large National Telephone Survey." Public Opinion Quarterly 64(2000): 125-48.

List, J.A. and J.F. Shogren. "Calibration of the Difference Between Actual and Hypothetical Valuations in a Field Experiment." Journal of Economic Behavior and Organization 37(1998):193-205.

Louviere, J.J., D.A. Hensher, and J.D. Swait. Stated choice methods: analysis and applications. Cambridge, U.K.: Cambridge University Press, 2000.

Lusk, J.L., and D. Hudson. "Willingness-to-Pay Estimates and Their Relevance to Agribusiness Decision Making." Review of Agricultural Economics 26(2004):152-69.

Lusk, J.L., J.A. Fox, T.C. Schroeder, J. Minterta, and M. Koohmaraie. "In-Store Valuation of Steak Tenderness." American Journal of Agricultural Economics 83(August 2001):539-50.

McFadden, D. "The Measurement of Urban Travel Demand." Journal of Public Economics 3(1974):303-28.

Onken, K.A., and J.C. Bernard. "Catching the 'Local' Bug: A Look at State Agricultural Marketing Programs." Choices 25(2010):1-7.

Patterson, P.M. "State-Grown Promotion Programs: Fresher, Better?" Choices 21(2006):41-46.

Patterson, P.M., H. Olofsson, T.J. Richards, and S. Sass. "An Empirical Analysis of State Agricultural Product Promotions: A Case Study on Arizona Grown." Agribusiness 15(1999):179-96.

Ratcliffe, J. "The Use of Conjoint Analysis to Elicit Willingness-to-Pay Values." International Journal of Technology Assessment in Health Care 16(January 2000):270-90.

Ready, R.C., J.C. Buzby, and D. Hu. "Difference Between Continuous and Discrete Contingent Value Estimates." Land Economics 72(August 1996):397-411.

Revelt, D., and K. Train. "Customer-Specific Taste Parameters and Mixed Logit." Working paper, Department of Economics, University of California, Berkeley, 1999.

Revelt, D., and K. Train. "Mixed Logit with Repeated Choices: Households' Choices of Appliance Efficiency Level." Review of Economics and Statistics 80(November 1998):1-11.

Train, K. Discrete Choice Methods with Simulation. Cambridge, U.K.: Cambridge University Press, 2003

Zapata, S., C. Carpio., O. Isengildina-Massa, and R. Lamie. "Do Internet-Based Promotion Efforts Work? Evaluating MarketMaker." Journal of Agribusiness 29(2011):159-80.

Table 2.1 Description of Variables Included in the OLS Method

Variable	Description	Category	Category Proportion
MOTIVATION	Which of the following reasons was the most important motivation for you to join the *Certified South Carolina* Campaign "Fresh on the Menu" Program?	1=Improve the quality of ingredients since SC produces the better quality products	20.69%
		2=Strong SC pride	15.52%
		3=Increase the sales of my restaurant by attracting customers interested in SC products	27.59%
		4=Support SC economy	32.75%
		5=Reduce harmful environmental impact (carbon footprint)	3.45%
SATISFACTION	How would you rate your overall satisfaction with the campaign?	0=Very dissatisfied	15.52%
		1=Dissatisfied	12.07%
		2=Neutral	29.31%
		3=Satisfied	18.97%
		4=Very satisfied	24.14%
IMAGE	How would you best describe the focus/image of your restaurant?	1=Fine-dining	30.36%
		2=Fast-Food	1.79%
		3=Family-oriented	10.71%
		4=Bar and Restaurant	5.36%
		5=International Cuisine	3.57%
		6=American Cuisine	21.43%
		7=Health-Conscious	7.14%
		8=Other, please specify	19.64%
SIZE	Please describe the size of your restaurant business in 2009 in terms of total annual sales.	1=$1,000-$9,999	3.64%
		2=$10,000-$49,999	0.00%
		3=$50,000-$99,999	5.45%
		4=$100,000-$249,000	16.36%
		5=$250,000-$499,000	23.64%
		6=$500,000 and over	50.91%

Note: The response rate varies across questions with the minimum sample size of 55.

Table 2.2 Summary Statistics Describing the Characteristics of Restaurants Participating in the *Certified South Carolina* Campaign "Fresh on the Menu" Program

Question	Category	Category Proportion	Mean	Standard Deviation
Which of the following reasons was the most important motivation for you to join the *Certified South Carolina* campaign" Fresh on the Menu" Program?	1=Improve the quality of ingredients since South Carolina produces the better quality products	20.97%		
	2=Strong South Carolina pride	14.52%		
	3=Increase the sales of my restaurant by attracting customers interested in South Carolina products	25.81%		
	4=Support South Carolina economy	35.48%		
	5=Reduce harmful environmental impact (carbon footprint)	3.23%		
How did you learn about the campaign?	1=Magazines	3.20%		
	2=Direct Mailing	9.50%		
	3=Food Service Food Show	14.30%		
	4=Direct contact from the SCDA	27.00%		
	5=Fresh on the Menu website	15.90%		
	6=Other Restaurants	6.40%		
	7=Other	23.80%		
How would you best describe the focus/image of your restaurant?	Fine-dining	30.00%		
	Fast-Food	1.67%		
	Family-oriented	11.67%		
	Bar and Restaurant	5.00%		
	International Cuisine	3.33%		
	American Cuisine	23.33%		
	Health-Conscious	6.67%		
	Other	18.33%		

Table 2.2 (Continued)

Question	Category	Category Proportion	Mean	Standard Deviation
Please describe the size of your restaurant business in 2009 in terms of total annual sales	\$1,000-\$9,999	3.39%	\$385,080	\$22,860
	\$10,000-\$49,999			
	\$50,000-\$99,999	5.08%		
	\$100,000-\$249,000	15.25%		
	\$250,000-\$499,000	23.73%		
	\$500,000 and over	52.54%		
How would you best describe the ownership of your restaurant?	Locally Owned	93.55%		
	Franchise	6.45%		
Age	18-20 years		47.03 years	1.47 years
	21-30 years	5.36%		
	31-40 years	19.64%		
	41-50 years	33.93%		
	51-60 years	28.57%		
	61-69 years	10.71%		
	70 years or more	1.79%		
Gender	Male	62.96%		
	Female	37.04%		
Highest Level of Education	High School Diploma (including GED)	23.21%		
	College Degree	53.57%		
	Post-Graduate or Professional Degree	23.21%		

Notes: The sample size for this table is different from the sample size in Table 2.1 and the minimum sample size is 54. Since responses were given in the form of intervals, the mean and standard deviation were calculated by applying the parametric approach following Bhat (1994) and Zapata et al. (2011).

Table 2.3 Summary Statistics Describing the Perceived Effects of Restaurant Participation in the *Certified South Carolina* Campaign "Fresh on the Menu" Program

Question	Category	Category Proportion	Parametric Mean[c]	Standard Deviation
1. Please describe the costs of your participation in the *Certified South Carolina* Campaign "Fresh on the Menu" Program in the last year.	\$0-\$49 \$50-\$99 \$100-\$249 \$250-\$499 \$500 and over	55.74% 13.11% 11.48% 11.48% 8.20%	\$129.42	\$21.49
2. How do you think the campaign affected your costs of purchasing ingredients and preparation in the last year?[a]	Increase Decrease Unsure No change	36.50% 11.10% 14.30% 38.10%		
2-1. What percentage increase in the costs of purchasing ingredients and food preparation?[d]	0-10% 11-20% 21-30% 41-50% 81-90%	36.84% 42.11% 10.53% 5.26% 5.26%	17.97%	4.31%
2-2. What percentage decrease in the costs of purchasing ingredients and food preparation?[e]	0-10% 11-20% 21-30%	71.43% 14.29% 14.29%	9.56%	2.88%
3. How do you think the campaign affected your total sales during the last year?[a]	Increase Decrease Unsure No change	38.10% 0.00% 38.10% 23.80%		
3-1. What percentage increase in total sales?[d]	0-10% 11-20% 21-30% 31-40% 41-50% 61-70%	43.48% 34.78% 8.7% 4.35% 4.35% 4.35%	16.19%	3.11%
4. How do you think the campaign affected the number of clientele visiting your restaurant in the last year?[a]	Increase Decrease Unsure No change	31.70% 0.00% 41.30% 27.00%		
4-1. What percentage increase in the number of clientele?[d]	0-10% 11-20% 21-30% 31-40% 51-60%	36.84% 36.84% 15.79% 5.26% 5.26%	16.41%	2.92%

Table 2.3 (Continued)

Question	Category	Category Proportion	Parametric Mean[c]	Standard Deviation
5. How do you think the campaign affected the profitability of your restaurant in the last year?[b]	Increase	22.95%		
	Decrease	3.28%		
	Unsure	34.43%		
	No change	39.34%		
5-1. What percentage increase in profitability?[d]	0-10%	66.67%	15.2%	4.94%
	11-20%	8.33%		
	21-30%	8.33%		
	41-50%	8.33%		
	51-60%	8.33%		
5-2. What percentage decrease in profitability?[e]	0-10%	100%	5%	0%

[a] Sample size is 63;
[b] Sample size is 61;
[c] Since responses were given in the form of intervals, the parametric mean and standard deviation were calculated by applying the parametric approach following Bhat (1994) and Zapata et al. (2011).
[d] Questions only asked to individuals who selected "increase" in question 2, 3, 4 and 5, respectively;
[e] Questions are responded to people who select "decrease" in question 2 and 5, respectively;

Table 2.4 Mixed Logit Estimates

Attributes	Categories	Coefficient	Standard Error
LABEL	Mean Coefficient	0.9174**	(0.3899)
	Standard Deviation Coefficient	1.7167***	(0.4742)
	Willingness to Pay	$117.24	
SIGNAGE	Mean Coefficient	0.3275	(0.2609)
	Standard Deviation Coefficient	0.2451	(0.4853)
	Willingness to Pay	$41.85	
MULTI	Mean Coefficient	1.5528***	(0.4295)
	Standard Deviation Coefficient	2.2200***	(0.4800)
	Willingness to Pay	$198.44	
FOTM	Mean Coefficient	1.6991***	(0.4774)
	Standard Deviation Coefficient	2.5734***	(0.5360)
	Willingness to Pay	$217.14	
METHOD	Mean Coefficient	0.6308**	(0.2994)
	Standard Deviation Coefficient	0.9213**	(0.4258)
	Willingness to Pay	$80.61	
PAY	Mean Coefficient	-0.0078***	(0.0023)
Log Likelihood		-262.0784	
Log Likelihood from Conditional Logit (CL)		-317.192	
Chi-Square against CL		110.2272***	

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

Table 2.5 Comparison of Population Parameters and Means of Individual Parameters

Attributes	Population Parameters	Mean of Individual parameters
LABEL	0.9174	0.9391
SIGNAGE	0.3275	0.3297
MULTI	1.5528	1.5658
FOTM	1.6991	1.7016
METHOD	0.6308	0.6228

Table 2.6 The Effects of Participating Restaurant Characteristics on Their Individual WTP for Four Campaign Components

Variable	Category	WTP_{LABEL}		$WTP_{SIGNAGE}$		WTP_{MULTI}		WTP_{FOTM}	
		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Intercept		95.25	67.59	34.71***	2.35	130.23	122.14	-267.05**	125.57
MOTIVATION	1=Improve the quality of ingredients	92.31	55.90	5.50***	1.94	-101.13	101.02	216.83**	103.85
	2=Strong SC pride	164.22**	66.46	2.59	2.31	18.39	120.10	147.08	123.47
	3=Increase the sales of my restaurant	155.22***	50.26	6.28***	1.74	98.08	90.83	203.79**	93.37
	5=Reduce harmful environmental impact	-3.98	74.23	3.64	2.58	92.26	134.14	-170.10	137.90
SATISFACTION		1.53	16.67	-0.07	0.58	3.84	30.12	71.27**	30.97
IMAGE	1=Fine-dinning	-111.38	55.11	4.21**	1.91	75.95	99.59	262.14**	102.39
	2=Fast-Food	-124.44*	142.47	12.33**	4.94	-85.18	257.45	238.68	264.67
	3=Family-oriented	-140.22	79.67	-0.25	2.76	-19.78	143.98	299.42**	148.01
	4=Bar and Restaurant	-23.75*	91.82	1.29	3.19	31.45	165.92	364.45***	170.57
	5=International Cuisine	20.70	106.69	-2.58	3.70	213.36	192.79	235.09	198.20
	7=Health-Conscious	9.45	90.49	2.70*	3.14	142.07	163.53	97.71	168.12
	8=Others	-41.11	66.09	4.51	2.29	-71.33	119.43	282.63**	122.78
SIZE	1=Small	-9.64	41.18	1.12	1.43	16.00	74.42	-30.54	76.51

Notes: Detailed variable description is shown in table 2.1. Single, double and triple asterisks (*,**,***) denote statistical significance at 10%, 5%, and 1% levels, respectively.

Scenario 1

Campaign A	Components/Costs	Campaign B
Not included	**Labeling**	Included
Not included	**Point of Purchase Signage**	Not included
Not included	**Multimedia Advertising**	Not included
Included	**"Fresh on the Menu"**	Not included
Annual membership fee of $20	**Funding**	Annual donation of $100

If you were given three choices: Campaign A, Campaign B, or not having a campaign at all, which would you choose?

___Campaign A ___Campaign B ___Not campaign at all

Figure 2.1 Example of One of the Scenarios from the Restaurant Survey

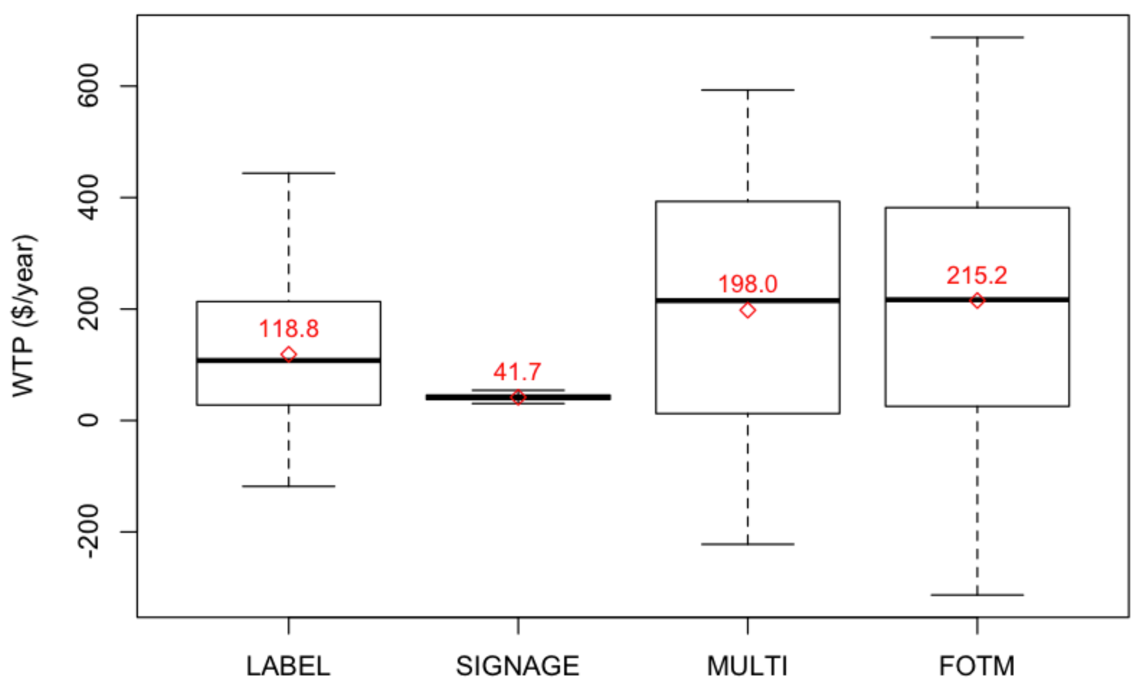


Figure 2.2 Box Plot of WTP for LABEL, SIGNAGE, MULTI, and FOTM

CHAPTER THREE

ARE REVISIONS OF USDA'S COMMODITY FORECASTS EFFICIENT?

Introduction

Recent years have seen increased volatility in international commodity markets. Most major crops' prices have spiked at least once since 2006; the OECD-FAO, Food and Agricultural Policy Research Institute, and the U.S. Department for Agriculture (USDA) drew a consistent conclusion that the prices would remain elevated in the next several years (European Commission: Agriculture and Rural Development, 2011). Financial market developments explain some of the volatility, as the global capital flows have been nearly unprecedented. Additionally, the increasing share of production in developing countries with higher yield variability results in unstable prices. Commodity markets' increased volatility makes the USDA forecasting job harder than ever.

World Agricultural Supply and Demand Estimates (WASDE), one of the most influential public sources of commodity forecasts, provides USDA's comprehensive estimates of supply and demand for major U.S. and global crops and U.S. livestock. Industry participants have relied on these forecasts in making production, marketing processing, and retailing decisions for many years. Numerous studies have revealed the significant impact of the WASDE reports on commodity markets (e.g., Karali, 2012; Adjemian, 2012; Isengildina, Irwin, and Good, 2008; Isengildina, Irwin, and Good, 2006a). With relatively low reserve stocks of commodities around the world, new information from various sources drives markets with much greater speed than in the past. Therefore, it is essential to assure the high standards of accuracy and efficiency for

WASDE reports. However, concerns have surfaced about the reliability of USDA forecasts. In December 2011, the Wall Street Journal reported that over the previous two years, USDA's monthly forecasts of how much farmers will produce has been, "off the mark to a greater degree than any other two consecutive years in the last 15 [years]."

Several recent studies examined the accuracy and efficiency of WASDE forecasts. Sanders and Manfredo (2002) found that beef and pork production forecasts inefficiently incorporated available information and showed the existence of positive serial correlation in errors of beef and poultry production forecasts. Sanders and Manfredo (2003) examined the WASDE price forecasts for cattle, hogs, and broilers and found overestimation in broiler price forecasts and inefficiency in a number of livestock price forecasts due to repeated forecast errors. Isengildina, Irwin, and Good (2004) evaluated corn and soybean price forecasts using interval accuracy tests and rejected forecast accuracy at the 95% level for both commodities. Botto et al. (2006) analyzed forecast accuracy of all categories for corn and soybeans, and they found inefficiency in soybean ending stocks and price forecasts. More recently, Isengildina-Massa, MacDonald, and Xie (2012) incorporated a variety of tests to evaluate the forecast performance of WASDE cotton forecasts for the U.S. and China. They discovered that the most pervasive rejection of efficiency across variables and countries occurred in tests of revision efficiency. Lewis and Manfredo (2012) concluded that the sugar production and consumption forecasts are less problematic as inefficiency was only found in a few cases. Although all of these studies demonstrated the inefficiency of WASDE across different commodities, none of them provided guidance on how to improve forecast accuracy.

Isengildina, Irwin, and Good (2006b) focused on forecast revision efficiency, which had been largely overlooked in the previous studies. The forecast revisions process is important to reveal how forecasts change across the forecasting cycle and how analyzing forecast revisions allows the detection of inefficiency due to systematic under/over-adjustments in forecasts. Isengildina, Irwin, and Good (2006b) found the existence of revision inefficiency in WASDE corn and soybean production forecasts and suggested a procedure based on Nordhaus's (1987) approach to successfully correct for inefficiency in revisions. However, their procedure was rather simplistic and the results were limited to corn and soybean production forecasts.

The goal of this study was to expand Isengildina, Irwin, and Good's work to include 1) evaluation of monthly revisions efficiency of all supply, demand, and price categories for U.S. corn, soybean, wheat, and cotton forecasts, published in the monthly WASDE reports between 1984/85 through 2011/12; and 2) development of a new inefficiency correction procedure that takes into account adjusting for outliers, controlling for the impact of other variables on inefficiency, and considering structural changes.

Data

This study focused on monthly WASDE U.S. corn, soybean, wheat, and cotton forecasts from 1984/85 through 2011/12. Typically, WASDE reports were released between the 9th and 12th of each month. Prior to May 1994, WASDE reports were published at 3:00 p.m. in the Eastern Time Zone of the U.S., but the report release time was changed to 8:30 a.m. between May 1994 and December 2012.

Vogel and Bange (1999) describe that forecasts of U.S. crop production are independently prepared by the National Agricultural Statistics Services, while supply (other than production), demand, and price forecasts are developed jointly by several USDA agencies. The World Agricultural Outlook Board coordinates the high-security interagency process by chairing an Interagency Commodity Estimates Committee (ICEC) of leaders responsible for each commodity. Joint forecast preparation enables USDA analysts to incorporate all available resources and assures that the estimates are consistent across all USDA publications.

WASDE supply and demand forecasts apply a full balance-sheet approach for each commodity, which means that the total supply must equal the demand. The total supply of a crop is comprised of beginning stocks, imports, and production. The demand side of the balance sheet includes domestic use, exports, and ending stocks. Domestic use is further subdivided into feed and residual, and food, seed and industrial for corn; crushings, seed, and residual for soybeans; and feed and residual, food, and seed for wheat.[12] The ending stocks for a marketing year t become the beginning stocks for year $t+1$. While price forecasts are published in interval form, other categories' forecasts are point estimates. To overcome this inconsistency and keep the analysis consistent across

[12] More detail on the balance-sheet nature of WASDE forecasts and the forecast generation procedure is given in Vogel and Bange (1999).

all categories, midpoints of the price forecast intervals are considered in our analysis.[13]

WASDE are forecasted on a marketing year basis, which spans from September to August for corn and soybeans, from June to May for wheat, and from August to July for cotton. The first forecasts for all crops of each marketing year are published in May preceding the marketing year. Beginning stocks and production forecasts are typically finalized after the harvest time of each crop, by October for wheat and January for corn, soybeans, and cotton[14]. Estimates for other forecast categories are generally finalized by November after the marketing year. Therefore, production and beginning stocks' forecasting cycles are 9 months for corn, soybeans, and cotton, and 6 months for wheat. The forecasting cycles are 19 months for all crops' other categories. Figure 3.1 illustrates the 2011/12 marketing year and the relative WASDE forecasting cycles for commodities included in this study.

WASDE forecasts are considered fixed-event forecasts because the series of forecasts are related to the same terminal event y_t^J, where J is the release month of the final estimate for a marketing year t, and $t=1(1984/85),\ldots,28(2011/12)$. $J=9$ for production and beginning stocks forecasts for corn, soybeans, and cotton, and $J=6$ for those two categories for wheat; $J=19$ for all crops' other categories. The terminal event

[13] USDA was prohibited from publishing forecasts of cotton prices from 1929 to 2008, but USDA's ICEC for cotton calculated unpublished price forecasts each month as point estimates. Since 2008, cotton price forecasts have been published in interval form. Also, for all four commodities, the price forecasts typically converge to point estimates by April of the marketing year.

[14] WASDE frequently published the revised estimate of final soybean production in October after the marketing year. The final forecasts of the cotton production were commonly revised in April and May of the subsequent year. Also, WASDE sometimes revised the final forecasts of the wheat beginning stocks and production in January and October, respectively. Because these additional revisions were somewhat sporadic in nature, they are not included in our analysis.

for supply and demand categories describes a total volume, while the terminal event for the price category represents a marketing year's average value for price. The forecasted value published in month j is denoted as y_t^j, where $j=1,\ldots,J$. Therefore, each subsequent forecast is an update of the previous forecast describing the same terminal event. Based on the definition of forecasting cycles from the data section, WASDE generates 18 updates/revisions for each U.S. category except for production and beginning stocks (8 updates for corn, soybeans, and cotton, and 5 updates for wheat).

Methods

Forecast Revision Efficiency

The tests of efficiency in forecast revisions were originally developed by Nordhaus in 1987 and have since been used extensively in the macroeconomic literature (e.g., Clements, 1997; Harvey et al., 2001; Patton and Timmermann, 2010; Dovern and Weisser, 2011) and less frequently in agricultural forecasting (Isengildina, Irwin, and Good, 2006b; Lewis and Manfredo, 2012). Within the Nordhaus framework, if fixed event forecasts are weak-form efficient, their revisions should follow a random walk.

In this study, forecast revisions were defined as the difference between two adjacent forecasts. In order to standardize for increasing crop size over time, forecast revisions were examined in log percentage form:

$$(3.1) \qquad r_t^j = 100 * \ln\left(\frac{y_t^j}{y_t^{j-1}}\right) \qquad j = 2,\ldots,J;\ t = 1,\ldots,28,$$

where r_t^j is a revision of a forecast for marketing year *t* released in month *j*-1. Figure 3.2 illustrates the layout of the fixed event forecasting cycle and the corresponding forecast revisions process using corn production as an example.

Following Isengildina, Irwin, and Good (2006b), efficiency of WASDE forecast revisions was examined as:

(3.2) $r_t^j = \lambda r_t^{j-1} + \varepsilon_t^j$ $\quad j = 2, \ldots, J;\ t = 1, \ldots, 28.$

Thus, for $j = 3$, λ represents the slope coefficient for all July revisions made from 1984/85 to 2011/12 regressed against the June revisions ($j - 1 = 2$) for the same years. The null hypothesis for efficiency in forecast revisions was $\lambda = 0$. If $\lambda > 0$, the forecasts are considered "smoothed", as they are partially based on the previous revision. If $\lambda < 0$, the forecasts are called "jumpy", as they tend to partially offset the previous revision. The test of H_o that $\lambda = 0$ required at least 3 rolling-event forecasts to generate a revision and a lagged revision which limited our ability to analyze revision efficiency in the first 2 forecasts of each marketing year. Therefore, month 3 was the first month analyzed. Equation (3.2) was estimated using the method of Ordinary Least Squares (OLS) for each forecast category for each crop.

Correction for Revision Inefficiency

The Basic Correction Procedure

The basic procedure for correcting revision inefficiency was described in Isengildina, Irwin and Good (2006b). Since in equation (3.2), revision inefficiency in one month (rejection of H_o that $\lambda = 0$), signals a failure in the previous month to appropriately incorporate all new information, an alternative measure for inefficiency correction that provides an adjustment parameter γ for a pending, as opposed to a past revision was used:

$$(3.3) \quad e_t^j = \alpha + \gamma r_t^{j+1} + \varepsilon_t^j \qquad j = 1, \ldots, J - 1;\; t = 1, \ldots, 28,$$

where e_t^j is the forecast error of a forecast for marketing year t released in month j, and r_t^{j+1} is the forecast revision for the same marketing year t released in the next month. Consistently with forecast revisions, forecast errors were calculated in log percentage form:

$$(3.4) \quad e_t^j = 100 * \ln\left(\frac{y_t^J}{y_t^j}\right) \qquad j = 1, \ldots, J-1;\; t = 1, \ldots, 28 \;.$$

Equation (3.3) was based on Nordhaus' (1987) derivation that the forecast error at time j should be fully corrected (on average) by the following revision(s), thus, if revisions are efficient, $\gamma=1$. According to Isengildina, Irwin and Good (2006b), out-of-sample correction of revision inefficiency should proceed along the following steps: 1) estimate γ coefficients using equation (3.3) and the data in the estimation subsample, 2) multiply published revisions by γ coefficients to derive efficient revisions,[15] and 3) calculate adjusted forecasts by adding efficient revisions to the previous months' forecasts.

For example, if $\hat{\gamma}$ was estimated using 1984/85-1993/94 May forecast errors (e_t^j, $t=1,\ldots,10$ and $j=1$) and June forecast revisions (r_t^{j+1}, $t=1,\ldots,10,$ and $j=1$), the adjusted

[15] We follow a more conservative approach by adjusting revisions and forecasts only when the estimated γ coefficients are significant at a significance level of 0.05. Results of adjusting all revisions and forecasts regardless of the significance of the estimated γ coefficients are available upon request.

revision for June 1994/95 ($\hat{r}_t^{j+1}$, *t=11* and *j=1*) was the product of $\hat{\gamma}$ and r_{11}^2. Because the forecast errors and revisions were defined in logarithm terms in this study, the June 1994/95 adjusted forecasts were calculated as $\hat{y}_{11}^2 = y_{11}^1 * e^{(\hat{r}_{11}^2/100)}$.

While Isengildina, Irwin and Good (2006b) demonstrated that such revision inefficiency correction improved the accuracy of corn and soybean production forecasts in their 1980/81-2004/05 validation subsample, their procedure may have suffered from several potential limitations. First, an OLS regression was used to estimate $\hat{\gamma}$ in equation (3.3), so the estimates might be influenced by the presence of outliers. Second, other variables might affect smoothing. For example, Isengildina, Irwin and Good (2013) argued that "big crops get bigger and small crops get smaller," which suggests that forecast size and direction should be considered in adjusting forecasts for smoothing. Third, stability of revision inefficiency over time would have implications on how well the correction procedure would improve accuracy: if the inefficiency is unstable, the adjustment procedure would perform poorly and modifications must be made. Our approach to incorporating these additional factors in the revision inefficiency correction procedure is described in the following sections.

Outlier Detection

Rousseeuw and Leroy (2005) argued that regression outliers (either in the dependent or independent variable) pose a serious threat to the interpretation of results from a standard least squares analysis. They suggested two approaches to identify and deal with outliers, including regression diagnostics and robust regression. Diagnostics include statistics, such as the Hat Matrix (Hoaglin and Welsch, 1978) and the Cook's D

(Cook, 1977), computed from the data so as to discover influential points. On the other hand, robust regression methods have been developed to find estimators that are not strongly affected by outliers as they assign less weight to "abnormal" values.

In this study, the existence of outliers in estimating equation (3.3) using the OLS method was detected by Cook's D, which is a measure that combines the information on leverage (a measure of how far an independent variable deviates from its mean) and residual (the difference between the predicted value and the observed value) of the observation. A data point is considered an outlier if the corresponding Cook's D value is bigger than $4/n$ (Rawlings, Pantula, and Dickey, 1998), where n is the sample size. To handle outliers, robust regression was used for estimating the γ coefficients in equation (3.3) because outliers could not be simply removed or corrected. In this study, a detected outlier represents a sudden change in revision inefficiency level. Robust regression has been applied in numerous fields, such as policy, finance, and economics, etc. (e.g. Alesina and Perotti, 1996; Preminger et. al., 2007; Finger, 2010). However, we are not aware of any previous studies that applied robust regression to agricultural forecasts. Maximum likelihood-type estimation (M-estimation) by Huber (1964) and multiple M-estimation (MM-estimation) methods by Yohai (1987) were considered in this study, since they were the most commonly used robust estimations and both methods were accessible in statistical software R.

Forecast Size and Direction

The influence of forecast size and direction on revision inefficiency should also be considered in the adjustment procedure because forecast size and direction could be some of the potential sources of smoothing (Isengildina, Irwin, and Good, 2013). In order to account for the effect of those two variables, out-of-sample linear trend forecasts were generated using the 5-year rolling approach. The rolling out-of-sample trend forecast approach was preferred to the recursive approach used by Isengildina, Irwin and Good (2013) because USDA commodity forecasts in the long term are volatile. Accordingly, the rolling trend forecast for 1989/90 was constructed as a linear trend forecast using data from 1984/85-1988/89 and the rolling trend forecast $\hat{y}_{trend,t}$ for the remaining years was consistently computed using the previous five years' observations. The rolling trend forecasts were estimated using only the final month WASDE estimates for each marketing year, so the trend forecasts remained the same across different months within one marketing year.

The Trend Difference (*TD*) was then defined as the log percentage difference between USDA forecast and the estimated rolling out-of-sample trend forecast:

$$(3.5) \quad TD_t^j = 100 * \ln\left(\frac{y_t^j}{\hat{y}_{trend,t}}\right) \qquad j = 1, \ldots, J;\ t = 6, \ldots, 28.$$

The *TD* captured the influence of both USDA forecast size and direction by comparing the actual forecast to a linear trend forecast. The sign of the *TD* indicated the forecast direction with a positive *TD* showing that the actual forecast was higher than the predicted value from the trend. The magnitude of the *TD* indicated the forecast size or how much larger or smaller the actual forecast was relative to the trend value. To take the forecast size and direction into account for revision inefficiency correction, equation (3.3) was modified as following:

(3.6) $e_t^j = \alpha + \gamma r_t^{j+1} + \beta TD_t^j + \varepsilon_t^j$ $j = 1, \ldots, J - 1$; $t = 6, \ldots, 28$.

Correction for revision inefficiency then proceeded as described in the basic procedure.

Stability of Revision Inefficiency Over Time

Stability of revision inefficiency was reviewed by blocking the full data period from 1984/85 through 2011/12 into twelve consecutive 10 year sub-periods as 1984/85-1993/94, 1985/86-1994/95, etc. The estimated λ coefficients ($\hat{\lambda}$) from equation (3.2) were then computed for each sub-period and plotted to provide a general view of instability in revision inefficiency over time. Furthermore, structural changes were tested formally using a Quandt Likelihood Ratio (QLR) test. The QLR test statistic is the maximum of all Chow F-statistics over a range of potential breakpoints, with a conventional search for such breakpoints within the inner 70% of the observations (excluding the first and last 15% observations) from the study period (Stock and Watson 2003).

If the structural break in revision inefficiency was identified, the basic correction procedure could be modified in the following ways. The first approach required the use of data after the breakpoint for the adjustment procedure. Consequently, the full data period of this study would be trimmed and the validation subsample would be shortened as well. Alternatively, a rolling approach to estimating $\hat{\gamma}$ in equation (3.3) could be applied instead of the recursive approach used by Isengildina, Irwin and Good (2006b). With the rolling approach, the γ coefficients for any year are estimated using previous five years' forecast errors and revisions[16]. The use of this 5-year rolling approach may help reduce the influence of potential structural changes that happened more than 5 years

[16] This study also applied 10-year rolling estimation, but 5-year window performed better in dealing with potential structural changes.

ago.

Accuracy Evaluation

Performance of alternative revision inefficiency correction procedures was evaluated based on their effect on forecast accuracy. Accuracy implications of the basic correction procedure were first evaluated by subtracting the monthly MAPEs of adjusted forecasts from those of the published WASDE forecasts over the validation subsample from 1994/95 to 2011/12. Then modified procedures described in the previous three sections were compared with the basic procedure in the corresponding validation subsample[17] to determine the preferred new correction procedure for each crop. Finally, the accuracy of corrected forecasts using the new procedure was assessed by comparing the monthly MAPEs of adjusted forecasts from the ones of the published WASDE forecasts, and the validation subsample was determined according to the selected new procedure.

In each step, the improvement of forecast accuracy was reported using the average difference in mean absolute percentage errors (MAPEs) across all months. We also considered the frequencies of improvement in forecast accuracy (cases with positive changes in absolute percentage errors) and frequencies of deterioration (cases with negative changes in absolute percentage errors). The reason these additional measures were analyzed is that the adoption of any correction procedure by USDA would require

[17] The validation sub-samples for adjusting outliers is from 1994/95 to 2011/12, for controlling forecast size and direction is from 1999/00 to 2011/12, for using post breakpoint data is from 10 years after the structural break to 2011/12, and for applying rolling approach in equation (3.3) is from 1994/95 to 2011/12.

careful examination of all potential costs and benefits of such procedure and using averages only may mask potentially serious costs.

Results

Forecast Revision Efficiency

The results of monthly evaluation of revision efficiency of WASDE corn, soybean, wheat, and cotton forecasts are reported in tables 3.1-3.4, respectively. Significant correlation between consecutive forecast revisions was found in all crops and all categories except for the seed category in wheat forecasts. Almost all correlations between consecutive forecast revisions were positive, suggesting a tendency for "smoothing" or systematic under-adjustments of the forecasts. Negative correlations were observed only once in corn and wheat and in 3 cases for soybeans. All 5 of the negative correlation cases occurred at the end of the forecasting cycle when the final revisions of the data were observed after the end of the marketing year. The preponderance of smoothing rather than jumpiness is consistent with other studies (e.g., Nordhaus, 1987; Coibon and Gorodnichenko, 2012).

Tables 3.1 and 3.2 demonstrate that smoothing in WASDE forecasts spans far beyond the production forecasts that have been analyzed by Isengildina, Irwin and Good (2006b). In fact, Table 3.1 shows that in corn forecasts, revision inefficiency was most common in the exports category with 11 out of 17 examined months of the forecasting cycle showing positive correlations between consecutive revisions. Out of the four crops examined in this study, smoothing was most prevalent in soybeans with the crushings, exports, ending stocks, and price categories showing inefficiency in 12, 14, 10, and 7 out of 17 months, respectively. Smoothing was the least common in wheat with the most affected categories of exports and prices exhibiting positive correlations in 5 and 6 out of 17 months, respectively. In cotton, smoothing was most frequent in production, domestic use, exports and ending stocks forecasts. Prevalence of smoothing seemed to be most common between November and January for corn, in August and from November to September for soybeans, from September to December for wheat, and from January to April for cotton.

Smoothing in production forecasts has been a focus of previous studies because it is commonly observed by forecast users and could affect other forecasts due to the balance-sheet nature of WASDE reports. We did find some evidence of the influence of smoothing in production on other categories as smoothing in November corn production forecast revisions was accompanied by smoothing in exports, ending stocks, and price forecast revisions, and smoothing in August and November soybean production forecast revisions was accompanied by smoothing in almost all other categories. We found similar patterns in July forecasts for wheat and in July and January forecasts for cotton. Our findings of smoothing in corn and soybean November production revisions are consistent with the findings in Isengildina, Irwin, and Good (2006b) in both the magnitude and significance level. The estimated coefficients can be interpreted as point elasticities and indicate, for example, that on average, a 10% revision in October corn production forecasts has been followed by a 7% revision in the same direction in November. The same revision coefficient for corn production forecasts in November (0.70) was also the case of the largest magnitude of smoothing in production forecasts, as other coefficients ranged from 0.27 to 0.5.[18]

Exports was the category most affected by smoothing across the four commodities most likely due to the added uncertainty associated with international trade information and conservativeness of the experts with incorporating this information into the forecasts. The magnitude of smoothing in exports forecasts ranged from 0.32 to 0.71 for corn, 0.22 to 1.25 for soybeans, 0.2 to 0.56 for wheat, and 0.22 to 1.07 for cotton. Among categories in domestic use forecasts, soybean crushings and cotton domestic use forecasts appeared to be most affected by smoothing. Domestic use forecasts are partially based on data collected from domestic processing plants and smoothing may reflect the slowness of incorporating these data. Smoothing in ending stocks forecasts was likely caused by problems in domestic use and exports forecasts and hence was most pronounced in soybeans and cotton. Among price forecasts, the biggest issues were found in soybeans with 8 out of 17 months affected by inefficiency, followed by wheat with smoothing detected in 6 months, corn where smoothing was limited to only 3 months, and cotton where smoothing was significant in only one month. USDA price forecasts are based on a combination of statistical models and market information and smoothing suggests that the new information may be incorporated too slowly during the certain parts of the forecasting cycle. It is interesting to observe that smoothing in soybean price forecasts, differently from other crops, appeared later in the forecasting cycle when the information about competing soybean crops grown in the Southern Hemisphere usually

[18] Big significant coefficients early in the production cycle should be interpreted with care as these forecasts are largely based on historical trends and very little new information. August is the first month when production forecasts are based on NASS estimates rather than trend patterns.

becomes available.

Correction for Revision Inefficiency

The Basic Correction Procedure

The summary statistics pertaining to the accuracy implications of the basic correction procedure for corn, soybeans, wheat, and cotton, are presented in Comparison 1 of tables 3.5-3.8, respectively, and include the average change in MAPEs across all months, the number of negative changes in MAPEs, and the number of positive changes in MAPEs. Negative changes indicate that errors became smaller after correcting for revision inefficiency and show the evidence of improvements from adjusting the forecasts using the basic procedure. Positive values indicate that published WASDE forecasts were more accurate than the adjusted forecasts.

Our findings demonstrate that the basic correction procedure in the vast majority of the cases did not improve the accuracy of the forecasts included in this study. All average changes in MAPEs in soybeans were non-negative, showing larger errors resulting from forecast adjustment. In corn, the only average reduction in MAPEs due to the basic correction procedure was observed in production forecasts, but even that change was very small (-0.005). The counts for MAPE changes in corn production forecasts indicate that out of 144 forecasts, only 38 forecasts were adjusted (only γ coefficients significant at 0.05% level were adjusted) and the accuracy improved in 16 cases and deteriorated in 22. Among wheat forecasts, the only case of average reduction in MAPEs was found in price forecasts (-0.004), but here again the frequency of accuracy deterioration was greater than frequency of accuracy improvements (14 vs. 10 cases). The basic procedure appeared to perform the best in cotton production and exports forecasts with average reductions in MAPEs of -0.122 and -0.011, respectively. While the average improvements in error in these forecasts are still very small, the frequency of accuracy improvements far outweighs that of accuracy deterioration in these cases (31 vs. 13 cases for production and 44 vs. 25 cases for exports). Interestingly, while our findings for corn production forecasts are somewhat consistent with Isengildina, Irwin, and Good (2006b) results, our results for soybean production forecasts were in sharp contrast with that previous study. This difference seems to be exclusively due to the differences in the sample periods (their study used the data from 1970 to 2004) since the basic adjustment procedure applied was identical.[19] This difference in results highlights the importance of the factors that may have an effect on the basic correction procedure investigated in this study.

Outlier Detection

The existence of outliers in equation (3.3) was examined using Cook's D. Outliers were found for all categories in all crops. For example, for corn production using the October data from 1984/95 to 2002/03, Cook's D for October 1988 was 0.52, which was larger than the critical value of 0.21 (4/19, where 19 is the sample size), suggesting that October 1988 was an outlier. Additionally, the residuals versus fitted plot, the normality plot, the scale location plot, and the residuals versus leverage plot shown in Figure 3.3

[19] Other differences are the use of RMSPEs to evaluate changes in accuracy in Isengildina, Irwin, and Good (2006b) study versus MAPEs in our study and we adjusted forecasts with only significant γ coefficients. We double-checked our results by adjusting all forecasts and using RMSPEs to examine changes in accuracy. We found that the differences still hold.

indicate that the same data point (labeled in these plots as '5') was a potential outlier.

Although the MM-estimation approach is often preferred to the M-estimation approach in robust regression because the latter could be biased in the presence of high leverage points, we found that the M-estimation performed better in this study since it generated smaller MAPEs than the MM-estimation.[20] The effect of using the M-estimation approach instead of the OLS estimation approach on forecast accuracy is summarized in Comparison 2 of tables 3.5-3.8. Based on the negative changes in MAPEs, indicating a reduction in error, the M-estimation was preferred for corn, soybeans, and cotton due to accuracy improvements in the majority of cases, as 4 out of 7 categories of corn, 4 out of 7 categories of soybeans, and 4 out of 6 categories of cotton experienced negative average changes in MAPEs. On the other hand, the OLS estimation was preferred for wheat because the M-estimation had a very limited (1 out of 7) positive impact on the accuracy of these forecasts. Therefore, the M-estimation was applied to estimating γ coefficients in equation (3.3) for corn, soybeans, and cotton while the OLS estimation was used for wheat in the remainder of the analyses.

Forecast Size and Direction

The impact of forecast size and direction on correction for revision inefficiency was investigated by including the variable TD in equation (3.3). The changes in MAPEs for four crops over the validation subsample 1999/2000-2011/12 were calculated by subtracting the MAPEs of adjusted forecasts including TD as in equation (3.6) from those

[20] The comparison of results using the MM-estimation and the M-estimation for all four commodities are available upon request.

adjusted using the basic procedure for the same time period. The assessment of the changes in MAPEs for corn, soybeans, wheat, and cotton is summarized in Comparison 3 of tables 3.5-3.8, respectively. The adjustment appeared to have the largest impact on the soybean balance sheet where beginning stocks, crushings, and price forecasts showed reductions in average error of -0.077, -0.015, and -0.061, respectively, and the number of smaller errors was greater or equal to the number of larger errors. Reductions in average MAPEs were found in corn price (-0.014) and wheat production forecasts (-0.054). The lack of accuracy improvement after accounting for forecast size and direction in the cotton balance sheet suggests that cotton forecasters have already take these factors into account. Based on these results, forecast size and direction were incorporated in correcting inefficiency in revisions of corn price; soybean beginning stocks, crushings, and price; and wheat production forecasts, but not in any other categories.

Stability of Revision Inefficiency Over Time

Stability of revision inefficiency over time was examined graphically and using a QLR test. Figure 3.4 gives a graphical example of revision inefficiency over time for corn production using consecutive 10 year sub-periods. Bars in the plot for July represent the λ coefficients calculated using equation (3.2) for each 10 year block of observations. Plots demonstrate that the estimated coefficients vary substantially depending on the sub-period used.

An example of the QLR test for corn production illustrating the detection of structural change in November 2000 is shown in figure 3.5. The QLR test was carried out for all categories of corn, soybean, wheat, and cotton forecasts, and we found that years

1987, 2006, and 2007 had significant coefficients 11, 8, and 9 times respectively, while other years were significant only once or twice across the four crops.[21] Therefore, we concluded that forecast revisions were unstable over the study period with structural breaks likely taking place in 1987 and 2006-2007.

As discussed in the methods section, the basic correction procedure can be modified in several ways to address the issue of instability. The first approach would use only the data after the breakpoint for the adjustment procedure. Considering the sample period of this study, it was not feasible to use post 2007/08 data for the analysis. However, the influence of a structural change in year 1987 was tested by trimming the data period to 1987/88-2006/07 with the validation subsample of 1997/98-2006/07. Using the trimmed data did not yield an improvement in forecast accuracy.[22] The second approach applied a 5-year rolling method to estimating the γ coefficients in equation (3.3) instead of the recursive method used in the basic correction procedure. This modified approach was evaluated by subtracting the MAPEs of the rolling estimation from those using the recursive estimation over the validation subsample 1994/95-2011/12 and forecast accuracy was reduced in all categories of all crops with the exception of the wheat price forecasts. Due to the lack of effectiveness, the modifications described above were not included in the adjustment procedure. Instead, we examined the impact of structural breaks on the effectiveness of our correction procedure from another angle by evaluating the changes in their effect on forecast accuracy over time. For this purpose, the

[21] The complete QLR test results are available upon request.

[22] The complete results of changes in MAPEs using all data versus trimmed data over the validation subsample of 1997/98-2006/07 are available upon request.

validation subsample of 1994/95-2011/12 was divided into three 6-years periods, where 1994/95-1999/00, 2000/01-2005/06, and 2006/07-2011/12 were considered stage 1, 2, and 3 respectively.

Tables 3.9-3.12 report the implications of the new correction procedure on forecast accuracy for corn, soybeans, wheat, and cotton, respectively, over the full validation subsample, as well as within three stages. The changes were computed by subtracting the MAPEs of published WASDE forecasts from those of adjusted forecasts using the new revision inefficiency correction procedure. The new procedures for four crops were formed according to the results of the previous two sections as following: equation (3.6) was used for correcting corn price forecasts; soybean beginning stocks, crushings, and price forecasts; and wheat production forecasts; while equation (3.3) was used for all other categories. The M-estimation was used for corn, soybeans, and cotton and the OLS estimation was applied for wheat.

A direct comparison of the new correction procedure with the basic correction procedure was made based on the results of the full validation subsample in the top part of tables 3.9-3.12 and the results in Comparison 1 of tables 3.5-3.8.[23] Relative to the basic correction procedure, the new procedure improved forecast accuracy in 4 out of 7

[23] Note that the validation subsample for category price in corn, beginning stocks, crushings, and price in soybeans, and production in wheat in Comparison 1 of table 3.5-3.8 starts in 1994/95, while the validation subsample of these categories in the top part of tables 3.9-3.12 starts in 1999/00. Therefore, the results for these categories in tables 3.9-3.12 using the new correction procedure should be compared with the ones using the basic procedure over the same validation subsample 1999/00-2011/12. The average MAPEs have decreased from 0.073 to 0.062 for corn price; increased from 0.02 to 0.034 for beginning stocks, decreased from 0.019 to 0.007 for crushings, and from 0.061 to -0.030 for price in soybeans; and from 0.016 to -0.038 for cotton production forecasts.

categories in corn, 5 out of 7 categories in soybeans, 1 out of 8 categories in wheat, and 4 out of 6 categories in cotton. In relative terms, the new procedure reduced the accuracy of corn beginning stocks, feed and residual, and food, seed, and industrial forecasts, soybean beginning stocks and ending stocks forecasts, and cotton beginning stocks and exports forecasts, while leaving the accuracy of other forecast categories unchanged. But, of course, the true value of the new procedure should be interpreted relative to the published WASDE forecasts as shown in tables 3.9-3.12. Overall, the revision inefficiency correction procedure developed in this study appears helpful to corn production and exports forecasts, soybean price forecasts, wheat production and price forecasts, and cotton production and ending stocks forecasts.

The results for 3 stages in tables 3.9-3.12 reveal the performance of the new correction procedure over time. Our results for corn production forecasts shown in Table 3.9 demonstrate that the new adjustment procedure reduced average MAPEs in all three stages. Our adjustment procedure improved the accuracy for corn exports and feed and residual forecasts in stage 2 but not in other stages. Among soybean forecasts, our adjustment procedure performed the best in stage 3 with average MAPE reductions in beginning stocks, exports, ending stocks, and price forecasts of 0.226, 0.107, 0.252, and 0.092, respectively. However, prior to stage 3, our adjustment procedure did not improve accuracy in these forecasts. The results were probably the strongest for soybean exports and price forecasts, where error reductions were much more common than error increases. In terms of raw units, our findings for soybean exports, for example, imply a reduction in forecast error in December of 2011/12 marketing year due to correction for forecast revision inefficiency as large as 1.4 million bushels for a 1.3 billion bushel soybean crop. Wheat forecasts were the least affected by revision inefficiency, but we still find potential accuracy improvements due to our adjustment procedure in production forecasts in stages 2 and 3, in exports forecasts in stage 2, and in price forecasts in stage 1 and 2. In the results for cotton, our adjustment procedure showed the most potential in cotton production forecasts with the largest overall average reduction in MAPEs, the average reduction in MAPEs increasing over time, and the frequency of accuracy improvements consistently much greater than accuracy deteriorations. Accuracy improvements due to correction for revision inefficiency in other cotton forecasts were more sporadic. These findings demonstrate the challenges in correcting revision inefficiency when inefficiency is unstable over time.

Summary and Conclusions

Numerous previous studies demonstrated inefficiencies in WASDE commodity forecasts. Our study focused on inefficiency in revisions of WASDE forecasts for U.S. corn, soybeans, wheat, and cotton. We also presented an adjustment procedure that could be used to correct revision inefficiency and improve the accuracy of these forecasts.

Results from the evaluation of the revision inefficiency show significant correlations between consecutive forecast revisions in all crops and all categories except for the seed category in wheat forecasts. Almost exclusively, inefficiency took the form of smoothing as revisions were positively correlated. We also discovered that among the forecasts of four crops, smoothing was most prevalent in soybeans and least common in wheat, and exports was the category most affected by smoothing.

The widespread evidence of revision inefficiency suggests that forecast accuracy could be improved if this inefficiency is corrected. Using the revision inefficiency correction procedure suggested by Isengildina, Irwin, and Good (2006b) study as the basic procedure, we modified the procedure to adjust for outliers and the impact of forecast size and direction on revision inefficiency. After a series of comparisons, the new correction procedures for four commodities were selected as following: using the OLS estimation for wheat and the M-estimation for corn, soybeans, and cotton; only considering forecast size and direction for corn price, soybean beginning stocks, crushings, and price, and wheat production forecasts. We also found that revision inefficiencies were unstable during our sample period, resulting in changes in the correction ability of the new procedure over time.

Our findings suggest that our adjustment procedure has the highest potential for improving accuracy in corn, wheat, and cotton production forecasts. It is important to note that the application of such a correction procedure over time should remove or decrease the degree of revision inefficiency, which should be taken into account in the continued adjustment of the correction procedure to be focused on the most relevant data.

Our limited ability to correct revision inefficiency using multiple statistical methods explored in this study provides insight about the nature of the inefficiency commonly called smoothing. Most previous studies (Nordhaus, 1987; Isengildina, Irwin and Good, 2006b; Coibon and Gorodnichenko, 2012) argue that smoothing is associated with conservativeness or inability of forecasters to adjust to innovations in a timely manner. However, if this conservativeness was systematic, we should be able to control for it using statistical methods. Instead, our findings show that the impact of smoothing is very unstable over time, yet a persistent characteristic of most forecasts revisions. This suggests that perhaps correlations in forecast revisions (smoothing) illustrate that forecasters tend to make the same mistakes within the forecasting cycle. In fact, some of the biggest improvements in suggested smoothing correction procedures were due to incorporating forecast size and direction for some forecasts. If repeating the same mistakes causes smoothing, it can only be corrected by knowing what these mistakes are. Therefore, studies that investigate efficiency of WASDE forecasts with respect to external factors (e.g., macro forces in Isengildina and Karali, 2013) may provide some guidance.

References

Adjemian, M. K. "Quantifying the WASDE Announcement Effect." American Journal of Agricultural Economics 94(2012):238-256.

Alesina, A., and R. Perotti. "Fiscal Discipline and the Budget Process." The American Economic Review 86(1996):401-407.

Botto, A. C., O. Isengildina, S. H. Irwin, and D. L. Good. "Accuracy Trends and Sources of Forecast Errors in WASDE Balance Sheet Categories for Corn and Soybeans." Paper presented at the Agricultural and Applied Economics Association Annual Meetings, Long Beach, CA, July 23-26, 2006.

Clements, M. P. "Evaluating the Rationality of Fixed Event Forecasts." Journal of Forecasting 16(1997):225-239.

Coibion O., and Y. Gordonichenko. "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts." Working Paper, No. 16537, National Bureau of Economic Research, 2010.

Cook, R. D. "Detection of influential observation in linear." Technometrics 19(1997):15-18.

Dovern, J., and J. Weisser "Accuracy, Unbiasedness and Efficiency of Professional Macroeconomic Forecasts: An Empirical Comparison for the G7." International Journal of Forecasting 27(2011):452-465.

European Commission: Agriculture and Rural Development. "Agricultural Commodity Markets Outlook 2011-2020, a Comparative Analysis" (2011). Available online at: http://ec.europa.eu/agriculture/analysis/tradepol/worldmarkets/outlook/2011_2020_en.pdf.

Finger, R. "Revisiting the Evaluation of Robust Regression Techniques for Crop Yield Data Detrending." American Journal of Agricultural Economics 92(2010):205-211.

Harvey, A. C. The Econometric Analysis of Time Series. MIT press, 1990.

Hoaglin, D. C., and R. E. Welsch. "The hat matrix in regression and ANOVA." The American Statistician 32(1978):17-22.

Huber, P. J. "Robust Estimation of a Location Parameter." The Annals of Mathematical Statistics 35(1964):73-101.

Isengildina, O., S. H. Irwin, and D. L. Good. "Do Big Crops Get Bigger and Small Crops Get Smaller? Further Evidence on Smoothing in U.S. Department of Agriculture Forecasts." Journal of Agricultural and Applied Economics 45(2013):95-107.

Isengildina, O., B. Karali, S.H. Irwin. "When do the USDA forecasters make mistakes?" Applied Economics 45(2013):5086-5103.

Isengildina-Massa, O., S. MacDonald, and R. Xie. "Comprehensive Evaluation of USDA Cotton Forecasts." Journal of Agricultural and Resource Economics 37(2012):98-113.

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, O., S. H. Irwin, and D. L. Good. "The Value of USDA Situation and Outlook Information in Hog and Cattle Markets." Journal of Agricultural and Resource Economics 31(2006):262-282.

Isengildina, O., S. H. Irwin, and D. L. Good. "Are Revisions to USDA Crop Production Forecasts Smoothed?" American Journal of Agricultural Economics 88(2006):1091-1104.

Isengildina, O., S. H. Irwin, and D. L. Good. "Evaluation of USDA Interval Forecasts of Corn and Soybean Prices." American Journal of Agricultural Economics 86(2004):990-1004.

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

Lewis, K. and M. Manfredo. "An Evaluation of the USDA Sugar Production and Consumption Forecasts." Paper presented at the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, St. Louis, Missouri, April 16-17, 2012.

Nordhaus, W. D. "Forecasting Efficiency: Concepts and Applications." The Review of Economics and Statistics 4(1987):667-674.

Patton, A. J., and A. Timmermann. "Why Do Forecasters Disagree? Lessons from the Term Structure of Cross-sectional Dispersion." Journal of Monetary Economics 57(2010):803-820.

Preminger, A., and R. Franck. "Forecasting Exchange Rates: a Robust Regression Approach." International Journal of Forecasting 23(2007):71-84.

Rawlings, J. O., S. G. Pantula, and D. A. Dickey. Applied Regression Analysis: a Research Tool. New York: Springer,1998.

Rousseeuw, P. J., and A. M. Leroy. Robust Regression and Outlier Detection. John Wiley & Sons, 2005.

Sanders, D. R., and M. R. Manfredo. “USDA Livestock Price Forecasts: a Comprehensive Evaluation.” Journal of Agricultural and Resource Economics 28(2003):316-334.

Sanders, D. R., and M. R. Manfredo. “USDA Production Forecasts for Pork, Beef, and Broilers: An Evaluation.” Journal of Agricultural and Resource Economics 27(2002):114-28.

Stock, J. H., and M. W. Watson. Introduction to Econometrics. New York: Pearson Education, 2003.

Vogel, F. A., and G. A. Bange. “Understanding USDA Crop Forecasts.” National Agricultural Statistics Service and World Agricultural Outlook Board, U.S. Department of Agriculture, Miscellaneous Publication, No. 1554, 1999.

Yohai, V. J. “High Breakdown-point and High Efficiency Robust Estimates for Regression.” The Annals of Statistics 15(1987):642-656

Table 3.1 Tests of Revision Efficiency for WASDE Corn Forecasts, 1984/85-2011/12 Marketing Years

Month	Beginning Stocks	Production	Feed and Residual	Food, Seed and Industrial	Exports	Ending Stocks	Price
Jul	0.45	-0.02	0.18	-0.04	0.11	-0.33	-0.36
Aug	0.01	0.45***	-0.12	-0.19	0.00	0.30	-0.08
Sep	0.77***	0.05	0.10	0.02	0.40***	0.03	0.14
Oct	0.29	0.38	0.05	0.50**	0.13	0.47	0.21
Nov	-0.06	0.70***	0.21	-0.05	0.32*	0.30***	0.57***
Dec	--	--	0.07	0.00	0.57***	0.03	0.20**
Jan	--	--	0.87	0.46***	0.39**	0.85**	0.60***
Feb			0.00	0.28*	0.39***	0.09	0.06
Mar			0.00	0.00	0.29	0.14	0.00
Apr			--	-0.10	0.66***	0.63	0.32
May			0.06	0.09	0.51***	0.21	-0.13
Jun			0.14**	0.41***	0.36**	0.07	-0.22
Jul			-4.59	0.05	0.71***	0.45	0.65
Aug			0.01	-0.05	0.35**	0.07	0.00
Sep			0.00	0.03	0.52***	0.65***	-0.01
Oct			-0.89	0.68***	0.01	-0.71*	-0.05
Nov			-0.01	-0.09	0.08	0.00	0.00

Notes: Reported values are λ coefficients from regression $r_t^j = \lambda r_t^{j-1} + \varepsilon_t^j$ which is estimated using the OLS method. Single, double, and triple asterisks (*, **, ***) denote statistical significance at 10%, 5%, and 1%. Missing values are generated when the dependent and/or independent variables in the regression are zeroes.

Table 3.2 Tests of Revision Efficiency for WASDE Soybean Forecasts, 1984/85-2011/12 Marketing Years

Month	Beginning Stocks	Production	Crushings	Seed and Residual	Exports	Ending Stocks	Price
Jul	0.48 **	0.23	-0.04	-0.47	1.25 **	0.02	0.00
Aug	0.36 *	0.65 ***	0.58 ***	0.37 *	0.49 **	0.59 ***	0.21
Sep	0.06	0.03	-0.01	-0.05	-0.01	0.15	0.10
Oct	0.45	0.28	0.43 **	0.31	0.47 *	-0.01	0.52
Nov	0.00	0.28 ***	0.30 ***	0.14 **	0.31 **	0.21 *	0.21 *
Dec	--	0.00	-0.06	0.03	0.52 ***	0.18 *	0.33 *
Jan	--	-2.23	0.50 **	0.64	0.67 ***	0.99 ***	0.15
Feb			0.50 ***	-0.06	0.75 ***	0.17	0.11
Mar			0.35 **	0.00	0.64 ***	0.32 *	0.75 ***
Apr			0.33 **	-0.83	0.51 ***	-0.01	0.46 ***
May			0.50 ***	0.03	0.36 **	0.37 *	0.66 ***
Jun			0.90 ***	0.00	0.39 ***	0.63 ***	0.22 **
Jul			0.44 ***	2.85	0.76 ***	0.40 **	0.98 ***
Aug			0.54 ***	0.03	0.70 **	0.39 *	0.07
Sep			0.56 ***	0.92 ***	0.22 **	0.25 **	0.08
Oct			-0.03	-0.58	0.05	-0.88 *	0.17
Nov			-0.13 *	-0.04	-0.14	0.00	-0.10 *

Notes: Reported values are λ coefficients from regression $r_t^j = \lambda r_t^{j-1} + \varepsilon_t^j$ which is estimated using the OLS method. Single, double, and triple asterisks (*, **, ***) denote statistical significance at 10%, 5%, and 1%. Missing values are generated when the dependent and/or independent variables in the regression are zeroes.

Table 3.3 Tests of Revision Efficiency for WASDE Wheat Forecasts, 1984/85-2011/12 Marketing Years

Month	Beginning Stocks	Production	Food	Seed	Feed and Residual	Exports	Ending Stocks	Prices
Jul	0.76 **	0.93 **	0.11 **	0.17	0.91 **	0.69	0.46	0.77 *
Aug	0.00	0.10	0.59	0.00	0.11	0.37	-0.10	0.15
Sep	--	0.10	0.07	--	0.01	0.20 *	0.12	0.29 **
Oct	--	0.31	0.00	0.80	0.40	0.46 **	0.28	0.42 ***
Nov			0.07	0.00	-0.03	0.37 **	0.13 *	0.20 **
Dec			0.20	0.00	0.00	0.56 **	0.59 *	0.65 ***
Jan			0.00	-1.00	--	0.12	0.05	0.65 ***
Feb			0.20	0.00	0.03	0.33 *	0.09	0.08
Mar			0.17	0.00	0.00	0.05	0.24	0.12
Apr			0.00	-0.50	--	0.13	-0.06	0.09
May			0.33	0.00	0.00	-0.01	0.09	-0.18
Jun			-0.06	0.00	0.00	0.17	0.12	0.09
Jul			0.04	-0.58	-1.84	0.01	0.68 **	-0.08
Aug			0.63	-0.01	-0.28 ***	-0.16	0.00	0.00
Sep			0.06	0.00	0.03	-0.01	--	0.00
Oct			0.07	--	0.22	0.00	--	0.00
Nov			0.00	0.00	0.02	0.00	0.00	--

Notes: Reported values are λ coefficients from regression $r_t^j = \lambda r_t^{j-1} + \varepsilon_t^j$ which is estimated using the OLS method. Single, double, and triple asterisks (*, **, ***) denote statistical significance at 10%, 5%, and 1%. Missing values are generated when the dependent and/or independent variables in the regression are zeroes.

Table 3.4 Tests of Revision Efficiency for WASDE Cotton Forecasts, 1984/85-2011/12 Marketing Years

Month	Beginning Stocks	Production	Domestic Use	Exports	Ending Stocks	Price
Jul	0.54**	0.95*	0.82***	1.07***	0.55	0.28
Aug	0.32***	0.22	0.21	0.22	0.18	0.25
Sep	0.01	0.12	0.39**	0.01	-0.02	-0.10
Oct	-0.04	0.44***	0.32	0.41*	0.14	0.53
Nov	0.12	0.45***	0.31**	0.06	0.09	0.15
Dec	0.00	0.27**	0.15	0.35	0.18	0.37**
Jan	0.00	0.50***	0.22***	0.61***	0.57***	-0.10
Feb			1.70***	0.36***	0.60***	0.06
Mar			0.40***	0.27	0.40**	-0.13
Apr			0.38**	0.60***	0.25*	0.13
May			0.51**	0.16	0.02	0.12
Jun			0.13	0.19	0.35*	0.05
Jul			0.48**	0.20	0.50**	-0.08
Aug			0.19	0.84***	0.32***	-0.13
Sep			0.26	0.22***	0.22	0.25
Oct			0.23	0.30	0.04	0.10
Nov			0.01	0.00	0.14*	0.00

Notes: Reported values are λ coefficients from regression $r_t^j = \lambda r_t^{j-1} + \varepsilon_t^j$ which is estimated using the OLS method. Single, double, and triple asterisks (*, **, ***) denote statistical significance at 10%, 5%, and 1%.

Table 3.5 Evaluation of Revision Inefficiency Correction Procedures for Corn Forecasts

	Beginning Stocks	**Production**	**Feed and Residual**	**Food, Seed, and Industrial**	**Exports**	**Ending Stocks**	**Price**
Comparison 1: MAPEs of forecasts adjusted using the basic correction procedure minus MAPEs of published WASDE forecasts, 1994/95-2011/12							
Average difference	0.007	-0.005	0.024	0.053	0.064	0.376	0.050
Negative changes	2	16	4	4	14	20	1
Positive changes	4	22	6	5	22	28	4
Sample Size	144	144	324	324	324	324	324
Comparison 2: MAPEs of forecasts adjusted using the M-estimation minus those adjusted using the OLS estimation in equation (3.3), 1994/95-2011/12							
Average difference	0.099	-0.014	0.002	0.058	-0.084	-0.099	-0.009
Negative changes	10	24	6	7	31	24	3
Positive changes	17	14	6	7	16	23	5
Sample Size	144	144	324	324	324	324	324
Comparison 3: MAPEs of forecasts adjusted including forecast size and direction minus those not considering forecast size and direction, 1999/00-2011/12							
Average difference	0.111	0.168	0.015	0.024	0.422	0.585	-0.014
Negative changes	10	19	7	5	24	15	3
Positive changes	13	22	8	7	32	31	1
Sample Size	104	104	234	234	234	234	234

Notes: Negative changes indicate the improvements in forecast accuracy. Positive changes illustrate larger errors or deterioration of forecast accuracy. Sample size reflects the shorter forecasting cycle for beginning stocks and production forecasts and loss of observations used to calculate the forecast size and direction variable.

Table 3.6 Evaluation of Revision Inefficiency Correction Procedures for Soybean Forecasts

	Beginning Stocks	**Production**	**Crushings**	**Seed and Residual**	**Exports**	**Ending Stocks**	**Price**
Comparison 1: MAPEs of forecasts adjusted using the basic correction procedure minus MAPEs of published WASDE forecasts, 1994/95-2011/12							
Average difference	0.242	0.021	0.004	0.177	0.032	0.262	0.065
Negative changes	4	4	15	9	43	9	19
Positive changes	8	7	12	10	27	15	26
Sample size	144	144	324	324	324	324	324
Comparison 2: MAPEs of forecasts adjusted using the M-estimation minus those adjusted using the OLS estimation in equation (3.3), 1994/95-2011/12							
Average difference	0.235	-0.003	0.001	-0.049	-0.003	0.024	-0.049
Negative changes	13	7	13	13	40	18	39
Positive changes	17	5	16	10	33	14	22
Sample size	144	144	324	324	324	324	324
Comparison 3: MAPEs of forecasts adjusted including forecast size and direction minus those not considering forecast size and direction, 1999/00-2011/12							
Average difference	-0.077	0.050	-0.015	0.444	0.017	0.618	-0.061
Negative changes	11	10	12	13	22	12	26
Positive changes	11	9	12	14	37	18	21
Sample size	104	104	234	234	234	234	234

Notes: Negative changes indicate the improvements in forecast accuracy. Positive changes illustrate larger errors or deterioration of forecast accuracy. Sample size reflects the shorter forecasting cycle for beginning stocks and production forecasts and loss of observations used to calculate the forecast size and direction variable.

Table 3.7 Evaluation of Revision Inefficiency Correction Procedures for Wheat Forecasts

	Beginning Stocks	**Production**	**Food**	**Feed and Residual**	**Exports**	**Ending Stocks**	**Price**
Comparison 1: MAPEs of forecasts adjusted using the basic correction procedure minus MAPEs of published WASDE forecasts, 1994/95-2011/12							
Average difference	0.117	0.029	0.000	0.107	0.072	0.000	-0.004
Negative changes	0	11	0	2	9	0	10
Positive changes	2	12	0	6	18	0	14
Sample size	90	90	324	324	324	324	324
Comparison 2: MAPEs of forecasts adjusted using the M-estimation minus those adjusted using the OLS estimation in equation (3.3), 1994/95-2011/12							
Average difference	0.000	-0.031	0.000	0.000	0.039	0.007	0.015
Negative changes	0	10	0	4	16	3	15
Positive changes	0	9	0	6	18	3	10
Sample size	90	90	324	324	324	324	324
Comparison 3: MAPEs of forecasts adjusted including forecast size and direction minus those not considering forecast size and direction, 1999/00-2011/12							
Average difference	0.008	-0.054	0.007	0.001	0.026	0.162	0.060
Negative changes	0	9	2	4	6	0	13
Positive changes	4	8	3	4	15	1	11
Sample size	65	65	234	234	234	234	234

Notes: Negative changes indicate the improvements in forecast accuracy. Positive changes illustrate larger errors or deterioration of forecast accuracy. Sample size reflects the shorter forecasting cycle for beginning stocks and production forecasts and loss of observations used to calculate the forecast size and direction variable.

Table 3.8 Evaluation of Revision Inefficiency Correction Procedures for Cotton Forecasts

	Beginning Stocks	**Production**	**Domestic Use**	**Exports**	**Ending Stocks**	**Price**
Comparison 1: MAPEs of forecasts adjusted using the basic correction procedure minus MAPEs of published WASDE forecasts, 1994/95-2011/12						
Average difference	0.119	-0.122	0.072	-0.011	0.028	0.096
Negative changes	4	31	18	44	26	14
Positive changes	4	13	17	25	22	17
Sample size	144	144	324	324	324	324
Comparison 2: MAPEs of forecasts adjusted using the M-estimation minus those adjusted using the OLS estimation in equation (3.3), 1994/95-2011/12						
Average difference	0.004	-0.005	-0.011	0.020	-0.035	-0.006
Negative changes	4	26	22	22	29	15
Positive changes	15	19	17	46	21	14
Sample size	144	144	324	324	324	324
Comparison 3: MAPEs of forecasts adjusted including forecast size and direction minus those not considering forecast size and direction, 1999/00-2011/12						
Average difference	0.031	0.085	0.022	0.287	0.167	0.162
Negative changes	6	19	20	13	13	18
Positive changes	8	22	27	37	23	23
Sample size	104	104	234	234	234	234

Notes: Negative changes indicate the improvements in forecast accuracy. Positive changes illustrate larger errors or deterioration of forecast accuracy. Sample size reflects the shorter forecasting cycle for beginning stocks and production forecasts and loss of observations used to calculate the forecast size and direction variable.

Table 3.9 Evaluation of the New Revision Inefficiency Correction Procedure over Time for Corn Forecasts

	Beginning Stocks	Production	Feed and Residual	Food, Seed, and Industrial	Exports	Ending Stocks	Price
				1994/95-2011/12			
Average difference	0.106	-0.019	0.026	0.111	-0.020	0.278	0.062
Negative changes	10	18	4	5	22	13	0
Positive changes	17	20	7	7	19	19	3
Sample size	144	144	324	324	324	324	234
				Stage 1: 1994/95-1999/00			
Average difference	0.151	-0.025	0.000	0.127	0.007	0.327	
Negative changes	1	5	0	0	4	4	
Positive changes	8	8	0	2	4	7	
Sample size	48	48	108	108	108	108	
				Stage 2: 2000/01-2005/06			
Average difference	0.028	-0.012	-0.001	0.036	-0.233	0.363	0.041
Negative changes	6	6	2	0	13	6	0
Positive changes	5	6	1	1	6	9	2
Sample size	48	48	108	108	108	108	108
				Stage 3: 2006/07-2011/12			
Average difference	0.139	-0.021	0.079	0.145	0.165	0.142	0.094
Negative changes	3	7	2	5	5	3	0
Positive changes	4	6	6	4	9	3	1
Sample size	48	48	108	108	108	108	108

Notes: The evaluation is carried out by subtracting the MAPEs of published WASDE forecasts from the MAPEs of the new correction procedure. The new revision inefficiency correction procedure for corn includes the use the M-estimation in estimating the γ coefficients, the use of equation (3.6) for category price, and the use of equation (3.3) for other categories. The validation subsamples for price are from 1999/00-2011/12. So, no results are given for price in stage 1. Negative changes indicate the improvements in forecast accuracy. Positive changes illustrate larger errors or deterioration of forecast accuracy.

Table 3.10 Evaluation of the New Revision Inefficiency Correction Procedure over Time for Soybean Forecasts

	Beginning Stocks	Production	Crushings	Seed and Residual	Exports	Ending Stocks	Price
			1994/95-2011/12				
Average difference	0.034	0.018	0.007	0.128	0.029	0.286	-0.030
Negative changes	5	0	8	11	38	13	22
Positive changes	2	5	9	10	24	16	10
Sample size	104	144	234	324	324	324	234
			Stage 1: 1994/95-1999/00				
Average difference		0.000		-0.212	0.027	0.766	
Negative changes		0		2	10	1	
Positive changes		0		1	6	7	
Sample size		48		108	108	108	
			Stage 2: 2000/01-2005/06				
Average difference	0.410	0.050	0.012	0.158	0.167	0.345	0.027
Negative changes	1	0	4	4	10	6	9
Positive changes	2	3	3	4	10	7	7
Sample size	48	48	108	108	108	108	108
			Stage 3: 2006/07-2011/12				
Average difference	-0.226	0.012	0.008	0.426	-0.107	-0.252	-0.092
Negative changes	4	0	3	5	18	6	13
Positive changes	0	2	5	5	8	2	3
Sample size	48	48	108	108	108	108	108

Notes: The evaluation is carried out by subtracting the MAPEs of published WASDE forecasts from the MAPEs of the new correction procedure. The new revision inefficiency correction procedure for soybeans includes the use of the M-estimation in estimating the γ coefficients, the use of equation (3.6) for category beginning stocks, crushings, and price, and the use of equation (3.3) for other categories. The validation subsamples for beginning stocks, crushings, and price are from 1999/00-2011/12. So, no results are given for beginning stocks, crushings, and price in stage 1. Negative changes indicate the improvements in forecast accuracy. Positive changes illustrate larger errors or deterioration of forecast accuracy.

Table 3.11 Evaluation of the New Revision Inefficiency Correction Procedure over Time for Wheat Forecasts

	Beginning Stocks	Production	Food	Feed and Residual	Exports	Ending Stocks	Price
			1994/95-2011/12				
Average difference	0.117	-0.038	0.000	0.107	0.072	0.000	-0.004
Negative changes	0	8	0	2	9	0	10
Positive changes	2	4	0	6	18	0	14
Sample size	90	65	324	324	324	324	324
			Stage 1: 1994/95-1999/00				
Average difference	0.351		0.000	0.016	0.113	0.000	-0.095
Negative changes	0		0	0	3	0	3
Positive changes	2		0	1	6	0	5
Sample size	30		108	108	108	108	108
			Stage 2: 2000/01-2005/06				
Average difference	0.000	-0.064	0.000	0.000	-0.027	0.000	-0.039
Negative changes	0	3	0	0	5	0	3
Positive changes	0	2	0	0	4	0	5
Sample size	30	30	108	108	108	108	108
			Stage 3: 2006/07-2011/12				
Average difference	0.000	-0.016	0.000	0.305	0.135	0.000	0.115
Negative changes	0	4	0	2	1	0	4
Positive changes	0	2	0	5	8	0	4
Sample size	30	30	108	108	108	108	108

Notes: The evaluation is carried out by subtracting the MAPEs of published WASDE forecasts from the MAPEs of the new correction procedure. The new revision inefficiency correction procedure for wheat includes the use of the OLS estimation in estimating the γ coefficients, the use of equation (3.6) for category production, and the use of equation (3.3) for other categories. The validation subsamples for production are from 1999/00-2011/12. So, no results are given for production in stage 1. Negative changes indicate the improvements in forecast accuracy. Positive changes illustrate larger errors or deterioration of forecast accuracy.

Table 3.12 Evaluation of the New Revision Inefficiency Correction Procedure over Time for Cotton Forecasts

	Beginning Stocks	**Production**	**Domestic Use**	**Exports**	**Ending Stocks**	**Price**
			1994/95-2011/12			
Average difference	0.122	-0.128	0.061	0.009	-0.007	0.090
Negative changes	4	34	19	39	20	12
Positive changes	15	12	17	24	13	15
Sample size	144	144	324	324	324	324
			Stage 1: 1994/95-1999/00			
Average difference	0.228	-0.019	0.041	0.321	-0.354	0.014
Negative changes	1	9	3	13	5	3
Positive changes	8	4	3	10	2	4
Sample size	48	48	108	108	108	108
			Stage 2: 2000/01-2005/06			
Average difference	-0.048	-0.124	0.221	-0.470	0.001	0.156
Negative changes	2	11	6	17	7	4
Positive changes	6	2	9	2	4	3
Sample size	48	48	108	108	108	108
			Stage 3: 2006/07-2011/12			
Average difference	0.187	-0.240	-0.079	0.176	0.332	0.100
Negative changes	1	14	10	9	8	5
Positive changes	1	6	5	12	7	8
Sample size	48	48	108	108	108	108

Notes: The evaluation is carried out by subtracting the MAPEs of published WASDE forecasts from the MAPEs of the new correction procedure. The new revision inefficiency correction procedure for cotton includes the use of the M-estimation in estimating the γ coefficients and the use of equation (3.3) for all categories. Negative changes indicate the improvements in forecast accuracy. Positive changes illustrate larger errors or deterioration of forecast accuracy.

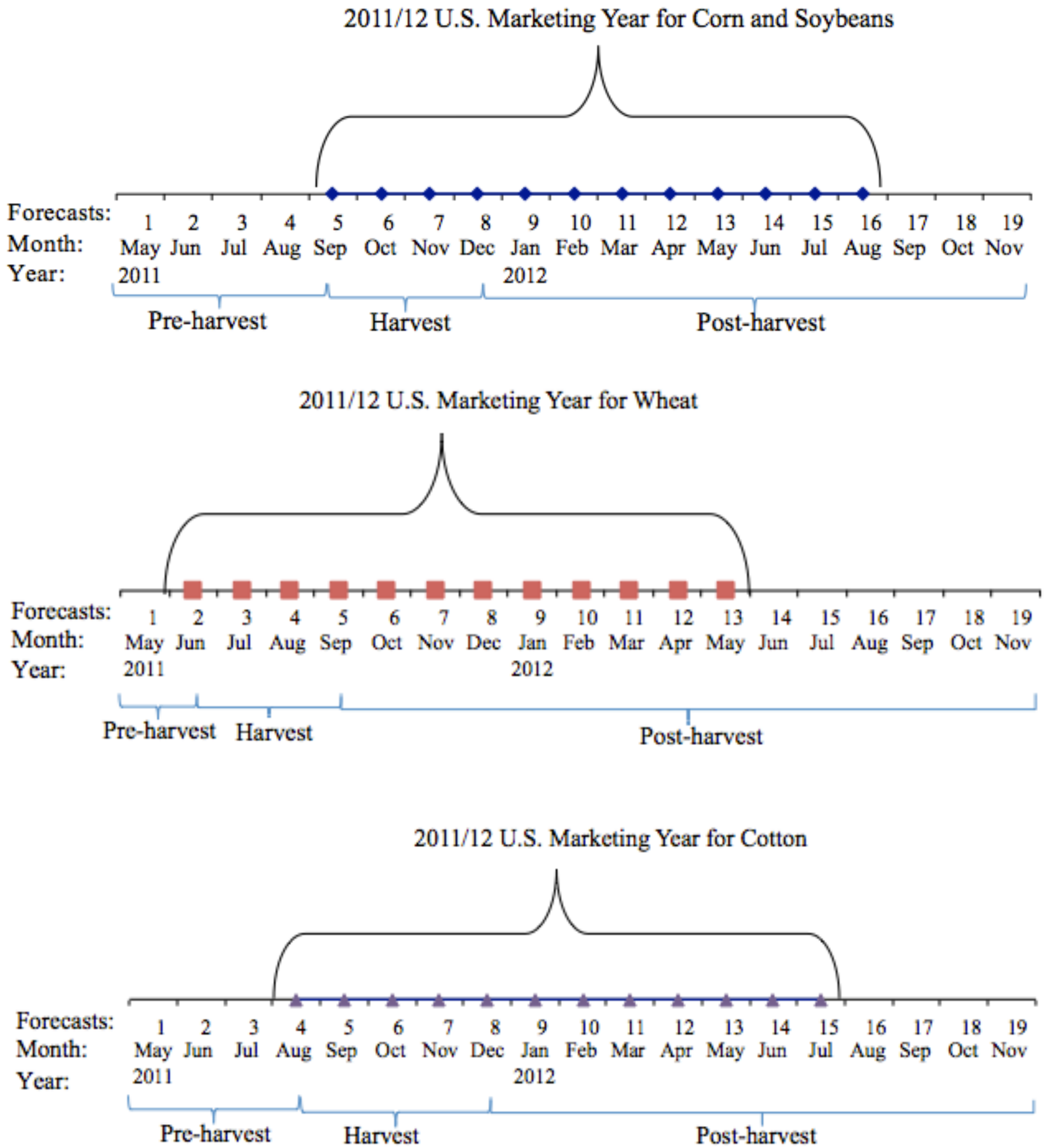


Figure 3.1 The WASDE Forecasting Cycle for Corn, Soybeans, Cotton and Wheat Relative to the 2011/12 U.S. Marketing Year

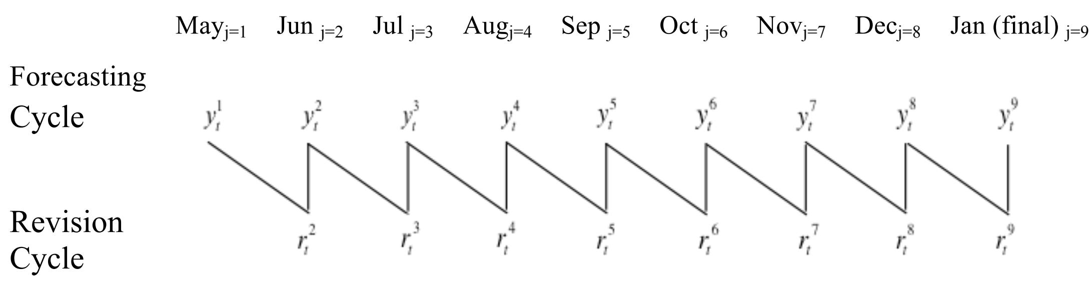


Figure 3.2 Corn and Soybean Production Forecasting Cycle and Corresponding Revision Cycle for a Marketing Year

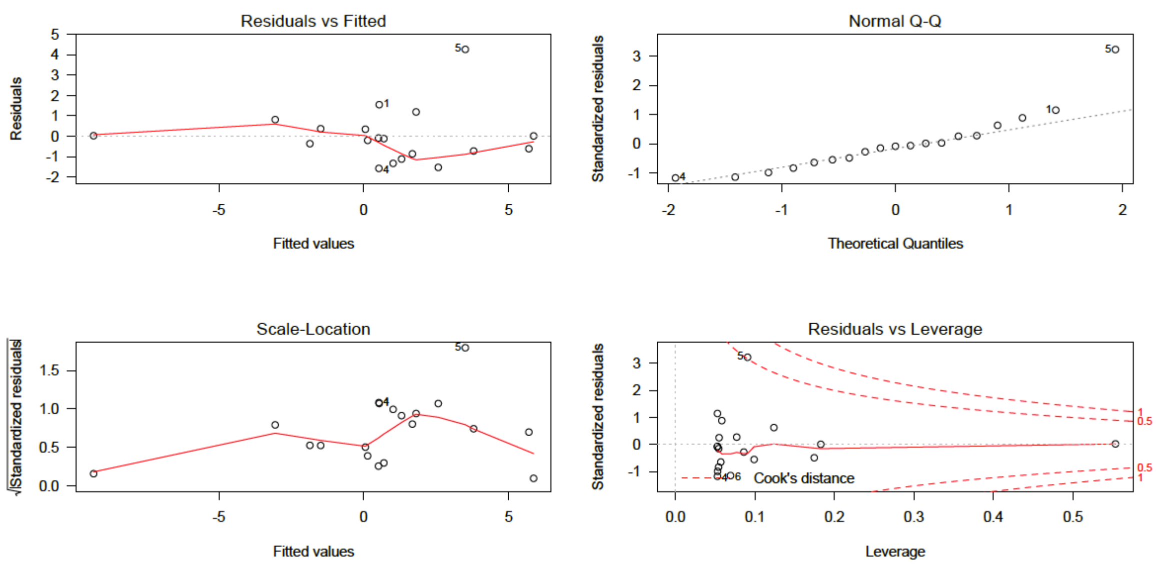
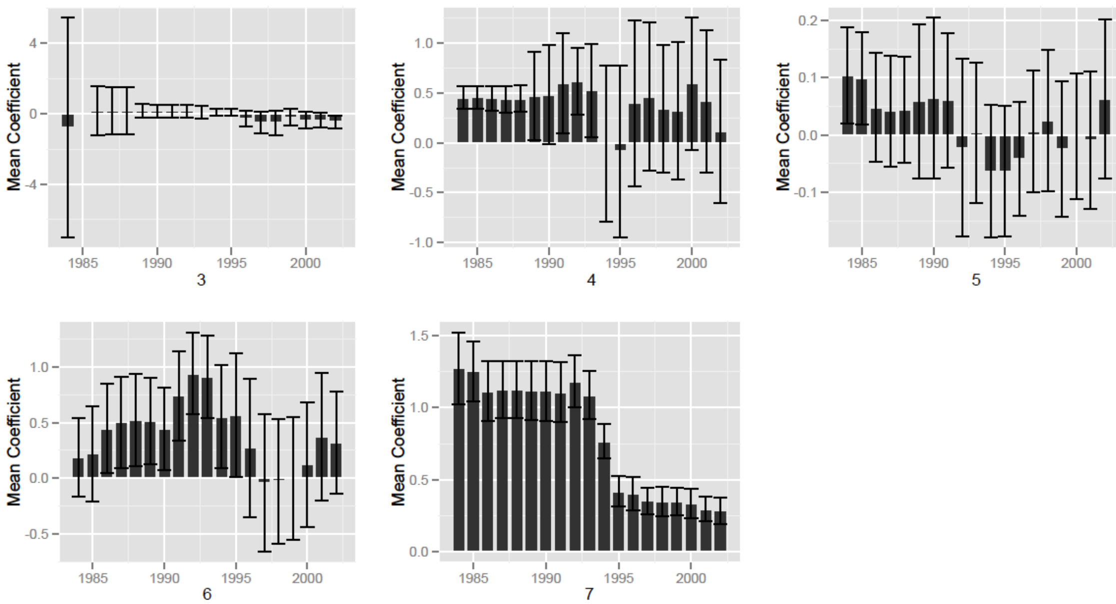
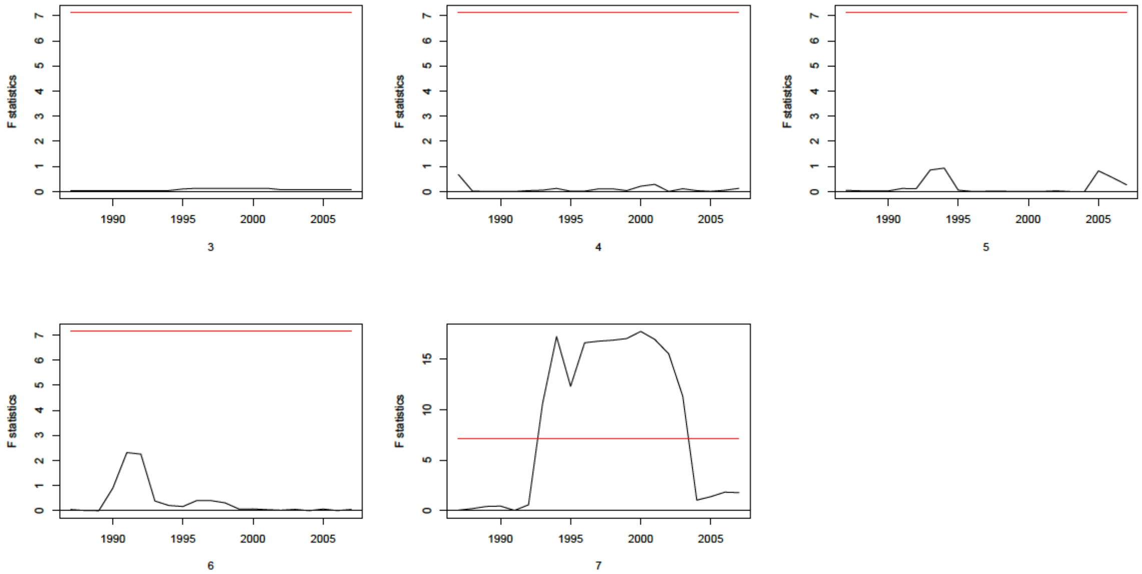


Figure 3.3 An Example of Outlier Detection For Corn Production using the October Data from 1984/95 to 2002/03



Notes: The graphs show the λ coefficients from regression $r_t^j = \lambda r_t^{j-1} + \varepsilon_t^j$ for j=3=July, j=4=August, j=5=September, j=6=October, j=7=November. Each point (bar) is calculated using a 10 year subsample starting in the year used as a label; for example, the bar labeled 1985 uses the 10 year sub-sample starting in 1985.

Figure 3.4 Stability of Revision Inefficiency Over Time: Corn Production



Note: The graphs show the F statistic for a QLR test for equation $r_t^j = \lambda r_t^{j-1} + \varepsilon_t^j$ for j=3=July, j=4=August, j=5=September, j=6=October, j=7=November; the upper horizontal line represents the critical value (7.12) for each month.

Figure 3.5 Structural change test (QLR) for corn production: 1984/85-2011/12

CHAPTER FOUR

QUANTIFYING PUBLIC AND PRIVATE INFORMATION EFFECTS ON THE COTTON MARKET

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 Cattle on Feed Report.

The information effect of 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. Although 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, 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) first studied to address 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.

Based on the above literature, we found most research has focused on the corn, soybean, cattle, and hog markets, leaving the effect of public information on other commodity market 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) forecasts of cotton prices were prohibited from 1929 to 2008; and (d) little is known about the impact of information on cotton markets relative to other commodities.

Cotton daily futures returns of nearby futures contracts from January 1995 through January 2012 are used in the analysis. 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.[24] 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 public information effect (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 be conducted using the 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 five main reports in cotton futures market. Furthermore, the methods reveal the report announcement effect on both the mean and the variance of returns.

Data

Public and Private Reports

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

[24] 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.

(NCC), World Bank, and International Monetary Fund (IMF) publish various cotton reports. Several reports identified in this study as main information sources for the cotton market include *Export Sales*, *Crop Progress*, *WASDE*, and *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 Outlook Board; they provide USDA's comprehensive estimates and forecasts of supply and demand for major U.S. and global crops and U.S. livestock to advise market participants about the current and expected market conditions. Historically *WASDE* were published about one hour after the close of trading of cotton futures. Starting in May 1994, the USDA changed the releasing 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 scheduled to be released after market close before 1996 and the publishing time was switched to before market opening since 1996. 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 impact 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 cotton futures market close, the event day is the day following the release. On the other hand, the event day is equivalent to 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[25] 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 Process* reports can be only traced back to 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

[25] 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.

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 were intended to be released on the same day, however, out of 1759 event days, 146 days and 1 day captures the impact of two and three reports, respectively. 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) and were 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 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, the expiration effects on prices and on the level of trading activity are avoided. Table 4.1 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:

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

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 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 (daily returns), where P_t and P_{t-1} are the event day's settlement and open price, respectively.

Cotton futures contract is subject to 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 4.1. Spikes can be seen in all three plots and they are related to the arrival of important new information. This study evaluates if the five reports (*Exports Sales*, *Crop Process*, *WASDE*, *Perspective Plantings*, and *Cotton This Month*) can be used to explain the volatility in returns. Volatility of cotton futures markets is plotted in figure 4.2 in terms of squared returns (a common measure of volatility, which emphasizes the deviations of returns). The plots in Panels A and C show that CTC and OTC measurements share a similar volatility pattern, where the returns were volatile in the year of 2001 and 2009. However, the plot for CTO measurement indicates that the returns of cotton futures market were most volatile around year 2005.[26] All three plots in figure 4.2 suggest heteroskedasticity in variance (the volatility of returns) 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 4.2. 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 between -0.5 and 0.5, suggesting the distribution of returns is approximately symmetric. The assumption for normality is rejected in all three cases based on the Jarque-Bera test, and the rejection

[26] Panel A, B, C in figure 4.2 have different scales. The largest volatility in Panel A is two times larger than the largest one in Panel B.

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 is bigger 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 disscussed in the previous section. The GARCH-type models have been widely used in commodity futures studies and they have been shown to more accurately model 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 fits their data the best. Isengildina-Massa, Irwin, and Good (2006) used a TARCH-in-mean 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.

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.[27] 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 was developed by Bollerslev (1986) and Taylor (1986) and the basic form of a GARCH (p,q) model is written as:

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

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

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

The function $g(x_t;\theta)$ in the mean equation (4.2) is 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

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

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 ($\sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2$), and the previous forecast variances ($\sum_{j=1}^{p} \beta_j h_{t-j}^2$). Coefficients of GARCH model are normally estimated by the maximum likelihood estimation (MLE) method using the algorithm developed by Marquardt (1963).

As stated 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 (4.4). 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.

Extensions of 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 4.3). 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.

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 process is claimed to be 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 impact on the conditional variance (h_t^2) because only the squared residuals are included in equation (4.4). However, previous literature suggests that "bad" news (when previous returns are negative) tends to have 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 word, the reaction of volatility toward different types of news is asymmetric. Therefore, it is necessary to examine if such asymmetric reactions exist in the cotton daily 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 (4.4) will be adjusted as:

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

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 (4.4) is very close to 0.9 (e.g. Yang and Brorsen, 1994; Hansen and Lunde 2001), indicating a large/small volatility is always followed by a large/small 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 decays much slower than an exponentially decay. 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 applied to fit the returns. IGARCH eliminates the intercept coefficient α_0 in equation (4.4) and restricts the sum of all other α_j and β_j coefficients to be one (Engle and Bollerslev, 1986).[28]

Full Model with External Effects

Although the objective of this study is to identify the public information effect on cotton futures market, it is necessary to account for other potential determinants of market volatility while considering the impact of public reports. Well-documented external factors include the day-of-the-week effects (e.g. Yang and Brorsen, 1994;

[28] 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.

Isengildina-Massa, Irwin, and Good, 2006) and the seasonality in variance (e.g. Hennessy and Wahl, 1996; Isengildina, Irwin, and Good, 2006). In addition, Williams and Wright (1991) asserted a theoretical argument that market conditions affect the reaction of a storable commodity's price to announcements. And the "market conditions" had latter been explained as commodity stock level or inventory conditions (Good and Irwin, 2006; Colling, Irwin, and Zulauf, 1996; Adjemian, 2012).

The impact of external effects 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 (4.2) and the variance equation (4.4). 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) is drawn from the USDA Economic Research Service's Cotton and Wool Situation and Outlook Yearbook. The procedure to generate the inventory level of each day is described in Adjemian (2012). He defined the stock level on the report day of the first month (R) is S_R 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 R and N is calculated as:

$$
(4.6) \quad \hat{S}_t = \begin{cases} S_R & \text{if } t=R \\ \hat{S}_{t-1} + \dfrac{S_N - S_R}{N-R} & \text{if } R<t<N \end{cases} .
$$

The calculated daily stock levels can be then ordered by their magnitudes and the lowest 1/5th are recorded as low stock levels. The stock level effect is tested by adding a dummy variable D_{LOW} into the variance equation (4.4) 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 impact of public reports on cotton daily futures returns is measured only in the variance 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 the weekend-holiday effect, which we define as the impact of a public report release after the futures market close on Friday or the day before a holiday. Since the futures market closes during weekends and holidays, the markets have longer time to react to the new information. We anticipate that the impact of public reports would be masked by this weekend-holiday effect. Two dummies D_{HWCP} and D_{HWCTM}[29] are generated and added into the variance equation. These dummy variables equal one on the first day after the weekends or holidays if the corresponding report releases after the futures market closes on the previous Fridays or the day before holidays, and zero otherwise.

[29] 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.

Results

Model Selection[30]

Although previous studies normally included ten lagged independent variables 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 the autoregressive process containing four lags, AR(4).[31] Additionally, the null hypothesis of no ARCH effect with lag of five[32] was rejected at the significance level of 99%, indicating the need for using a GARCH-type model.

The GARCH(1,1)-normal model was estimated first and the test statistics are presented in the first column of table 4.3. No higher order of GARCH model was needed as the LM test indicates there was 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 4.3a 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 implies the need for applying 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 4.3. The LM test result was 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 were smaller than the ones for

[30] Due to space limitation, the model selecting process is only explained in detail for the CTC returns.
[31] Details on the selection of AR(4) is available upon request.
[32] The null hypothesis of the Lagrange multiplier test with other lag values were also rejected.

GARCH(1,1)-normal, indicating that the GARCH(1,1)-t is preferred. In addition, the standardized residuals computed after fitting the GARCH(1,1)-t that more closely followed the straight line in the QQ plot in figure 4.3b suggesting that the GARCH(1,1)-t was 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 was -0.02, which suggests no existence of asymmetry. Furthermore, the insignificant asymmetric coefficient γ in equation (4.5) of the TGARCH-normal model led to the same conclusion.

Figure 4.4 contains the autocorrelations (ACF) and partial autocorrelations (PACF) plots of the squared CTC returns. Starting from lag one, the autocorrelations decayed 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 was very close to one. Both findings indicated that the daily cotton futures returns have the 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 4.3. Due to this change, that the intercept in the variance equation was 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 intercept to be zero. The QQ plot for IGARCH(1,1)-t in Figure 4.3 demonstrate that

IGARCH(1,1)-t is preferred to GARCH(1,1)-t as the standard residuals follows the straight line in figure 4.3c closer than in 3b.

GARCH(1,1)-t with mean was also tested and the results are reported in the last column of table 4.3. Neither the coefficient for h_t nor the log-likelihood ratio statistic was significant, indicating the conditional standard deviation should not be included in the mean equation (4.2).

Based on the results in table 4.3, 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[33]

The first column in table 4.4 presents the results for CTC returns including all external effects (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 forth 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

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

variance equation suggest that the conditional variance of cotton futures placed a weight of about 95.3% on the prior day's conditional variance estimate and a weight of 4.7% on the previous day's information about returns.

Impacts of Public and Private Reports

According to the results in the column 1 of table 4.4, the coefficients of the dummy variables are positive for most reports except *Crop Process*. 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 agricultural market was often perceived in terms of standard deviation, Isengildina-Massa, Irwin and Good (2006) suggested interpreting the impact of reports relative to the estimated average standard deviation of the daily futures returns. Therefore, the coefficients in table 4.4 can be translated to changes in standard deviation of the underlying futures returns using the comparative statistic equation:

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

where δ_i is the estimated coefficient for each report and the proxy of h_t is the estimated mean conditional variance from the IGARCH(1,1)-t model. According to the results in table 4.5, the mean estimated conditional standard deviation was 1.75%. The coefficients in table 4.5 were drawn from the first column of table 4.4 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 4.5 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% (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%.

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 4.6 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 a 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 a 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—a 10.45% and 15.18% return on collateral, respectively.

WASDE is considered one of the most valuable forecasting reports for agricultural commodity 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 were included in the full model and the results are reported in the column 2 of table 4.4. The monthly effects of *WASDE* reports are also plotted in figure 4.5. 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 4.4 presents the results with only *WASDE* in the model. The significant coefficient for the *WASDE* report was 0.6501, which was higher than the coefficient in the column 1 of that table, proving 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, when one or two other reports were also published.

Comparison of results for CTC, CTO, and OTC returns

While table 4.4 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 4.7 reports the model with selective external effects for CTC, CTO, and OTC returns. The external factors were chosen 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 Process* report was included only in CTO and OTC returns.

Impacts of Public and Private Reports

All CTC, CTO, and OTC returns were used in the study to demonstrate 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, futures price may reach a 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 4.7 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. The comparisons among different returns need to be conducted by using the ratios of coefficients of report relative to the corresponding mean of estimated conditional variance. Figure 4.6 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 reports. 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 4.6 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 would under-estimate 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 significant impact 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 event day[34] (OTC with the change of 3%, significant), this reaction is not strong enough to be significant relative to higher volatility of the CTC returns (1%).

Summary and Conclusions

This study estimated the impact 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.

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

Instead of investigating the information effect of a single report, this study analyzed the impact of five reports simultaneously, which avoided the issue of overestimation due to "clustering of reports". In fact, the results indicated the existence of the "clustering reports" problem as the coefficient of *WASDE* report was smaller when we included all 5 reports instead of having only the *WASDE* report. Having all five reports also allowed us to judge the relative impact of different reports. Results indicated the *Perspective Planting* had the largest impact in the cotton market, followed by the *WASDE* reports. Specifically, information contained 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 a 4.7% return on collateral for a trader in a single day, and the release of *WASDE* report brings more than 3.3% return. By further investigating the price reaction to *WASDE* report over time, we found that September *WASDE* report had the largest significant impact on price volatility. The impact of the other two public reports *Export Sales* and *Crop Progress* were not significant. The impact of the only private report included in this study, *Cotton this Month*, was much smaller and delayed 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 was 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 discovered that the cotton market reacted to the *Perspective Planning* report not immediately but slowly during the trading session. Similar results were 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 expectation toward the main information resource. This study reflects only one aspect (moves the price of futures market) of the use of USDA reports, while other purposes, such as the use of data for policy analysis or research, were 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 4.1 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 4.2 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 4.3 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 4.3 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 4.4 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 Process*)	-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 4.4 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 4.5 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 Process*)	-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 4.6 *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 4.7 Final Results for Cotton Daily Futures Returns, January 1995-January 2012

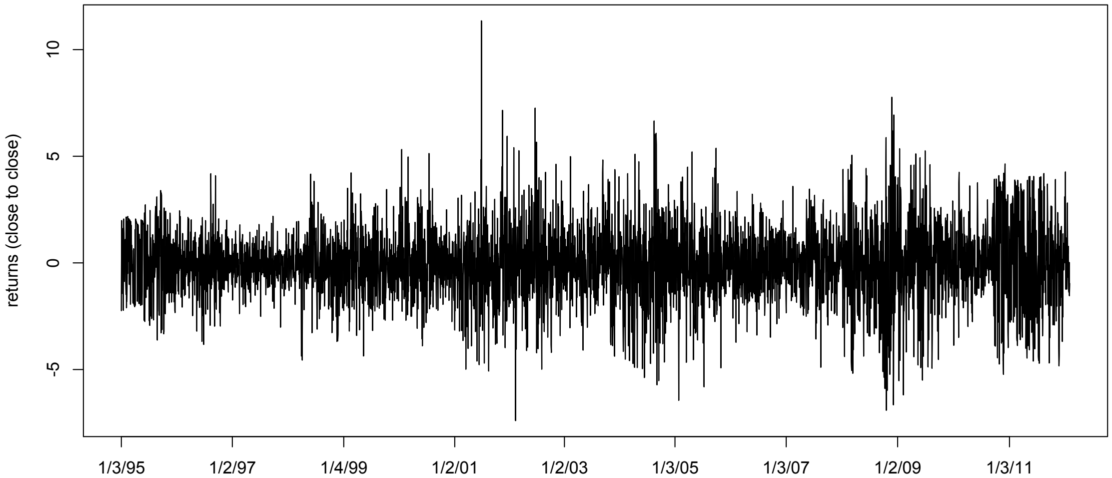
	Close-to-Close Returns		**Close-to-Open Returns**		**Open-to-Close Returns**	
	IGARCH(1,1)-t		GARCH(1,1)-t with Mean		IGARCH(1,1)-t	
Mean Equation						
Intercept	-0.0740		0.0398	***	0.0083	
h_t			-0.1066	***		
y_{t-1}	0.0166		0.0844	***	-0.0444	***
y_{t-2}	-0.0374	**	0.0130		-0.0141	
y_{t-3}	0.0083		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 Process*)	-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 4.7 Continued

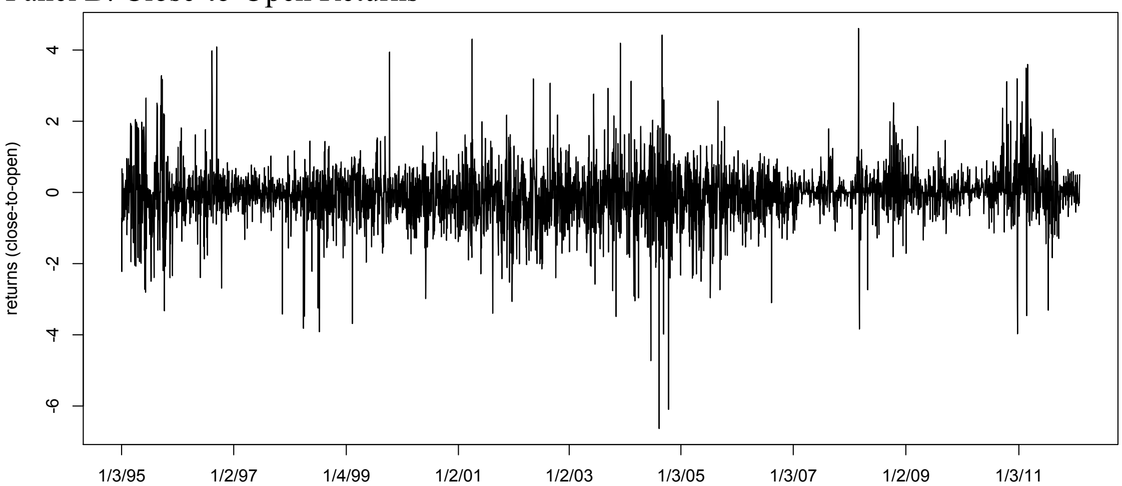
	Close-to-Close Returns		Close-to-Open Returns		Open-to-Close Returns	
D_{MAY} (May)	0.0639	*	-0.0026		0.0417	
D_{JUN} (June)	0.0381		0.0114	**	0.0328	
D_{JULY} (July)	0.0022		-0.0018		-0.0304	
D_{AUG} (August)	0.0343		0.0124	*	0.0236	
D_{SEP} (September)	0.0549		-0.0071		0.0438	
D_{OCT} (October)	0.0058		-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

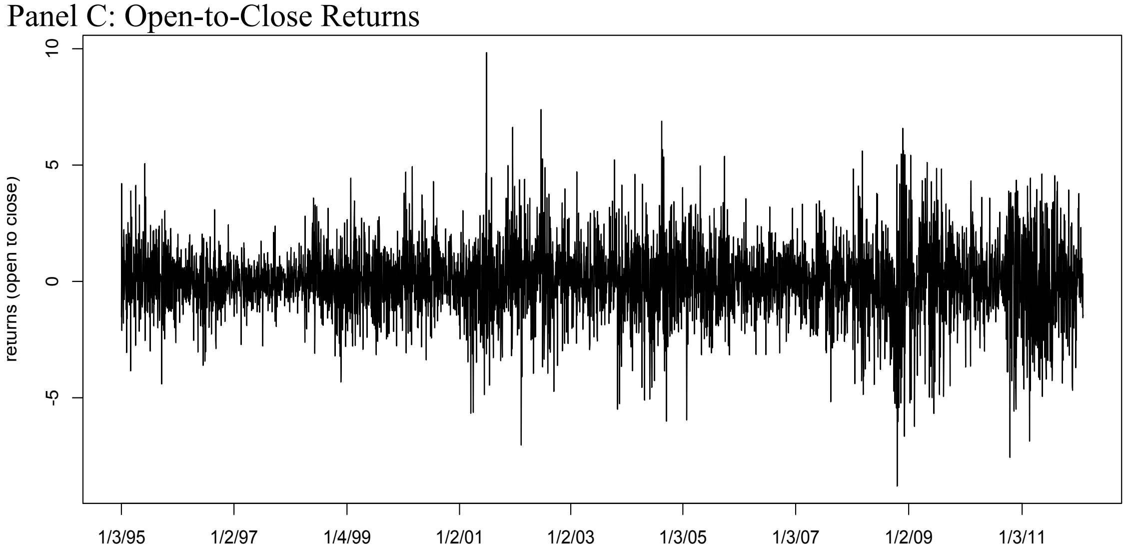
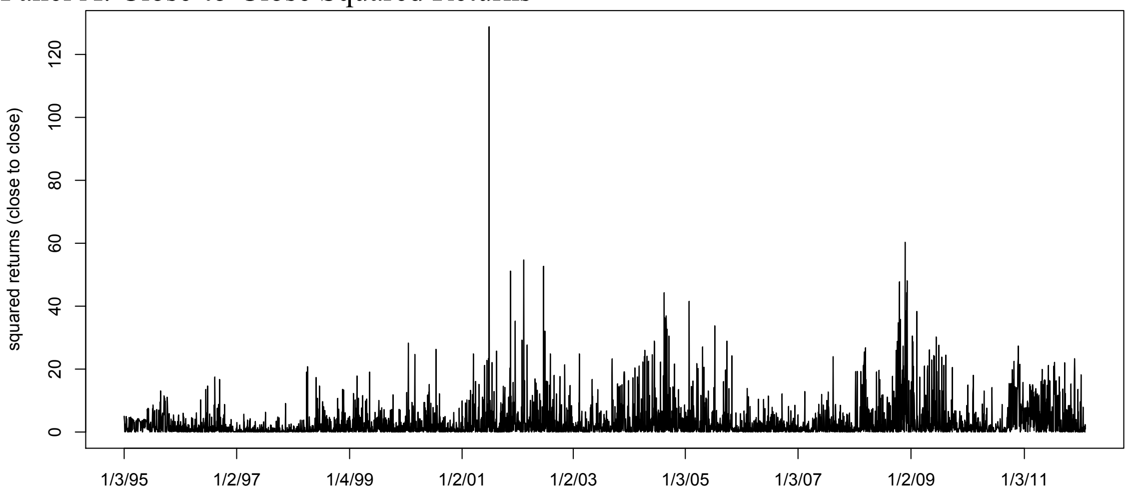
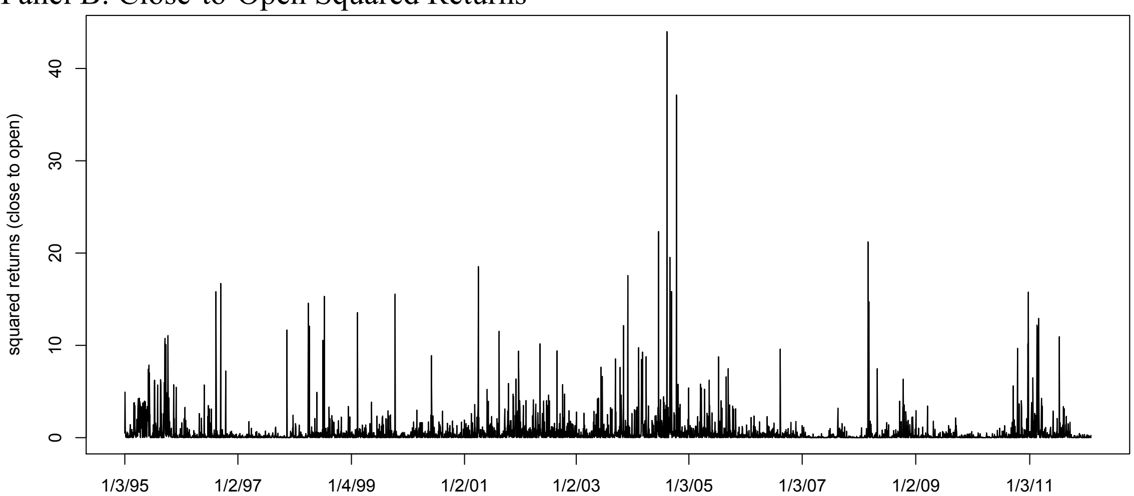


Figure 4.1 Cotton Daily Futures Returns, January 1995-Janaury 2012

Panel A: Close-to-Close Squared Returns



Panel B: Close-to-Open Squared Returns



Panel C: Open-to-Close Squared Returns

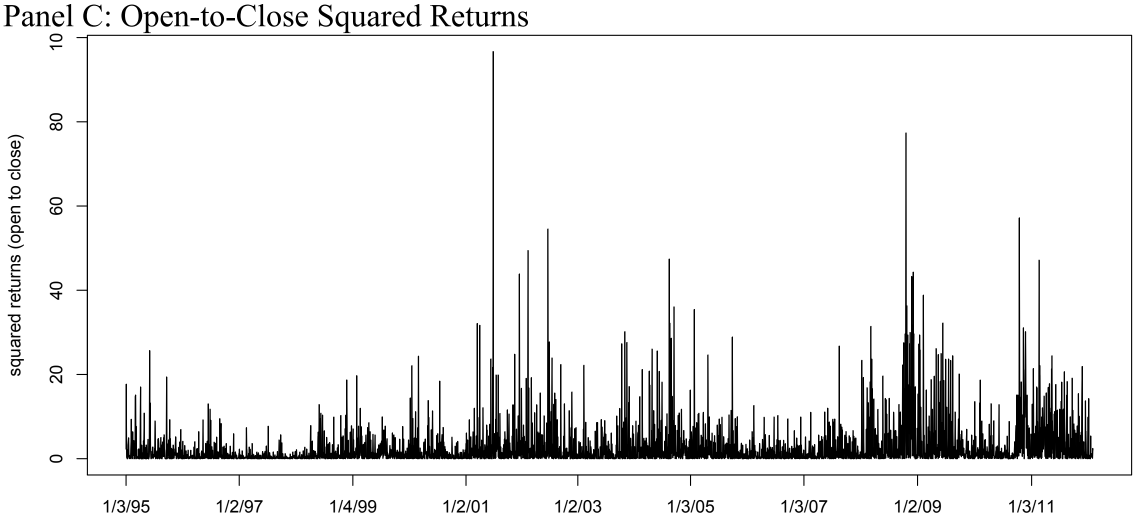


Figure 4.2 Cotton Daily Futures Squared Returns, January 1995-Janaury 2012

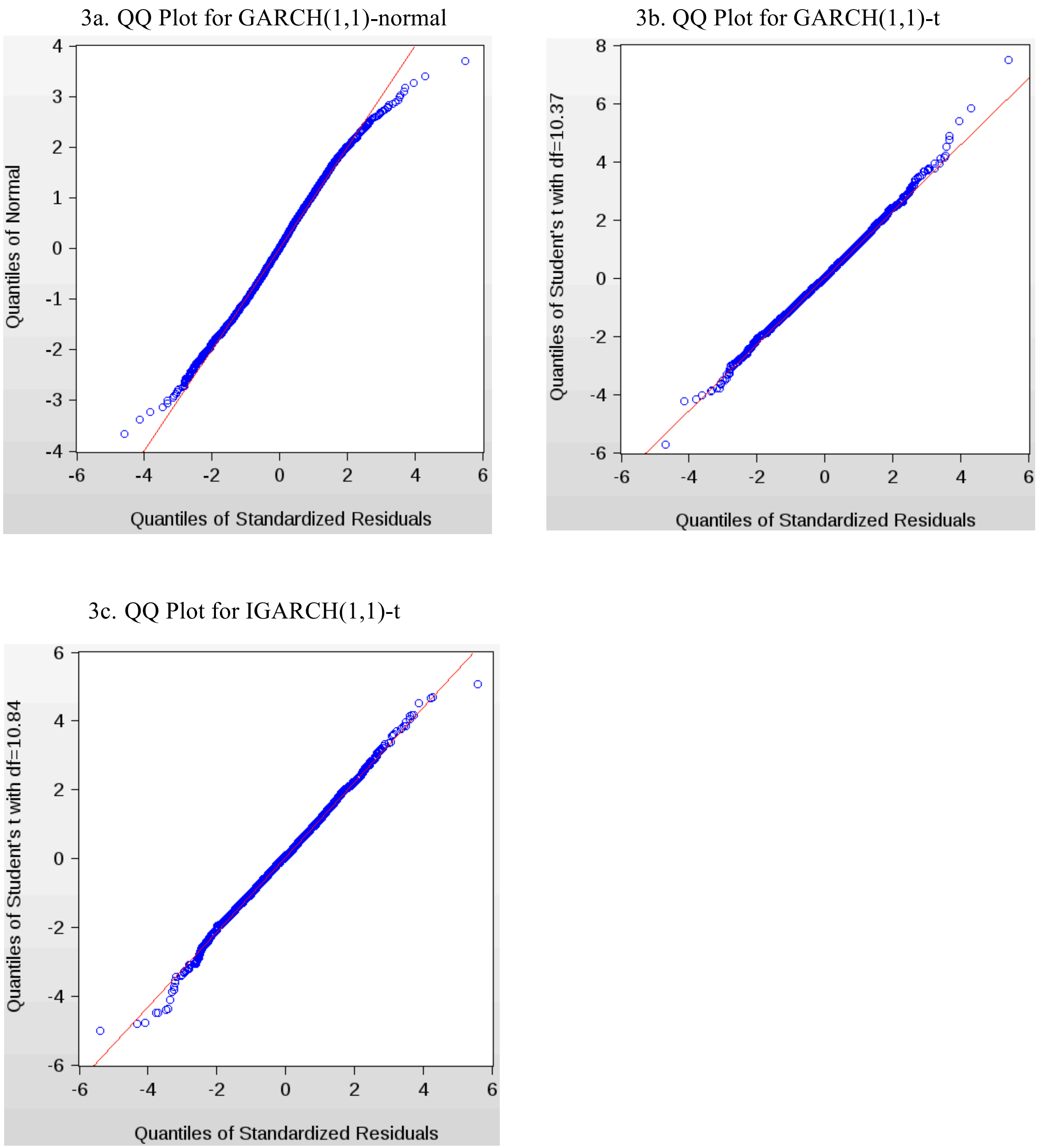


Figure 4.3 Quantile and Quantile Plot of GARCH(1,1)-normal, GARCH(1,1)-t, and IGARCH(1,1)-t models for Cotton Daily Futures Close-to-Close Returns, January 1995-Janaury 2012

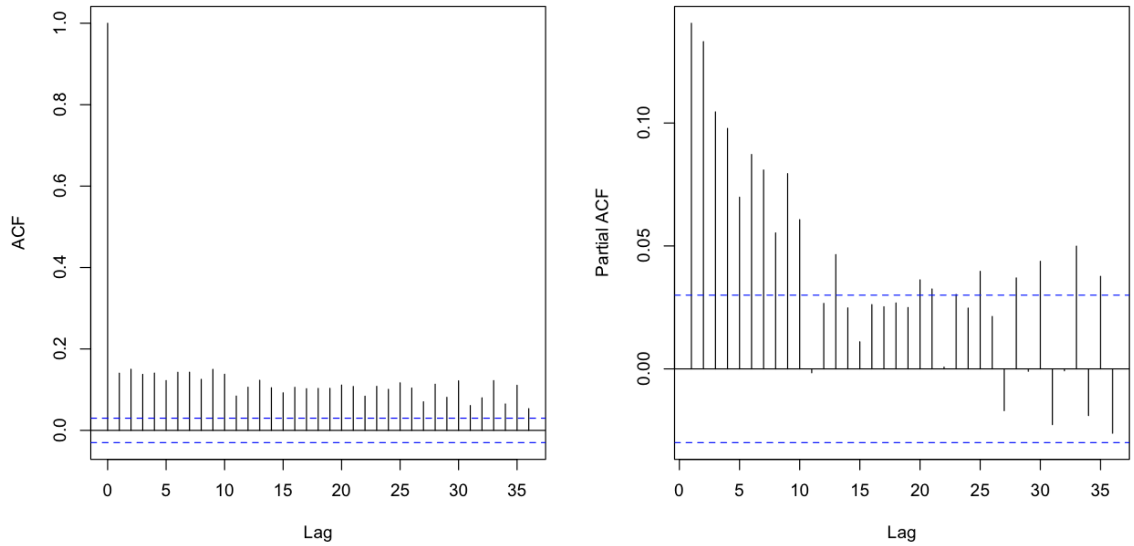


Figure 4.4 The Autocorrelations (ACF) and Partial Autocorrelations (PACF) Plots of the Squared Close-to-Close Returns, January 1995-Janaury 2012

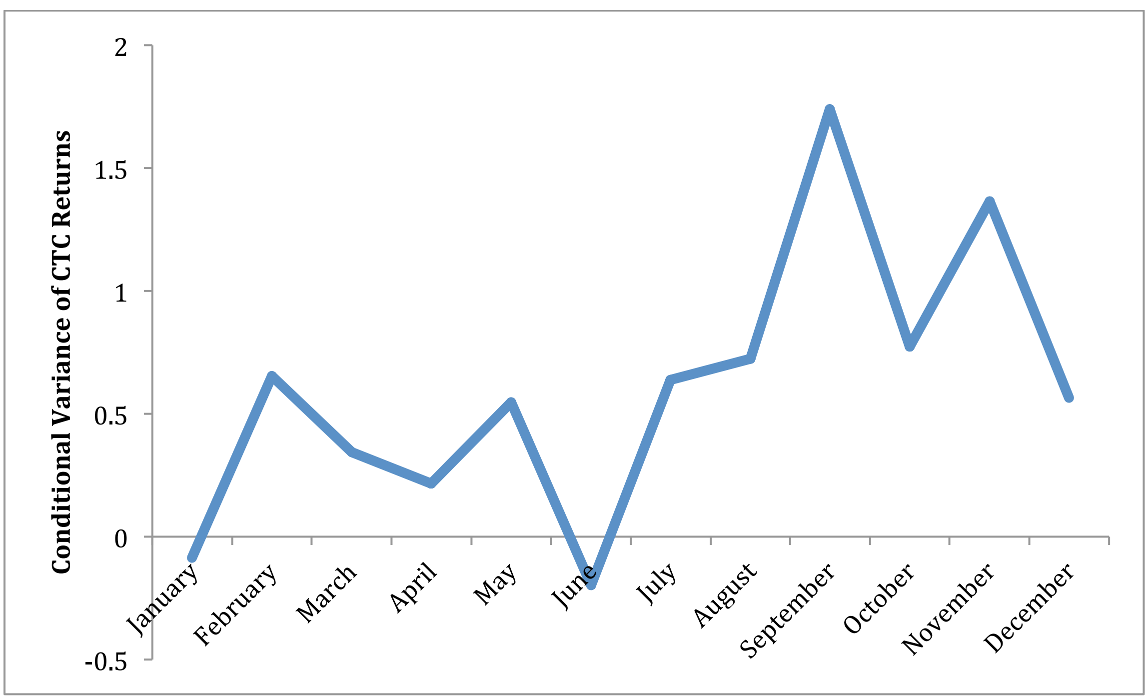


Figure 4.5 Monthly Effects of *WASDE* Reports on Cotton Daily Futures Close-to-Close Returns, January 1995-Janaury 2012

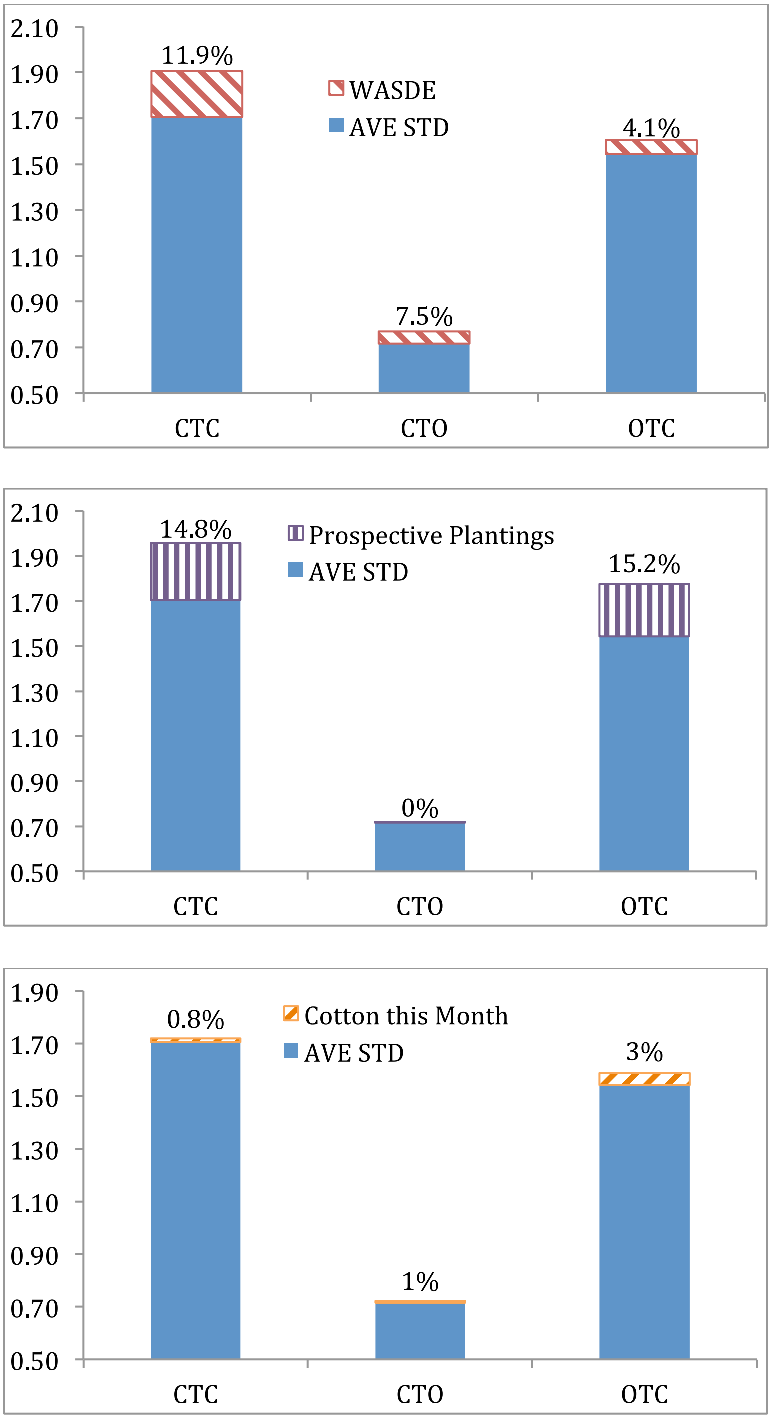


Figure 4.6 Progression of Market Reaction to *WASDE*, *Prospective Planting*, *Cotton This Month* Reports in Cotton Daily Futures Close-to-Close, Close-to-Open, and Open-to-Close Returns, January 1995-Janaury 2012

CHAPTER FIVE

DISSERTATION SUMMARY

The research implemented statistical tools for examining two economic issues: the impact of a regional agricultural campaign on participating restaurants and efforts of USDA forecasting reports in agricultural commodity markets. The first study estimated the perceived economic value of each of the four components of the *Certified South Carolina* campaign from the viewpoint of participating restaurants. A choice experiment was conducted as part of a restaurant manager survey to estimate average WTP for each campaign component using a mixed logit model. The four existing campaign components were treated as attributes in mixed logit model estimation, which also included the method of payment and the amount of payment for the campaign. Findings indicate that three existing campaign components--Labeling, Multimedia Advertising, and "Fresh on the Menu" have a significant positive economic value for restaurants participating in the program.

This study also shed light on determinants of restaurants' WTP for the campaign. We found that restaurants' image, satisfaction with the campaign, and motivation for participation significantly affect their WTP for the "Fresh on the Menu", Signage and Labeling campaign components. However, restaurants' size does not affect WTP for any component. These findings can help the South Carolina Department of Agriculture marketing the campaign to potential participants.

The second study focused on inefficiency in revisions of WASDE forecasts for U.S. corn, soybeans, wheat, and cotton. Results from the evaluation of the revision inefficiency showed significant correlations between consecutive forecast revisions in all crops and all categories except for the seed category in wheat forecasts. Almost exclusively, inefficiency took the form of smoothing as revisions were positively correlated. We also discovered that among the forecasts of four crops, smoothing was most prevalent in soybeans and least common in wheat, and exports was the category most affected by smoothing.

The widespread evidence of revision inefficiency suggested that forecast accuracy could be improved if this inefficiency is corrected. Therefore, the second study also attempted to develop an adjustment procedure that could be used to correct revision inefficiency and improve the accuracy of these forecasts. New correction procedures for four commodities were developed as follows: using the OLS estimation for wheat and the M-estimation for corn, soybeans, and cotton; only considering forecast size and direction for corn price, soybean beginning stocks, crushings, and price, and wheat production forecasts. Our findings suggest that the adjustment procedure has the highest potential for improving accuracy in corn, wheat, and cotton production forecasts.

This third study estimated the impact 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 analyzed the impact of five reports simultaneously, which avoided the issue of overestimation due to “clustering of reports”. In fact, the results indicated the existence of the “clustering reports” problem as the coefficient of *WASDE* report was smaller when we included all 5 reports instead of having only the *WASDE* report. Having all five reports also allowed us to judge the relative impact of different reports. Results indicated the *Perspective Planting* had the largest impact in the cotton market, followed by the *WASDE* reports.

The analysis in the third 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 demonstrated 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. On the other hand, the cotton market reacted to the *Perspective Planning* report not immediately but slowly during the trading session. Similar results were found in the reaction to the *Cotton This Month* report but with a much smaller magnitude.