Market Reaction to Inefficiencies in USDA Crop Production Forecasts

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Introduction

USDA is a main source of public information in the U.S. agricultural markets. The objective of USDA's public situation and outlook programs is to facilitate effective decision-making in an uncertain agricultural environment. Crop production forecasts are among the most important outputs of these programs. However, effective decision making can only be assured if USDA forecasts are accurate and efficient. In recent years multiple concerns have surfaced about the reliability of USDA forecasts. For example, in December 2011, the Wall Street Journal reported that over the previous two years, USDA's monthly forecasts of how much farmers will produce have been "off the mark to a greater degree than any other two consecutive years in the last 15 [years]."

Because of their importance to market participants, crop production forecasts have been extensively examined in the previous literature. For example, Egelkraut et al. (2003) compared the accuracy of USDA versus private forecasts of corn and soybean production over 1971-2000 and found that for corn, USDA forecasts were generally more accurate (except August forecasts) than private forecasts and improved faster during the forecasting cycle, while no substantial accuracy advantages were found in USDA soybean production forecasts. Isengildina, Irwin, and Good (2006) argued that revisions to USDA corn and soybean production forecasts were "smoothed" meaning that not all information available at the time the forecasts were made was incorporated in the forecasts and some was carried into the next forecast, which could cause substantial loss in accuracy. Isengildina, Irwin, and Good (2013) explored whether smoothing in corn and soybean production forecasts was associated with crop size and found that even though there was an ex-post correlation between smoothing and crop size, it was difficult to anticipate.

Thus, smoothing has been established as one of the main forms of inefficiency in USDA crop production forecasts. However, the inefficiency of these forecasts does not necessarily imply a reduction in welfare due to misallocation of economic resources. If markets anticipate and adjust for these forecast inefficiencies, the economic losses from resource misallocation may be negligible or non-existent (Orazem and Falk, 1989). There is substantial anecdotal evidence that market anticipates smoothing in USDA crop production forecasts. For example, AgResource, a prominent market advisory service, made this statement following the release of the June 2000 winter wheat production forecast: "NASS is going to be particularly sensitive about making a drastic reduction in their July and August estimate. ARC anticipates USDA will take a conservative approach and slowly reduce production levels in July, August and September." (June 26, 2000). Similar concerns were expressed by Agrivisor-Zwicker, another market advisory service, with respect to the September 1999 corn production forecast: "While some private guesses are coming in as much as 400 million bushels less the USDA's 9.561 billion bushel August estimate, few expect USDA to come off their August number by more than 200 million bushels" (September 2, 1999).

The purpose of this study is to develop a general framework for evaluation of market reaction to forecast inefficiency and to apply it to evaluation of USDA corn and soybean production forecasts. The proposed framework consists of three steps: 1) efficiency in fixed-event forecasts is evaluated using appropriate rationality tests; 2) efficiency in the difference between USDA and private forecasts (commonly referred to as "market surprise") is evaluated as inefficiency in USDA and/or private forecasts would likely cause inefficiency in surprise, 3) if inefficiency in surprise is found, observed surprise may be decomposed into predictable and unpredictable components; 4) market price reaction to predictable and unpredictable components in market surprise is examined. If markets are aware of forecast inefficiency, this information will already be incorporated in prices and therefore markets would react only to the unpredictable component of the forecasts. If market reaction to the predictable component is found, it indicates that markets do not efficiently incorporate information about smoothing in USDA forecasts. In-sample and out-of-sample tests are included to insure robustness of results.

Literature review

Limited information exists on how the markets react to forecast inefficiency. Runkle (1992) investigated whether futures markets react efficiently to predictable errors in USDA announcements of farrowing intentions. In an earlier study, Runkle (1991) demonstrated that the two-quarter-ahead intentions announcement is a biased forecast of actual farrowings, and that the one-quarter-ahead intentions announcement is an inefficient forecast of actual farrowings. In order to examine market reaction to these announcements, Runkle (1992) decomposed USDA forecast errors into predictable and unpredictable components. He found that the predictable component in these forecast errors had no effect on futures price changes following the announcement. Thus he concluded that market participants understand how the announced forecast deviates from an optimal forecast and take into account that deviation in determining their demand for futures after the announcement is made.

Mills and Schroeder (2002) examined whether industry analysts anticipate USDA cattle on feed inventory revisions prior to their occurrence. The inventory revisions contained statistically significant biases in all categories of the initial reports. Revisions were also found to be correlated over time. However, the authors found no statistically significant relationship between USDA inventory revisions and the private predictions of these revisions. They concluded that the persistence of cattle on feed revisions was not anticipated by industry analysts.

Isengildina, Irwin, and Good (2004) examined whether private forecasts were efficient expectations of USDA forecasts of corn and soybean production forecasts during 1970/71 through 2003/04 marketing years. Their analysis revealed that market expectations of USDA revisions were generally unbiased except for October corn and September soybean production revisions. Some deviations from rationality were also detected in expectations of November soybean production revisions in the earlier years and in November corn production revisions in the later years. Market analysts appeared to under-predict USDA revisions in corn and over-predict revisions in soybeans. Information about smoothing calculated based on historically observed correlations in forecast revisions was not efficiently incorporated in November expectations of corn production forecasts.

Xao, Lence, and Hart (2014) evaluated efficiency in USDA and private forecasts of corn, soybean and wheat ending stocks. They found that USDA forecasts are unbiased and private forecasts were unbiased expectations of USDA forecasts, but both USDA and private forecasts of ending stocks were inefficient. The authors demonstrated that ending stocks market surprise had a predictable component, but stopped short from testing whether markets reacted to it. Frank, Garcia and Irwin calculated a predictable component in Hogs and Pigs market surprise using several alternative approaches based on the notion that USDA announcements may be biased estimates of final inventories. The authors found only small differences in market reaction to conventional surprise versus surprise that accounted for bias with the adjusted surprise explaining the market reaction slightly better. Thus, it appears that the previous studies provide conflicting responses to the question of market reaction to predictable components in inefficient forecasts.

Data

This study examines whether markets anticipate inefficiency in USDA forecasts of corn and soybean production[1] over 1980/81 through 2014/15 marketing years. USDA forecasts of corn and soybean production are fixed–event forecasts, which means that each marketing year *t* (*t* = 1980/81, …, 2014/15) a series of forecasts ($q^U_{\tau-h,t}$) are available for the same terminal event at time τ, which is annual crop production. These forecasts are typically released by the USDA from August through November and finalized in January. Thus, the final estimate released by USDA in January is denoted as $q^U_{\tau,t}$ and the first forecast released in August is $q^U_{\tau-4,t}$ for a four period forecasting cycle ($h = 1, \cdots, 4$). Forecast revisions are computed as the difference between the current and the previous forecast: $r^U_{\tau-h,t} = q^U_{\tau-h,t} - q^U_{\tau-h-1,t}$, h = 0, …, 3. Forecast errors are computed as the difference between the final estimate and the forecast: $e^U_{\tau-h,t} = q^U_{\tau,t} - q^U_{\tau-h,t}$, h = 1, …, 4. All quantities are converted into natural logarithms to account for crop size changes over time.

The market expectations of these forecasts are introduced in this study as combinations of private pre-release estimates. Industry analysts' pre-release estimates have been used in several previous studies as a proxy of market expectations of government reports (e.g., Grunewald, McNulty, and Biere, 1993; Colling and Irwin, 1990; Garcia et al., 1997; Egelkraut et al., 2003). This study uses an average of production forecasts by Conrad Leslie and Informa Economics

[1] See Irwin, Sanders, and Good (2014) for a detailed description of the methodology behind USDA crop production forecasts.

(formerly Sparks Companies, Inc.) as a proxy for market expectations of USDA forecasts during the period 1980-2000. The average analyst forecast for 2001-2005 is represented by the simple average of the Informa Economics estimate and the average analyst estimate reported by the Dow Jones Newswire survey. The Dow Jones survey average is used for 2006-2012.[2] Similar to USDA forecasts, $q^{P}_{\tau-h,t}$ represents h-month ahead private analysts' forecast of the final crop production ($q^{U}_{\tau,t}$) for marketing year t and forecast revisions and errors are computed as: $r^{P}_{\tau-h,t} = q^{P}_{\tau-h,t} - q^{P}_{\tau-h-1,t}$, $h = 0, \ldots, 3$ and $e^{P}_{\tau-h,t} = q^{U}_{\tau,t} - q^{P}_{\tau-h,t}$, $h = 1, \ldots, 4$, respectively. The difference between USDA and private forecasts reflects the new information contained in the USDA forecast which was not previously available from the private forecasts, and therefore defined as market surprise, $S_{\tau-h,t} = q^{U}_{\tau-h,t} - q^{P}_{\tau-h,t}$, $h = 0, \ldots, 4$.

Table 1 presents descriptive statistics and tests of bias for forecast revisions, errors, and market surprise for USDA and private analysts' corn production forecasts. Mean absolute values shown in panel A demonstrate that private forecasts revisions were significantly larger than USDA revisions in September and November. While USDA revisions were larger than private revisions in October and January, these differences were not statistically significant.[3] The test of bias reveals that January USDA revisions and October private revisions had a tendency to be positive, while September private revisions tended to be negative. Thus, one would expect private analysts to revise their August estimates of corn production down by about 1% in September and revise their September estimate up by about 0.5% in October. USDA typically revises their November corn production estimate up in January by about 0.4%.

[2] See Good and Irwin (2006) for further details on the pre-release analysts' forecasts for corn and soybeans.

[3] The t-test results comparing USDA versus private revisions and errors are not shown in the table due to space limitations but available from the authors upon request.

Our analysis of corn production forecast errors shown in panel B of table 1 reveals that USDA forecasts of corn production were more accurate in September and October while private forecasts were more accurate than USDA in August and November, but these differences were statistically significant only for October forecasts. This evidence is consistent with the notion that inefficient forecasts (based on the evidence of biased revisions discussed above) tend to be less accurate. Forecast errors were biased only for November USDA forecasts, which showed about 0.4% underestimation of the final corn production. No bias in market surprise was found in the results shown in panel C. The magnitude of surprise appears to get smaller from August to November during the forecasting cycle, but picks back up in January. This may be due to the fact that while August through November forecasts are based on objective yield estimates available during production cycle, final January estimates are based on December producer survey (Irwin, Sanders, and Good, 2014).

Slightly different patterns are observed in soybean production forecasts presented in table 2. Panel A shows that bias is found only in November revisions by USDA which tended to revise their October estimate up by about 0.7%. September and November USDA revisions were significantly smaller in magnitude than private revisions and while October and January private revisions were smaller than USDA revisions, these differences were not statistically significant.[4] Panel B shows that private forecast errors were slightly smaller than USDA in all forecast months but these differences were statistically significant only in September. Bias was found in September private forecast errors with tendency to underestimate final production by about 1.6%. No bias in market surprise was found in panel C, while the pattern of decreasing

[4] The t-test results are available from authors upon request.

magnitude of surprise that picks back up in January is consistent with our findings for corn production forecasts discussed above.

Conceptual Framework

Theoretical framework for fixed-event forecast rationality testing was originally developed by Nordhaus (1987). According to Nordhaus, weak form efficiency of fixed-event forecasts may be described by two conditions: (1) the current forecast error is independent of all previous forecast revisions; (2) forecast revisions are uncorrelated with past revisions. Most previous studies test fixed-event forecast efficiency in terms of first order correlation in revisions; that is, they test Nordhaus' second proposition. However, Isengildina, Irwin, and Good (2013) demonstrated that correlations in forecast revisions may extend beyond one lag. Additionally, Isengildina, Irwin, and Good (2013) showed that inefficiency may be prevalent in years with big and small crops; suggesting that deviations from typical crop size should be incorporated in efficiency testing.

The efficiency of USDA crop production forecasts is tested in this study as:

(1) $$r^U_{\tau-h,t} = \alpha^U_0 + \alpha^U_1 f_{\tau-h-1,t} + \sum_{j=1}^{J} \lambda^U_j r^U_{\tau-h-j,t} + \epsilon^U_{\tau-h,t},$$

where $r^U_{\tau-h,t}$ is current USDA forecast revision and $\sum_{j=1}^{J} r^U_{\tau-h-j,t}$ are preceding months' forecast revisions. The variable $f_{\tau-h-1,t}$ is out-of-sample percent deviation of the previous month's forecast level from a 10-year rolling linear trend.[5] The null hypothesis for fixed-event forecast efficiency is $\alpha^U_0 = 0, \alpha^U_1 = 0,$ and $\forall \lambda^U_j = 0$. If $\alpha^U_0 \neq 0$, revisions are biased, and if $\alpha^U_1 \neq 0$ this bias tends to be present in big or small crop years. If $\lambda^U_j > 0$, the forecasts are considered "smoothed," as they are partially based on the previous revision. If $\lambda^U_j < 0$, the forecasts are

[5] We use deviation from trend rather than change from the previous year's forecast level to reflect the size of current crop relative to the "norm."

called "jumpy," as they tend to partially offset the previous revision. The same test can be applied to evaluation of efficiency of crop production forecasts published by the private agencies:

(2) $$r^{P}_{\tau-h,t} = \alpha^{P}_{0} + \alpha^{P}_{1} f_{\tau-h-1,t} + \sum_{j=1}^{J} \lambda^{P}_{j} r^{P}_{\tau-h-j,t} + \epsilon^{P}_{\tau-h,t},$$

where $r^{U}_{\tau-h,t}$ and $\sum_{j=1}^{J} r^{U}_{\tau-h-j,t}$ refer to current and preceding revisions of private analysts' forecasts, respectively, and all other variables and hypotheses tests are the same as described above.

If private agencies forecast USDA figures, the following test will help understand the extent of anticipation of smoothing in USDA forecasts by private analysts:

(3) $$r^{PU}_{\tau-h,t} = \alpha^{PU}_{0} + \alpha^{PU}_{1} f_{\tau-h-1,t} + \sum_{j=1}^{J} \lambda^{PU}_{j} r^{U}_{\tau-h-j,t} + \epsilon^{PU}_{\tau-h,t},$$

where the dependent variable from equation 1 is replaced with its expectation by private analysts calculated as $r^{PU}_{\tau-h,t} = q^{P}_{\tau-h,t} - q^{U}_{\tau-h-1,t}$. Since all independent variables are the same as in equation 1, hypotheses tests are interpreted similarly as well, only that they reflect expectation of smoothing in USDA forecasts by private analysts.

The following test of bias conditional on crop size will help understand how well private analysts are able to anticipate USDA forecast revisions:

(4) $$r^{U}_{\tau-h,t} = \gamma_0 + \gamma_1 r^{PU}_{\tau-h,t} + \gamma_2 f_{\tau-h-1,t} + \varepsilon_{\tau-h,t},$$

where $r^{U}_{\tau-h,t}$ is a USDA forecast revision and $r^{PU}_{\tau-h,t}$ is a private expectation of this revision as defined in equation 3. The null hypothesis of no bias is $\gamma_0 = 0$ and $\gamma_1 = 1$; $\gamma_1 > 1$ indicates underestimation of USDA revisions by private analysts and $\gamma_1 < 1$ indicates overestimation.

In the presence of private forecasts, the new information contained in the USDA forecast is defined as market surprise, $S_{\tau-h,t} = q^{U}_{\tau-h,t} - q^{P}_{\tau-h,t}$. If inefficiency is observed in either

$q^{U}_{\tau-h,t}$ or $q^{P}_{\tau-h,t}$ using equations (1) and (2), it will likely be carried over into market surprise, making it inefficient as well, unless private analysts perfectly anticipate and mimic smoothing in USDA forecasts. Efficiency of market surprise can be tested using the same approach as applied to revisions in equations (1) and (2) and will have the following specification:

(5) $$S_{\tau-h,t} = \delta_0 + \delta_1 f_{\tau-h-1,t} + \sum_{j=1}^{J} \lambda_j S_{\tau-h-j,t} + \nu_{\tau-h,t}$$

with H_0: $\delta_0 = 0\ and\ \delta_1 = 0$ and $\forall\lambda_j = 0$. In this case $\delta_0 \neq 0$ and $\delta_1 \neq 0$ would indicate overestimation or underestimation of smoothing in USDA forecasts by private analysts and whether it is associated with crop size. If $\forall\lambda_j > 0$, it would imply inefficiency in the form of consistency and predictability in market surprise. Thus, equation (5) implies that observed surprise can be decomposed into two parts: (a) the true market surprise or the unpredictable component, given by the estimated residuals $\hat{\nu}_{\tau-h,t}$; and (b) the predictable component, given by the estimated surprise $\hat{S}_{\tau-h,t} = \hat{\delta}_0 + \hat{\delta}_1 f_{\tau-h-1,t} + \sum_{j=1}^{J} \hat{\lambda}_j S_{\tau-h-j,t}$.[6]

Finally, the test of market reaction to forecast inefficiency is based on the premise that prices react to the true market surprise, $\hat{\nu}_{\tau-h,t}$, rather than the predictable component of market surprise, $\hat{S}_{\tau-h,t}$:

(6) $$\Delta P_{d,\tau-h,t} = \pi_0 + \pi_1 \hat{S}_{\tau-h,t} + \pi_2 \hat{\nu}_{\tau-h,t} + \xi_{d,\tau-h,t}$$

[6] Several previous studies also attempted to isolate a predictable component of market surprise in their analyses. For example, McKenzie (2008) suggests that surprise can be decomposed into anticipated and unanticipated components as $S_{\tau-h,t} = \theta_0 + \nu_{\tau-h,t}$ (equation 9, p. 355). Mills and Shroeder's (2004) approach, expressed as $r^{PU}_{\tau-h,t} = \mu_0 + \mu_1 r^{U}_{\tau-h,t} + o_{\tau-h,t}$ (equation 3, p. 366) can also be reduced to $S_{\tau-h,t} = \theta_0 + \nu_{\tau-h,t}$ for $\mu_1 = 1$. Frank, Garcia, and Irwin's (2008) linear projection of surprise (equation 3.1, page 76) can also be reduced to $S_{\tau-h,t} = \theta_0 + \nu_{\tau-h,t}$. It is clear that our approach extends previous attempts by directly incorporating information about smoothing in the predictable component of market surprise.

where $\Delta P_{d,\tau-h,t} = 100 \times (\ln P_{d,\tau-h,t} - \ln P_{d-1,\tau-h,t})$, d is the date of Crop Production report release, $\ln P_{d,\tau-h,t}$ is the natural logarithm of the settlement prices on day d of the new crop futures contracts (December contract for August through November corn forecasts; November contract for August through October and January contract for November soybean forecasts). The null hypothesis is $\pi_1 = 0$, which would indicate that the market participants are aware of inefficiency in the production forecasts and this information is already incorporated in prices. Furthermore, since corn and soybeans are closely related commodities, previous studies show that cross commodity effects may also be relevant for price reaction, therefore corn (soybean) surprise was included in soybean (corn) price reaction test described by equation (6).

Empirical Results

Table 3 shows fixed-event efficiency test results for USDA and private corn and soybean production forecasts using equations (1) and (2). Significant constant coefficient indicates bias in revisions and suggests that October revisions of private forecasts of corn production tend to be positive, while January revisions tend to be negative. In soybeans, November revisions of USDA forecasts tend to be positive. Most of these findings are supported by the descriptive statistics shown in tables 1 and 2. Significant positive correlations with past revisions are observed in multiple cases in November and January indicating the presence of smoothing in these forecasts. The most extensive evidence of smoothing is observed in November corn production revisions with a very similar magnitude in USDA and private forecasts. Our findings indicate that a 1% revision in October was typically followed by a 0.58% revision in the same direction in November. In private forecasts, this pattern was more pronounced in the big crop years, increasing the following revision by 0.06% for each 1% deviation from the trend yield. Based on the R-squared measures, this evidence of smoothing explains about 50% of the variation in November corn production forecast revisions. January revisions of corn production forecasts are also affected by smoothing with correlation coefficient of 0.54 between January and November revisions of USDA forecasts. However, in this case, smoothing appears more pronounced in small years and less pronounced in big years. January revisions of private corn production forecasts show the only evidence of smoothing extending beyond one lag with 0.18 correlation with November revision and 0.27 correlation with October revision. Smoothing explains 59% and 40% of the variation in January corn production revisions of private and USDA forecasts, respectively. In soybeans, smoothing of about 0.3% is observed in November and January USDA revisions and in November private forecast revisions.

Table 4 sheds light at how well private analysts understand smoothing in USDA crop production forecast revisions by presenting estimation results from equation (3). The dependent variable is the difference between the private forecast and the previous USDA forecast, or the private expectation of USDA revision. The independent variables are the same as in table 3, so we can compare coefficients from table 4 to coefficients for USDA revisions in table 3. Our results show that private analysts do, in fact, anticipate smoothing in November and January revisions for both commodities. However, the magnitude of smoothing is underestimated. All coefficients for the lagged USDA revision in table 4 are smaller than the ones in table 3. Another misunderstanding is in the positive coefficients for deviation from trend in corn equations that would suggest that smoothing is more pronounced in big crop years, which is not consistent with what we observed in table 3. On the other hand, private analysts appear to have a very good understanding of bias in USDA November soybean revisions.

According to the F-test results presented in table 5, private forecasts are unbiased predictions of USDA estimates in most cases except October and November corn production revisions and September soybean production revisions. Estimated coefficients for October and November predictions of USDA corn production revisions are both greater than one indicating that private analysts underestimated USDA revisions by about 30% in October and 16% in November. On the contrary, estimated coefficient for September soybean revisions is less than one suggesting that private analysts overestimated USDA revisions by about 20%.

Tables 6 and 7 combine in-sample market surprise efficiency tests and price reaction tests for corn and soybeans, respectively. If inefficiency in the form of correlation with previous surprise is found in panel A, observed surprise can be decomposed into predictable and unpredictable components. Panel B examines price reaction to observed and decomposed surprises. Panel C extends this analysis to include cross-commodity effects. Panel A of table 6 demonstrates significant positive correlation with previous surprise in October, November, and January surprise for corn. These results can be considered in conjunction with our results shown in table 4 which suggest that private analysts underestimate smoothing in USDA forecasts. Then, results in panel A of table 6 indicate consistency in this underestimation. Inefficiency associated with September surprise appears most persistent, as it affects both October and November surprises. Thus, a 10% positive September surprise would be followed by a 3.47% surprise in October and a 2.1% November surprise in the same direction.[7] Correlation between January and November surprise is the largest indicating that a 1% difference between USDA and private forecasts in November is usually followed by a 0.73% difference in January. Significant

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[7] The difference between this analysis and the test of bias shown in table 5 is that the test of bias looks at over-or underestimation of USDA forecasts by private agencies for a specific month across marketing years, while the surprise efficiency analysis shown in table 6 examines the dynamics in this over- or underestimation across months within a marketing year.

negative coefficient for the deviation from trend variable indicates that this correlation is weaker in big crop years and stronger in small crop years. These findings along with fairly large R-squared coefficients for January and November regressions suggest that our traditional measure of market surprise may have a fairly large predictable component. If market is aware of this inefficiency, prices will react only to the unpredictable but not the predictable component.

Results shown in panel B indicate that market reaction to observed October surprise is similar in magnitude to market reaction to unpredicted surprise and no reaction to predicted component is observed, suggesting that decomposing surprise does not add much information in this case. In November and January, there is still no market reaction to the predicted component, but the market reaction to the unpredicted component is stronger than the reaction to the observed surprise, and our ability to explain variation in price reaction with decomposed surprise is stronger as well, suggesting that observed inefficiency in surprise is understood and anticipated by the market. Panel C demonstrates that information from the soybean markets does not have much impact on changes in corn prices, as none of the included variables were significantly different from zero.

Soybean market surprise efficiency and price reaction tests presented in panel A of table 7 reveal positive correlation with previous surprise ranging from 0.19% in November to 0.29% in September. Thus, the consistency in surprise is not as wide spread as what we found in corn and the R-squared values for these regressions are lower, suggesting a smaller predictable component. Panel B demonstrates that while decomposing surprise does not help improve our ability to explain variation in price changes, soybean market does appear to react to both predicted and unpredicted components of market surprise in November, suggesting that this inefficiency is not taken into account by the market. Panel C demonstrates that information from the corn market has significant impact on soybean markets in November, but interestingly it is mostly the predictable rather than the unpredictable component of market surprise, suggesting that inefficiency in November corn surprise is not taken into account by the soybean market. Overall, the in-sample results demonstrate that while inefficiency in surprise appears more common in the corn markets, it is also better understood and incorporated into prices by the market. Corn market information affects soybean markets but not the other way around.

Out-of-sample analysis presented in tables 8 and 9 focuses on inefficiency in surprise caused by the first degree autocorrelation and ignores additional lags and cross-commodity effects due to smaller number of observations. Table 8 results are based on surprise efficiency tests that are conducted using the first 20 years of data (1970-1989) and price reaction tests conducted using the last 25 years of data (1990-2014). Panel A demonstrates that significant positive correlation with lagged surprise was found in October and November corn surprises, while were positively correlated with crop size in October and negatively correl6ated in November. These findings were used to decompose market surprise into predictable and unpredictable components. Price reaction test results in panel B are very similar to in-sample results and show little to no benefits to decomposing the market surprise in October, but substantial improvements in R-squared for November regression. As before, markets appear to incorporate information about this inefficiency and react only to the unpredictable component of market surprise. Table 9 expands the surprise efficiency test subsample to 30 years (1970-1999) and reduces price reaction test subsample to 15 years (2000-2014). Results appear robust and once again similar to the in-sample results, especially since correlation with lagged surprise was found in January in table 6 as well. The only difference in this set of results is the price reaction to the predictable component of corn surprise as well as the unpredictable component in

November. This finding is indicative of deterioration in the market understanding of inefficiency in market surprise in the recent years.

Our findings for soybeans in table 8 reveal bias and autocorrelation in January surprise, which is not consistent with the in-sample findings shown in table 7. When this information is used to decompose observed market surprise, prices appear to react to both predicted and unpredicted components, suggesting that prices do not incorporate this inefficiency in market surprise. Incidentally, no significant autocorrelation was found in the surprise efficiency tests shown in table 9. This finding, in combination with the results from tables 7 and 8 points to an unstable nature of correlations in market surprise in the soybean market, which helps understand why the market does not take this information fully into account and appears to react to the predictable component in tables 7 and 8.

Summary and Conclusions

The goal of this study was to examine how markets react to inefficiencies in corn and soybean production forecasts released by USDA. A general evaluation framework was proposed which consisted of: 1) evaluating efficiency of fixed-event forecasts using appropriate rationality tests; 2) assessing efficiency in market surprise, which allows decomposing market surprise into predictable and unpredictable components if inefficiency is found; 3) testing market price reaction to predictable and unpredictable components in market surprise. Thus, the first step of the evaluation framework answers the question: Are USDA production forecasts biased, inefficient or smoothed? We found that November soybean revisions tended to be positive and both November and January revisions for both commodities were correlated with previous revisions indicating smoothing. Private analysts' estimates of USDA forecasts reflect industry's understanding of inefficiencies in these forecasts. We found that private estimates were unbiased predictions of USDA revisions with three exceptions: October and November corn revisions were underestimated by 30% and 16% and September soybean revisions were overestimated by 20%. Private analysts appear to have a good understanding of bias in USDA November soybean revisions. While private analysts appear to anticipate smoothing in November and January revisions, they tend to underestimate it. Inability of private analysts to correctly anticipate smoothing in USDA forecasts would result in inefficiency in market surprise.

Step 2 of our framework addressed the question: Is market surprise inefficient, predictable? Indeed, it is, particularly in corn market. We found that a 10% positive difference between USDA and private corn production forecasts in September is followed by a 3.47% surprise in October and a 2.1% surprise in November. Correlation between January and November corn surprise was the largest indicating that a 1% surprise in November is usually followed by a 0.73% surprise in January. In soybeans, inefficiency in surprise was a lot less widespread with correlations with previous surprise of 0.29 and 0.19 detected for September and November, respectively. Correlations in surprise suggest that the observed market surprise that is affected by inefficiency has a predictable component.

In step 3 we evaluated whether futures prices react to both predictable and unpredictable components in market surprise. Even though some sporadic evidence of market inefficiency with respect to USDA smoothing information has been observed in the out-of-sample tests for November corn production revisions, and in the in-sample tests for November soybean production revisions, where market reacted to both predictable and unpredictable components, these results did not hold up in the other cases. In the vast majority of results, we found that even when decomposing surprise allowed us to better explain variation in futures prices, prices reacted to unpredictable component only. This pattern suggests that even though the private analysts have some misunderstanding of smoothing in USDA forecasts, the market as a whole, seems to correct for it and incorporates this information efficiently. This finding may help explain a moderate market reaction to large revisions in USDA production forecasts which is sometimes observed. For example, Irwin, Good, and Newton (2014) in their Farmdoc daily report describe market reaction to August 2014 corn production report as: “The forecast was smaller than expected, but this seemingly bullish news was shrugged off by the market. Comments by traders and market analysts indicate there is a widespread expectation that the forecast will increase in subsequent *Crop Production* reports. This would explain the weak reaction of market prices to the release of the August report.”

Overall, the findings of this study are consistent with Runkle’s (1992) and contrast Mills and Schroeder (2002) and Isengildina, Irwin, and Good’s (2004) results. These differences are likely due to the differences in methodology and estimation approach, as market reaction tests are applied in the current and Runkle’s (1992) study, while predictability of USDA revisions was explored in the analyses of Mills and Schroeder (2002) and Isengildina, Irwin and Good’s (2004) work. Our proposed framework differs from Runkle’s (1992) approach in that while he focuses on examination of price reaction to the predictable and unpredictable components in forecast error (which is unobserved prior to the end of the forecasting cycle), we focus on price reaction to decomposed market surprise. Furthermore, our analysis demonstrates that market surprise rationality analysis accounts for inefficiencies in both USDA forecasts and their private expectations, while error rationality analysis focuses on inefficiency in USDA forecasts only. Thus, even though USDA forecasts are not always efficient, the markets seem to be aware of these inefficiencies and appear to take them into account in their reaction. Therefore, it is not likely that inefficiencies in USDA reports would result in significant resource misallocations and subsequent economic losses.

References

Beck, N. and J.N. Katz. "What to do (and not to do) with Time-Series Cross-Section Data." *The American Political Science Review* 89(1995):634-647.

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

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.

Cook, R. D. "Detection of Influential Observation in Linear Regression." *Technometrics* 19(1977):15-18.

Egelkraut, T.M., P. Garcia, S.H. Irwin and D.L Good. "An Evaluation of Crop Forecast Accuracy for Corn and Soybeans: USDA and Private Information Agencies." *Journal of Agricultural and Applied Economics* 35(2003):79-95.

Frank, J., P. Garcia, and S.H. Irwin. "To What Surprises Do Hog Futures Markets Respond?" *Journal of Agricultural and Applied Economics* 40(2008):73-87.

Garcia, P., S.H. Irwin, R.M. Leuthold, and L. Yang. "The Value of Public Information in Commodity Futures Markets." *Journal of Economic Behavior and Organization* 32(1997):559-570.

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.

Irwin, S.H., D.R. Sanders, and D.L. Good. "Evaluation of Selected USDA WAOB and NASS Forecasts and Estimates in Corn and Soybeans." Marketing and Outlook Research Report 2014-01, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, January 2014.

Irwin, S., D. Good, and J. Newton. "Do Big Corn Crops Always Get Bigger?" *Farmdoc daily* (4):156, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, August 20, 2014. Available at http://farmdocdaily.illinois.edu/2014/08/do-big-corn-crops-always-get-bigger.html

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

Isengildina, O., S.H. Irwin, 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, D.L. Good. "Does the Market Anticipate Smoothing in USDA Crop Production Forecasts?" Selected Paper presented at the American Agricultural Economics Association Annual Meetings, Denver, CO, August, 2004.

Mills, J.B., and T.C. Schroeder. "Are Cattle on Feed Report Revisions Random and Does Industry Anticipate Them?" Selected Paper presented at the Western Agricultural Economics Association Annual Meetings, Long Beach, CA, July 2002.

NOAA. National Oceanic and Atmospheric Administration. "Billion-Dollar U.S. Weather and Climate Disasters: 1980-2014." 2015. Available at https://www.ncdc.noaa.gov/billions/events.

Nordhaus, W.D. "Forecasting Efficiency: Concepts and Applications." *Review of Economics and Statistics* 69(1987):667-674.

Orazem, P., and B. Falk. "Measuring Market Responses to Error-Ridden Government Announcements." *Quarterly Review of Economics and Business* 29(1989):41-55.

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

Runkle, D.E. "Are Farrowing Intentions Rational Forecasts?" *American Journal of Agricultural Economics* 73(1991):594-600.

Runkle, D.E. "Do Futures Markets React Efficiently to Predictable Errors in Government Announcements?" *Journal of Futures Markets* 12(1992):635-643.

Xao, J., S.H. Lence, and C. Hart. "USDA and Private Analysts Forecasts of Ending Stocks: How Good Are They?" Selected Paper presented at the American Agricultural and Applied Economics Association's Annual Meetings, Minneapolis, MN, July 2014.

Table 1. Summary Statistics for Corn Production Forecasts, 1970/71-2014/15.

Panel A. Forecast Revisions (Current-Previous Forecast)

	USDA				Private			
	September	October	November	January	September	October	November	January
Mean Abs.	2.136	1.722	1.528	1.102	2.795	1.554	1.909	0.764
Mean	-0.455	0.231	0.293	0.369	-1.074	0.512	0.499	-0.151
Std. Dev.	3.460	2.291	2.022	1.452	4.015	2.048	2.370	1.076
t-test	-0.883	0.677	0.973	1.706*	-1.795*	1.659*	1.397	-0.794
p-val	0.382	0.502	0.336	0.095	0.079	0.104	0.169	0.433
N	45	45	45	45	45	44	44	32

Panel B. Forecast Errors (Final-Forecast)

	USDA				Private			
	August	September	October	November	August	September	October	November
Mean Abs.	4.656	3.656	2.182	1.102	4.118	3.710	2.531	0.764
Mean	0.439	0.894	0.663	0.369	-0.328	0.798	0.135	-0.151
Std. Dev.	6.638	4.644	2.920	1.452	6.733	4.808	3.186	1.076
t-test	0.443	1.291	1.522	1.706*	-0.275	0.939	0.239	-0.794
p-val	0.660	0.203	0.135	0.095	0.785	0.355	0.813	0.433
N	45	45	45	45	32	32	32	32

Panel C. Market Surpise (USDA-Private)

	August	September	October	November	January
Mean Abs.	1.884	1.061	0.949	0.606	0.974
Mean	-0.302	0.318	0.155	0.029	0.158
Std. Dev.	2.250	1.327	1.215	0.839	1.411
t-test	-0.899	1.605	0.847	0.232	0.633
p-val	0.374	0.116	0.402	0.818	0.531
N	45	45	44	45	32

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

Table 2. Summary Statistics for Soybean Production Forecasts, 1970/71-2014/15

Panel A. Forecast Revisions (Current-Previous Forecast)

	USDA					Private			
	September	October	November	January		September	October	November	January
Mean Abs.	2.370	2.353	1.471	1.295		2.831	2.037	1.924	0.882
Mean	-0.433	0.377	0.658	-0.067		-0.942	0.615	0.554	0.025
Std. Dev.	3.786	3.217	1.737	1.664		4.139	2.759	2.458	1.201
t-test	-0.766	0.787	2.543***	-0.268		-1.527	1.495	1.512	0.117
p-val	0.447	0.436	0.014	0.790		0.134	0.142	0.138	0.907
N	45	45	45	45		45	45	45	32

Panel B. Forecast Errors (Final-Forecast)

	USDA					Private			
	August	September	October	November		August	September	October	November
Mean Abs.	5.004	4.111	2.304	1.295		4.906	4.047	1.750	0.882
Mean	0.537	0.969	0.592	-0.067		-0.018	1.618	0.600	0.025
Std. Dev.	6.324	5.040	2.788	1.664		6.668	5.122	3.112	1.201
t-test	0.569	1.290	1.424	-0.268		-0.015	1.787*	1.091	0.117
p-val	0.572	0.204	0.161	0.790		0.988	0.083	0.283	0.907
N	45	45	45	45		32	32	32	32

Panel C. Market Surpise (USDA-Private)

	August	September	October	November	January
Mean Abs.	1.855	1.277	1.338	0.862	1.021
Mean	-0.253	0.257	0.019	0.124	0.026
Std. Dev.	2.149	1.696	1.723	1.071	1.326
t-test	-0.789	1.016	0.074	0.774	0.113
p-val	0.434	0.315	0.941	0.443	0.911
N	45	45	45	45	32

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

Table 3. Fixed-Event Forecast Efficiency Tests, 1970/71-2014/15

Panel A. Corn

Dependent variable: Current Revision	USDA			Private		
	October	November	January	October	November	January
Revision (1st lag)	0.198	0.586***	0.541***	0.061	0.584***	0.180**
	(0.120)	(0.107)	(0.132)	(0.094)	(0.136)	(0.080)
Revision (2nd lag)		-0.008	-0.075		-0.086	0.272***
		(0.083)	(0.116)		(0.080)	(0.082)
Revision (3rd lag)			0.063			-0.034
			(0.069)			(0.040)
Deviation from trend	0.021	0.016	-0.486***	0.016	0.058***	-0.007
	(0.025)	(0.017)	(0.014)	(0.022)	(0.018)	(0.009)
Constant	0.367	0.185	0.177	0.601*	0.217	-0.439***
	(0.322)	(0.219)	(0.183)	(0.317)	(0.282)	(0.144)
R-squared	0.171	0.534	0.395	0.048	0.495	0.590
Adj. R-squared	0.131	0.500	0.334	0.002	0.457	0.529
F-test	4.32**	15.64***	6.52***	1.04	13.05***	9.72***
p-val	0.020	0.000	0.000	0.364	0.000	0.000
N	45	45	45	44	44	32

Panel B. Soybeans

Dependent variable: Current Revision	USDA			Private		
	October	November	January	October	November	January
Revision (1st lag)	0.122	0.261***	0.290*	-0.181	0.314**	0.157
	(0.165)	(0.078)	(0.167)	(0.123)	(0.143)	(0.100)
Revision (2nd lag)		-0.105	0.026		-0.047	0.085
		(0.078)	(0.090)		(0.109)	(0.092)
Revision (3rd lag)			-0.110			-0.069
			(0.083)			(0.058)
Deviation from trend	0.011	0.019	0.001	0.088**	0.041	-0.001
	(0.049)	(0.023)	(0.024)	(0.040)	(0.036)	(0.020)
Constant	0.460	0.557**	-0.314	0.678	0.409	-0.265
	(0.494)	(0.235)	(0.260)	(0.411)	(0.356)	(0.223)
R-squared	0.031	0.279	0.175	0.103	0.224	0.257
Adj. R-squared	-0.016	0.227	0.093	0.060	0.167	0.147
F-test	0.66	5.29***	2.13*	2.41*	3.94**	2.33*
p-val	0.520	0.004	0.095	0.102	0.015	0.081
N	45	45	45	45	45	32

Note: Single, double and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively.
F-test null: b1=b2=b3=c=0

Table 4. Expectation of Smoothing in USDA Forecasts by Private Analysts, 1970/71-2014/15

Dependent variable: Private forecast-Previous USDA forecast	Corn			Soybeans		
	October	November	January	October	November	January
USDA Revision (1st lag)	0.031	0.451***	0.162***	0.155	0.185**	0.123**
	(0.078)	(0.083)	(0.049)	(0.131)	(0.080)	(0.056)
USDA Revision (2nd lag)		-0.019	0.012		-0.050	0.026
		(0.065)	(0.047)		(0.081)	(0.029)
USDA Revision (3rd lag)			-0.070**			0.011
			(0.028)			(0.027)
Deviation from trend	0.029*	0.028**	0.010**	0.013	0.039	-0.000
	(0.016)	(0.013)	(0.005)	(0.039)	(0.024)	(0.008)
Constant	0.263	0.206	-0.091	0.46	0.534**	-0.078
	(0.202)	(0.171)	(0.069)	(0.393)	(0.243)	(0.092)
R-squared	0.157	0.593	0.573	0.072	0.242	0.295
Adj. R-squared	0.116	0.563	0.510	0.028	0.187	0.191
F-test	3.83**	19.88***	9.07***	1.63	4.37***	2.83**
p-value	0.030	0.000	0.000	0.207	0.009	0.044
N	44	45	32	45	45	32

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

Table 5. Test of Bias in Private Expectations of USDA Revisions, 1970/71-2014/15

Dependent variable: USDA forecast-Previous USDA forecast	Corn				Soybeans			
	September	October	November	January	September	October	November	January
Private forecast - Previous USDA forecast	1.012***	1.306***	1.159***	1.179**	0.793***	1.050***	0.852***	0.958**
	(0.074)	(0.136)	(0.088)	(0.486)	(0.056)	(0.103)	(0.094)	(0.462)
Deviation from trend	-0.019	0.001	-0.011	-0.029**	0.040*	-0.010	-0.017	-0.020
	(0.017)	(0.011)	(0.008)	(0.012)	(0.022)	(0.021)	(0.012)	(0.017)
Constant	0.294	0.098	-0.035	0.096	0.204	-0.025	0.164	-0.005
	(0.204)	(0.180)	(0.128)	(0.237)	(0.230)	(0.272)	(0.165)	(0.239)
R-squared	0.859	0.728	0.841	0.221	0.850	0.716	0.674	0.141
Adj. R-squared	0.852	0.715	0.834	0.167	0.843	0.702	0.658	0.081
F-test (Ho:b=1)	0.03	5.06**	3.28*	0.14	13.46***	0.23	2.50	0.01
p-val	0.871	0.030	0.077	0.716	0.001	0.631	0.121	0.928
N	45	44	45	32	45	45	45	32

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

Table 6. In-Sample Forecast Surprise Efficiency and Price Reaction Tests for Corn, 1970-2014.

Panel A. Forecast Surprise Efficiency Tests

Dependent variable: USDA - Private forecast	September	October	November	January
USDA-Private (1st lag)	0.075	0.347***	0.186*	0.734**
	(0.089)	(0.133)	(0.106)	(0.353)
USDA-Private (2nd lag)		-0.040	0.210**	0.065
		(0.078)	(0.094)	(0.204)
USDA-Private (3rd lag)			-0.009	-0.105
			(0.051)	(0.210)
USDA-Private (4th lag)				0.153
				(0.107)
Deviation from trend	-0.016	0.014	-0.004	-0.024**
	(0.013)	(0.010)	(0.007)	(0.011)
Constant	0.312	0.062	-0.102	0.231
	(0.200)	(0.181)	(0.119)	(0.238)
R-squared	0.055	0.168	0.254	0.374
Adj. R-squared	0.010	0.106	0.178	0.253
F-test	1.22	2.70*	3.32**	3.10**
p-val	0.305	0.059	0.020	0.025
N	45	44	44	32

Panel B. Price Reaction Tests

Dependent variable: Close-to-Close Change in the New Crop Corn Futures	October		November		January	
Observed Surprise	-1.230***		-1.112***		-1.426***	
	(0.289)		(0.287)		(0.367)	
Predicted Surprise		-0.599		0.272		-0.886
		(0.687)		(0.521)		(0.597)
Unpredicted Surprise		-1.336***		-1.623***		-1.749***
		(0.307)		(0.306)		(0.461)
Constant	0.282	0.185	0.199	0.168	0.452	0.366
	(0.334)	(0.347)	(0.236)	(0.217)	(0.513)	(0.515)
R-squared	0.311	0.329	0.267	0.423	0.335	0.364
Adj. R-squared	0.294	0.295	0.250	0.393	0.313	0.320
N	42	42	43	42	32	32

Panel C. Price Reaction Tests with Cross-Commodity Interactions

Dependent variable: Close-to-Close Change in the New Crop Corn Futures	October	November		January
Observed Corn Surprise	-1.271***	-1.070***		-1.217***
	(0.304)	(0.312)		(0.435)
Predicted Corn Surprise			0.292	
			(0.537)	
Unpredicted Corn Surprise			-1.581***	
			(0.336)	
Observed Soybean Surprise	0.100	-0.092		-0.417
	(0.203)	(0.251)		(0.463)
Predicted Soybean Surprise			0.001	
			(0.461)	
Unpredicted Soybean Surprise			-0.089	
			(0.257)	
Constant	0.281	0.206	0.141	0.430
	(0.337)	(0.239)	(0.277)	(0.515)
R-squared	0.316	0.270	0.425	0.353
Adj. R-squared	0.281	0.233	0.363	0.309
N	42	43	42	32

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

Table 7. In-Sample Forecast Surprise Efficiency and Price Reaction Tests for Soybeans, 1970-2014.

Panel A. Forecast Surprise Efficiency Tests

Dependent variable: USDA - Private forecast	September	October	November	January
	September	October	November	January
USDA-Private (1st lag)	0.286**	0.143	0.186**	0.361
	(0.116)	(0.164)	(0.091)	(0.248)
USDA-Private (2nd lag)		0.147	-0.099	0.076
		(0.131)	(0.097)	(0.139)
USDA-Private (3rd lag)			0.053	0.223
			(0.077)	(0.157)
USDA-Private (4th lag)				-0.169
				(0.116)
Deviation from trend	0.003	-0.013	-0.026**	-0.017
	(0.023)	(0.021)	(0.011)	(0.016)
Constant	0.336	-0.014	0.01	-0.178
	(0.246)	(0.268)	(0.156)	(0.246)
R-squared	0.136	0.075	0.199	0.238
Adj. R-squared	0.094	0.007	0.119	0.091
F-test	3.29**	1.10	2.48*	1.62
p-val	0.047	0.360	0.059	0.189
N	45	45	45	32

Panel B. Price Reaction Tests

Dependent variable: Close-to-Close Change in the New Crop Soybean Futures	September		November	
Observed Surprise	-0.531***		-0.921***	
	(0.190)		(0.266)	
Predicted Surprise		-0.207		-1.098*
		(0.480)		(0.582)
Unpredicted Surprise		-0.583***		-0.875***
		(0.204)		(0.301)
Constant	0.083	-0.006	-0.021	-0.003
	(0.305)	(0.330)	(0.272)	(0.280)
R-squared	0.163	0.175	0.227	0.229
Adj. R-squared	0.142	0.133	0.208	0.190
N	42	42	43	43

Panel C. Price Reaction Tests with Cross-Commodity Interactions

Dependent variable: Close-to-Close Change in the New Crop Soybean Futures	September	November	
Observed Soybean Surprise	-0.521***	-0.747***	
	(0.189)	(0.279)	
Predicted Soybean Surprise			-0.538
			(0.666)
Unpredicted Soybean Surprise			-0.817**
			(0.332)
Observed Corn Surprise	0.272	-0.593*	
	(0.230)	(0.347)	
Predicted Corn Surprise			-1.999*
			(1.116)
Unpredicted Corn Surprise			-0.580
			(0.358)
Constant	-0.010	-0.021	0.410
	(0.314)	(0.266)	(0.456)
R-squared	0.192	0.279	0.340
Adj. R-squared	0.151	0.243	0.268
N	42	43	42

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

Table 8. Forecast Surprise Efficiency (1970-1989) and Out of-Sample Price Reaction Tests (1990-2014).

Panel A. Forecast Surprise Efficiency Tests (1970-1989)

Dependent variable: USDA - Private forecast	Corn				Soybeans			
	September	October	November	January	September	October	November	January
USDA-Private (1 lag)	0.129	0.553***	0.450**	1.311	0.158	0.063	0.021	1.871**
	(0.125)	(0.132)	(0.165)	(1.054)	(0.224)	(0.155)	(0.194)	(0.575)
Deviation from trend	-0.019	0.026***	-0.014*	-0.027	-0.021	0.004	-0.034**	-0.055*
	(0.017)	(0.009)	(0.008)	(0.023)	(0.038)	(0.019)	(0.014)	(0.025)
Constant	0.176	0.259	0.077	0.380	0.012	0.209	0.115	-1.052*
	(0.320)	(0.188)	(0.182)	(0.734)	(0.485)	(0.295)	(0.239)	(0.472)
R-squared	0.136	0.584	0.329	0.576	0.038	0.010	0.241	0.869
Adj. R-squared	0.034	0.532	0.245	0.364	-0.075	-0.106	0.152	0.804
F-test	1.34	11.22***	3.92**	2.72	0.33	0.09	2.70*	13.31**
p-val	0.289	0.001	0.041	0.180	0.721	0.916	0.096	0.017
N	20	19	19	7	20	20	20	7

Panel B. Price Reaction Tests (1990-2014)

Dependent variable: Close-to-Close Change in the New Crop Futures	Corn				Soybeans	
	October		November		January	
Observed Surprise	-1.354***		-1.136**		-2.447***	
	(0.392)		(0.441)		(0.397)	
Predicted Surprise		-0.828		0.465		-2.530***
		(0.728)		(0.496)		(0.426)
Unpredicted Surprise		-1.391***		-1.492***		-2.415***
		(0.396)		(0.341)		(0.406)
Constant	0.167	-0.083	0.119	-1.156	0.124	-0.014
	(0.487)	(0.570)	(0.344)	(0.266)	(0.386)	(0.454)
R-squared	0.352	0.374	0.224	0.581	0.623	0.629
Adj. R-squared	0.322	0.314	0.190	0.543	0.607	0.595
N	24	24	25	25	25	25

Table 9. Forecast Surprise Efficiency (1970-1999) and Out of-Sample Price Reaction Tests (2000-2014).

Panel A. Forecast Surprise Efficiency Tests (1970-1999)

Dependent variable: USDA - Private forecast	Corn				Soybeans			
	September	October	November	January	September	October	November	January
USDA-Private (1 lag)	0.103	0.422***	0.443***	0.750**	0.209	0.132	0.058	0.515
	(0.106)	(0.124)	(0.157)	(0.341)	(0.162)	(0.171)	(0.117)	(0.450)
Deviation from trend	-0.011	0.019**	-0.007	-0.027**	-0.004	-0.004	-0.031**	-0.021
	(0.016)	(0.009)	(0.009)	(0.012)	(0.029)	(0.022)	(0.012)	(0.024)
Constant	0.081	0.139	-0.020	0.292	0.368	0.177	0.069	-0.081
	(0.262)	(0.173)	(0.165)	(0.330)	(0.329)	(0.302)	(0.181)	(0.374)
R-squared	0.064	0.363	0.234	0.414	0.058	0.024	0.189	0.161
Adj. R-squared	-0.005	0.314	0.175	0.330	-0.012	-0.049	0.128	0.041
F-test	0.93	7.41***	3.97**	4.94**	0.83	0.33	3.14*	1.34
p-val	0.408	0.003	0.031	0.024	0.446	0.723	0.060	0.293
N	30	29	29	17	30	30	30	17

Panel B. Price Reaction Tests (2000-2014)

Dependent variable: Close-to-Close Change in the New Crop Futures	Corn					
	October		November		January	
Observed Surprise	-1.534**		-0.478		-3.076***	
	(0.571)		(0.856)		(0.736)	
Predicted Surprise		1.453		0.921*		-1.715
		(1.946)		(0.502)		(1.465)
Unpredicted Surprise		-1.463**		-1.326**		-3.367***
		(0.539)		(0.467)		(0.781)
Constant	0.36	-0.928	0.377	0.103	-0.320	-0.737
	-0.796	(1.101)	(0.426)	(0.226)	(0.816)	(0.900)
R-squared	0.376	0.493	0.024	0.757	0.573	0.611
Adj. R-squared	0.324	0.401	-0.052	0.716	0.540	0.546
N	14	14	15	15	15	15