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The Impact of Measurement Error on Estimates of the Price Reaction to USDA Crop Reports

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Abstract

This paper investigates the impact of USDA crop production reports in corn and soybean futures markets. The analysis is based on all corn and soybean production reports released over 1970-2006. The empirical analysis compares the typical OLS event study approach to the new Identification by Censoring (ITC) technique. Corn and soybean production reports are analyzed both separately and together for impact in corn and soybean futures prices. ITC proves to be the more useful method because it avoids the pitfalls of errors in variables that cause downward bias in OLS coefficients. Price reaction coefficients estimated via ITC are one to four times larger than OLS estimates for a one price and one event analysis. In the two price, two event case, ITC estimates are one to six times larger. Market reaction to the unanticipated information in USDA forecasts is substantially larger than estimated in previous studies.

Keywords: event study, USDA Crop Production reports, measurement error, Identification Through Censoring

Crop reports prepared by the U.S. Department of Agriculture (USDA) provide important and widely-disseminated production forecasts for various crops on a state, regional, and national level. Market participants attribute substantial influence to crop reports for major commodities. For example, when discussing the August 2002 crop report for corn and soybeans, Rich Feltes, Vice President and Director of Commodity Research for Refco, Inc, stated, "It would be an understatement to say this is the crop report of the last decade. It's certainly the most exciting report since 1993 (Bennett, 2002)." Previous research shows that price variability following the release of USDA crop reports typically is several times normal levels (Sumner and Mueller, 1989). The marked decline in futures trading volume on the days leading up to the release of crop reports is further evidence of the value of production forecasts contained in the reports (French, Leftwich, and Uhrig, 1989). The decline indicates hedgers and speculators tend to await release of the new information before making trading decisions.

Theory predicts that markets react only to the unanticipated information contained in USDA crop production reports (Falk and Orazem, 1985). Based on this theory, the traditional approach to measuring market impact is to regress the futures price change immediately following release of reports on the market "surprise," where the surprise is measured as the difference between the announced USDA forecast and market expectations prior to release of the reports. An average of private firm forecasts typically is used to measure market expectations before the announcement. Previous studies using this approach (French, Leftwich, and Uhrig, 1989; Orazem and Falk, 1989; Baur and Orazem, 1994; Garcia et al., 1997; Good and Irwin, 2006) find that futures prices react to USDA announcements by a statistically significant magnitude and in the direction predicted by theory. However, as noted by Carter (1999) and Garcia and Leuthold (2004), the explanatory power of price reaction regressions is surprisingly low, with few R^2 estimates above 40% and most between 10% and 30%.

The low explanatory power may not be a mystery if one considers the problem of noise, or measurement error, in estimating price reaction regressions. Ideally, the market surprise should equal the announced USDA forecast minus the true market expectation of final production just prior to release of the USDA forecast (Orazem and Falk, 1989). Obviously, it is next to impossible to obtain the true market belief given the potentially large number of market participants and incentives to protect private information. As a result, proxies for the true market belief must be employed in empirical estimations. There are several potential sources of measurement error in the proxies used in earlier studies. Only small and potentially unrepresentative samples of private firm expectations may be available. The measured expectations also may be stale, in the sense that the expectations are out of date compared to the latest information about crop prospects. It is also unclear if private forecasts reflect expectations of announced USDA forecasts or final USDA production estimates. Recent research shows that announced USDA forecasts are inefficient (Isengildina, Irwin, and Good, 2006), in the sense that revisions to adjacent monthly corn and soybean production forecasts are positively correlated, or "smoothed." It is uncertain whether private forecasts incorporate expectations of systematic errors in USDA forecasts. The net result is that a classic errors-in-variables problem is present in past event studies, and therefore, estimated price reaction coefficients are likely biased downward.

The conventional approach to dealing with measurement error is instrumental variable (IV) estimation. Orazem and Falk (1989) propose this approach to deal with measurement errors in market surprises for different types of government data reports, including USDA crop reports. After accounting for measurement error in expectations, Orazem and Falk find that estimates of price reaction coefficients in soybean futures over 1950-1986 increase about 20%. The major drawback to IV estimation is the "weak instruments problem," which Hausman (2001) notes can arise when: i) the instruments do not have a high degree of explanatory power for the variable measured with error, ii) the size of the measurement error is large, or iii) the number of instruments becomes large. When the weak instruments problem is present, IV estimates of parameters may exhibit a large bias, even when the sample size is large (Bound, Jaeger, and Baker, 1995). In addition, related measurement error tests have notoriously low power to reject the null hypothesis no measurement error when weak instruments are used. A further and unique problem is introduced when searching for an instrument to use in identifying market surprises associated with USDA crop reports. Intuitively, it should difficult, if not impossible, to find an instrumental variable that is highly correlated to observed surprises; otherwise the surprises would not be surprises!

Rigobon and Sack (2006) recently developed a new econometric technique called identification-through-censoring (ITC) to deal with measurement errors in surprises for U.S. macroeconomic announcements. This technique avoids weak instrument problems by utilizing the information in non-announcement days to identify measurement error on announcement days. Rigobon and Sack's empirical results are encouraging, as the magnitude of market response to macroeconomic announcements is markedly larger using the ITC estimator than the standard event study OLS estimator. Coefficients estimates generally are two to three times larger using the ITC estimator.

Given the importance of USDA crop reports, it is critical that market participants, government officials, and researchers have a clear understanding of the relationship between USDA reports and market reaction to this information. The objective of this paper is to estimate the impact of USDA crop reports on corn and soybean futures prices after adjusting for measurement error in market surprises. USDA crop reports released in August, September, October, and November over 1970-2006 are analyzed. The first part of the analysis estimates conventional OLS price reaction regressions. The second part of the analysis estimates price reaction coefficients produced by Rigobon and Sack's ITC method and compares them to the OLS estimates.

Theoretical Model

The typical event study proceeds in a regression framework where the reaction of a given asset price is regressed on the surprise component of a data release. Equation (1) represents this approach as,

$$\Delta s_t = \gamma z_t^* + \epsilon_t \tag{1}$$
$$z_t = U_t - E_t[U_t]$$

where Δs_t is the change in market price from just prior to the release to immediately after the release, z_t^* is the surprise component at time t, U_t is data announcement at time t, $E_t[U_t]$ is the market's expectation of the announcement, and ϵ_t is an i.i.d error term representing the movement in the asset price not driven by the data surprise. The price reaction sensitivity is represented by γ. The model assumes the surprise, z_t^*, is the only information consistently affecting the market during the event window.

As highlighted in the previous section, the potential problem with equation (1) stems from measurement error in the right-hand side variable, z_t^*. The bias in γ estimates due to measurement error can be demonstrated with a simple example. Assume the following "classical" form of measurement error is present in the observed data surprise, z_t.

$$z_t = z_t^* + \eta_t \tag{2}$$

where η_t is an i.i.d error term representing noise (measurement error). Substituting (2) into (1), the estimated model is,

$$\Delta s_t = \gamma \cdot z_t + v_t \tag{3}$$

$$v_t = \epsilon_t - \gamma \cdot \eta_t.$$

If γ is positive, the error term for the estimated model, v_t, will be negatively correlated with z_t, and vice versa. The correlation leads to a bias in the OLS estimate of γ towards zero, also referred to as attenuation bias.

Following Rigobon and Sack (2006), the bias can be explicitly derived if it is assumed that the variance of the true surprise is, $\sigma_{z^*}^2$, the measurement error of the observed surprise has zero mean conditional on the true surprise ($E_t[\eta_t|z_t^*]$) and variance of σ_η^2. In addition, the part of the asset price movement not explained by the surprise also has a zero mean conditional on both the true surprise and the measurement error ($E_t[\epsilon_t|\eta_t, z_t^*]$) and variance σ_ϵ^2. Under these assumptions, the OLS regression estimate of γ is,

$$\hat{\gamma}_{OLS} = \gamma \left(1 - \frac{\sigma_\eta^2}{\sigma_{z^*}^2 + \sigma_\eta^2}\right). \tag{4}$$

The OLS estimate is biased toward zero with the bias increasing as the size of the variance of the measurement error increases relative to the variance of the true surprise. Hence, the conventional OLS event study model will result in underestimates of the market impact of data announcements.

Rigobon and Sack (2006) address the measurement error problem by proposing a new event study model called Identification Through Censoring (ITC). The ITC technique approaches the problem of error-in-variables as a problem of identification. Because most data announcements, including USDA crop reports, are released on pre-specified days, a sample of days when the magnitude of the surprise variable is exactly zero can be identified. When the surprise variable is exactly zero, the error-in-variables must equal zero. The "censoring" of the measurement error provides the identification.[1]

The ITC model of one market and one event is represented as follows,

$$\Delta s_t = \begin{cases} \gamma \cdot z_t^* + \epsilon_t & t \in D \\ \epsilon_t & t \notin D \end{cases} \tag{5}$$

$$z_t = z_t^* + \eta_t$$

where D is the set of days on which the announcement takes place. Assuming that the error term, ϵ_t, is homoskedastic the following set of moment conditions hold,

$$\begin{aligned} Var(\Delta s_{t-1}) &= \sigma_\epsilon^2 \\ Var(\Delta s_t) &= \gamma^2 \sigma_{z^*}^2 + \sigma_\epsilon^2 \\ Var(z_t) &= \sigma_{z^*}^2 + \sigma_\eta^2 \\ Cov(\Delta s_t, z_t) &= \gamma \sigma_{z^*}^2 \end{aligned} \tag{6}$$

The variance of the asset price observed at t-1, a day prior to the data release when no announcement takes place, provides the appropriate identification information. More specifically, the four moment equations have four unknowns, and the sensitivity of market price to the true surprise (z_t^*) can be solved for as follows,

$$\gamma = \frac{var(\Delta s_t) - var(\Delta s_{t-1})}{cov(\Delta s_t, z_t)}. \tag{7}$$

Note that the estimator is a function of three easily observable variables. It also has an intuitive structure, in the sense that the numerator is the difference betweeen return variances and the denominator is the covariance between price changes after the announcement and observed surprises.

The ITC method can be expanded to include more than one event. Consider a model for two markets and two events. The two event ITC model is,

$$\begin{aligned} \Delta s_{1,t} &= \gamma_{1,1} z_{1,t}^* + \gamma_{1,2} z_{2,t}^* + \epsilon_{1,t} \\ \Delta s_{2,t} &= \gamma_{2,1} z_{1,t}^* + \gamma_{2,2} z_{2,t}^* + \epsilon_{2,t} \\ z_{1,t} &= z_{1,t}^* + \eta_{1,t} \\ z_{2,t} &= z_{2,t}^* + \eta_{2,t} \end{aligned} \tag{8}$$

where a subscript 1 or 2 on Δs_t refers to market 1 or 2, respectively, and a subscript 1 or 2 on z_t^* refers to event 1 or 2, respectively. This formulation assumes $\epsilon_{1,t}$ and $\epsilon_{2,t}$ are possibly correlated and also that $\eta_{1,t}$ and $\eta_{2,t}$ are possibly correlated. From equation (8), thirteen moment conditions can be identified, with 13 knowns and 13 unknowns,

$$
\begin{aligned}
&(a) \quad Var(\Delta s_{1,t-1}) = \sigma^2_{\epsilon_1} \\
&(b) \quad Var(\Delta s_{2,t-1}) = \sigma^2_{\epsilon_2} \\
&(c) \quad Var(\Delta s_{1,t}) = \gamma^2_{1,1}\sigma^2_{z^*_1} + \gamma^2_{1,2}\sigma^2_{z^*_2} + \sigma^2_{\epsilon_1} + 2\gamma_{1,1}\gamma_{1,2}Cov(z^*_1, z^*_2) \\
&(d) \quad Var(\Delta s_{2,t}) = \gamma^2_{2,1}\sigma^2_{z^*_1} + \gamma^2_{2,2}\sigma^2_{z^*_2} + \sigma^2_{\epsilon_2} + 2\gamma_{2,1}\gamma_{2,2}Cov(z^*_1, z^*_2) \\
&(e) \quad Cov(\Delta s_1, z_1) = \gamma_{1,1}\sigma^2_{z^*_1} + \gamma_{1,2}Cov(z^*_1, z^*_2) \\
&(f) \quad Cov(\Delta s_2, z_2) = \gamma_{2,2}\sigma^2_{z^*_2} + \gamma_{2,1}Cov(z^*_1, z^*_2) \\
&(g) \quad Var(z_1) = \sigma^2_{z^*_1} + \sigma^2_{\eta_1} \\
&(h) \quad Var(z_2) = \sigma^2_{z^*_2} + \sigma^2_{\eta_2} \\
&(i) \quad Cov(\Delta s_1, z_2) = \gamma_{1,1}Cov(z^*_1, z^*_2) + \gamma_{1,2}\sigma^2_{z^*_2} \\
&(j) \quad Cov(\Delta s_2, z_1) = \gamma_{2,2}Cov(z^*_1, z^*_2) + \gamma_{2,1}\sigma^2_{z^*_1} \\
&(k) \quad Cov(\Delta s_1, \Delta s_2) = \gamma_{1,1}\gamma_{2,1}\sigma^2_{z^*_1} + \gamma_{1,1}\gamma_{2,2}Cov(z^*_1, z^*_2) + \gamma_{1,2}\gamma_{2,1}Cov(z^*_1, z^*_2) + \\
&\qquad \gamma_{1,2}\gamma_{2,2}\sigma^2_{z^*_2} + Cov(\epsilon_1, \epsilon_2) \\
&(l) \quad Cov(z_1, z_2) = Cov(z^*_1, z^*_2) + Cov(\eta_1, \eta_2) \\
&(m) \quad Cov(\Delta s_{1,t-1}, \Delta s_{2,t-1}) = Cov(\epsilon_1, \epsilon_2)
\end{aligned} \tag{9}
$$

In equation set (9) all of the left-hand side values are observable from the data. In theory, the 13 moment equations and 13 unknowns can be solved analytically to obtain estimators for $\gamma_{1,1}$, $\gamma_{1,2}$, $\gamma_{2,1}$, and $\gamma_{2,2}$. This is quite complex given the non-linearities involved, and hence, an alternative and more practical approach to estimation is needed. Fortunately, the problem can be cast in terms of generalized methods of moments (GMM) estimation, as will be outlined later. Not only does GMM allow estimation to proceed in a relatively straightforward manner, it also provides estimates of asymptotic standard errors that can be used to assess the reliability of price reaction coefficients.

The ITC estimator eliminates the bias from error-in-variables affecting traditional OLS estimates. Yet, the estimator is only as good as its identifying assumptions. The two main identification assumptions needed are that errors-in-variables is classical and the variance of the asset prices is predictable because an accurate judgment of the variance is needed in the absence of the event.

Data

The sample for the study begins in 1970, the first year private forecast data is available, and ends in 2006, the last year with a complete set of USDA forecasts. All USDA crop production forecasts for corn and soybeans released in August, September, October, and November of each year are collected.

Following Good and Irwin (2006), a simple average of production forecasts from private firms is used to measure market expectations before USDA announcements. The private firms used in this analysis are Conrad Leslie and Sparks Companies, Inc. (now Informa Economics, Inc.) from 1970 to 2000[2] and the average of Sparks Companies, Inc and Oster/Dow Jones (ODJ) from 2001 to 2006.[3] The firms typically release forecasts about five to seven days prior to the USDA report and the forecasts quickly become public knowledge. The market has sufficient time to reflect the new information in prices before USDA forecasts are released.

The market surprise is defined as the USDA forecast minus the average of private forecasts,

$$\begin{aligned} z_{1t} &= [ln(Q^{US}_{1,t}) - ln(Q^{PR}_{1,t})] \cdot 100 \\ z_{2t} &= [ln(Q^{US}_{2,t}) - ln(Q^{PR}_{2,t})] \cdot 100 \end{aligned} \tag{10}$$

where $Q^{US}_{1,t}$ ($Q^{US}_{2,t}$) is the announced USDA production forecast for U.S. corn (soybeans) for a given month and $Q^{PR}_{1,t}$ ($Q^{PR}_{2,t}$) is the average of private forecasts for corn (soybeans) for the same month.

Following previous studies (e.g. Garcia et al., 1997), futures contract price changes are computed from the close on the day prior to the announcement to the open on the day after the announcement,

$$\Delta s_{1t} = [ln(P^o_{1,t}) - ln(P^c_{1,t-1})] \cdot 100 \tag{11}$$
$$\Delta s_{2t} = [ln(P^o_{2,t}) - ln(P^c_{2,t-1})] \cdot 100$$

where $P^o_{1,t}$ ($P^o_{2,t}$) is the opening futures price after the announcement for corn (soybeans) and $P^c_{1,t-1}$ ($P^c_{2,t-1}$) is the closing price prior to the announcement. The futures contract months include December for corn and November for soybeans. In addition, the change in futures contract prices is computed for five days before the announcement. This data is used in sensitivity analysis of the ITC estimation procedure. If the daily limit is reached by a relevant futures price, the price change is then measured by first non-limit open or closing price. The number of limit adjustments are 12 for corn and 10 for soybeans, with most adjustments occurring in the early 1970s.

Figure 1 provides a graphical view of the relationship between market surprises and price changes following release of USDA August production forecasts for corn. The market surprise is plotted on the left y-axis and the price change is on the right y-axis. A positive data point is bearish since the USDA production forecast is larger than the market expectation, and hence, supply is larger than expected; conversely, a negative data point is bullish since USDA report is less than the market expectation. The following section investigates the association graphed in figure 1 by employing both traditional OLS estimation and ITC estimation.

Results

OLS Estimates

Traditional OLS results will be presented first as a benchmark for ITC results. One event models for corn and soybeans are,

$$\Delta s_{1,t} = \gamma_1 z_{1,t} + \epsilon_{1,t} \tag{12}$$
$$\Delta s_{2,t} = \gamma_2 z_{2,t} + \epsilon_{2,t}$$

where γ_1 is them sensitivity of corn futures prices to corn surprises and γ_2 is the sensitivity of soybean futures prices to soybean surprises. Results from estimating equation (12) via OLS are presented in table 1. Corn sensitivity coefficient estimates vary between -0.58 and -1.55 and soybean coefficients vary between -0.55 and -0.90. All coefficients are significant and negative. Interpretation is straightforward. For example, the estimate for August corn, -1.08, implies that 1 percentage point positive surprise will result in a 1.08% drop in corn futures prices. The explanatory power of the regressions is higher for corn than soybeans. While the R^2 values are nontrivial, they are nonetheless consistent with "low" values found in previous studies.

Several specification tests are applied to the conventional OLS models. The Breusch-Pagan test for heteroskedasticity tests a null hypothesis of constant error variance against the alternative that the error variance changes with the level of the response (fitted values). The results show only one instance of significant heteroskedasticity (November corn). The Breusch-Godfrey LM test indicates autocorrelation also is evident in only one case (August soybeans). Ramsey reset tests display evidence of significant mis-specification for corn in August and November and soybeans in September and November.

The indication of mis-specification error in the price reaction regressions may be due to a missing variable in the regression. Since corn and soybeans compete for the same acreage on many farms, a missing variable in the corn regression may be the soybean surprise and similarly, a missing variable in the soybean regression may be the corn surprise. This argument follows from the results in Garcia et al. (1997), where it was demonstrated that USDA corn surprises affect soybean futures prices and visa versa. Based on this argument, a potentially more accurate representation of market behavior is to use both surprise measurements as independent variables to capture the cross-crop effects on prices.

The OLS model can be expanded to include both corn and soybean futures prices since both prices are affected by the combined informational content of corn and soybeans USDA forecasts. Two event models using both corn and soybean surprises are,

$$\begin{aligned} \Delta s_{1,t} &= \gamma_{1,1} \cdot z_{1,t} + \gamma_{1,2} \cdot z_{2,t} + \epsilon_{1,t} \\ \Delta s_{2,t} &= \gamma_{2,1} \cdot z_{1,t} + \gamma_{2,2} \cdot z_{2,t} + \epsilon_{2,t} \end{aligned} \tag{13}$$

where $\gamma_{1,1}$ is the sensitivity of the corn futures price to corn surprises, $\gamma_{1,2}$ is the sensitivity of the corn futures price to soybean surprises, $\gamma_{2,1}$ is the sensitivity of the soybean futures price to corn surprises, and $\gamma_{2,2}$ is the sensitivity of soybean futures price to the soybean surprises. Estimation results for equation (13) are presented in table 2 and clearly show corn futures prices are more sensitive to the corn surprise than to soybean surprise. Results are mixed for soybeans futures prices, with two cases where soybean futures prices are more sensitive to the corn surprise than to the soybean surprise (August and November). In general, when comparing cross-commodity effects, soybean futures price movements are more affected by the corn surprise than corn futures prices are by the soybean surprise. Own-commodity slopes decrease when comparing the one event model in table 2 to the two event model in table 3. This is not surprising since the cross-commodity surprises present in the two event model take on some of the price impact. All of the cross-commodity slope coefficients are negative, but significance is concentrated in soybean model cross-coefficients. R^2 is an average of four percentage points larger when both corn and soybean surprises are included in the regressions.

Analogous to the one event OLS model, a series of mis-specification tests are conducted on the OLS two surprise model. The Breusch-Pagan test shows no significant evidence of heteroskedasticity and the Breusch-Godfrey LM test indicates only one case of significant autocorrelation (August corn). When the Ramsey reset test for mis-specification was originally conducted on the two event model, strong evidence of mis-specification was found in November for both corn and soybeans. After careful examination of the data, November 1993 observations were determined to be outliers. The reason for the uncharacteristic values was the abnormal weather conditions in 1993, where large floods in Iowa and Illinois combined with damp and cloudy weather to substantially diminish the crop. Extreme price reaction was observed when this impact was revealed in the November 1993 crop report.[4] For this reason, the results in table 3 are presented without November 1993 observations and the only remaining evidence of mis-specification is found in August corn.

ITC Estimates

The technique of GMM is used to estimate price reaction coefficients for the ITC model. Equation system (5) is a set of moment conditions whose expected value is zero. The system is exactly identified because the number of moment conditions (m) equals the number of parameters (k). The GMM estimator is developed by subtracting the left hand side (LHS) from the right hand side (RHS) to generate moment conditions whose expected value is zero. The moment conditions are denoted by $g_n(\theta) = 0$ and the GMM estimator by $\hat{\theta}_{GMM}$. The GMM criterion function minimized to obtain the parameter estimates is,

$$\hat{\theta}_{GMM}(W_n) = arg \min_{\theta} g_n(\theta)' W_n g_n(\theta) \tag{14}$$

where W_n is a positive definite weighting matrix with dimensions m by m that is possibly a symmetric positive definite matrix. In this application, one-step GMM estimates are obtained so the weighting matrix, W, is set equal to an $m \times m$ identity matrix. Distribution theory for nonlinear GMM estimates of this type is asymptotic. By the weak law of large numbers,

$$\frac{\partial g_n(\theta)}{\partial \theta'} \xrightarrow{p} G_0(\theta) = \frac{\partial E[g_n(\theta)]}{\partial \theta'} \tag{15}$$

Also the normalized moments evaluated at θ_0 satisfy the Central Limit Theorem, to obtain,

$$\sqrt{n} g_n(\theta_0) \xrightarrow{d} N(0, \Lambda_0) \tag{16}$$

Mean value expansions of the moment conditions about the true parameter vector leads to the following asymptotic distribution for the nonlinear GMM parameter estimates,

$$\sqrt{N}\left(\hat{\theta} - \theta_0\right) \xrightarrow{d} \text{Normal}\left(0, A_0^{-1} B_0 A_0^{-1}\right) \tag{17}$$

where $A_0 = G_0' G_0$ and $B_0 = G_0' \Lambda_0 G_0$, G_0 is defined in equation (16), and $\Lambda_0 \equiv E\left[g(\theta_0) g(\theta_0)'\right] = \text{Var}\left[g(\theta_0)\right]$.

Table 3 presents GMM estimation results for the ITC model with one event and one surprise. The corn coefficients range from -0.99 to -2.09 and the soybean coefficients range from -1.17 to -3.09. All of the coefficients are significant at least at the 0.01 level. Note that the standard error of the ITC coefficients is based on asymptotic normality. When comparing the standard errors of the GMM coefficient estimates to the OLS estimates a large difference appears since GMM assumes asymptotic standard errors, or in other words, presumes asymptotic standard errors that may not correctly account for small sample properties. Thus the standard errors may be biased downward, but nonetheless they provide similar indications of statistical significance as OLS estimates.

The OLS and ITC methods are not directly comparable through goodness-of-fit measures because the GMM estimation does not provide an R^2-like statistic. Theoretically, GMM will never obtain a better fit to the data than OLS based purely on the definition of the OLS procedure. Instead, following Rigobon and Sack (2006), the methods are compared based on the coefficient estimates of γ. Table 3 shows the ratio of ITC/OLS coefficient estimates, with corn ITC estimates 1.61 to 2.17 times larger than OLS estimates and soybean ITC coefficient 2.13 to 4.45 times larger than OLS estimates. The results suggest that the limited association between price movements following USDA crop report announcements and market surprises in previous studies is, to a significant degree, associated with the mis-measurement of market surprises. The ITC measure captures market response to the "true" surprise. Furthermore, the percent of the measured surprise not due to the "true" surprise ranges from 36 to 51 percent for corn and 54 to 78 percent for soybeans. The measured surprise contains a large amount of error/noise that lessens the reliability of estimates based on measured surprises.

The corn and soybean ITC estimates presented in table 3 use identification from three days prior to the event; the reason for day negative three stems from the sensitivity analysis presented in table 4. Results in panel A show that estimates do not fluctuate much based on the identification day used. Coefficients are consistent in sign and relative magnitude across both corn and soybeans but do indicate that using day negative one is not prudent since the market is unusually quiet on the day prior to the announcement. Panel B displays the sensitivity of the percentage of measured surprise due to noise; these values are also consistent in magnitude by month and by crop. Overall, the sensitivity analysis demonstrates that ITC estimates are not overly sensitive to the day chosen for identification, therefore day negative three is chosen for the analysis.

Table 5 displays the comparison of the coefficients for the two price, two event models. The own-commodity ITC corn coefficients are 1.76 to 2.49 times greater than OLS estimates, and the cross-commodity ITC soybean coefficients are 1.63 to 5.45 times larger than OLS estimates (for significant coefficients). Comparing the ITC corn own-commodity results for the one event model to the two event model does not reveal a clear pattern, with two coefficients larger and two smaller. Own-commodity ITC soybean coefficients are 1.18 to 6.84 times greater than OLS estimates, cross-commodity ITC corn coefficients are 0.91 to 1.21 times higher than OLS estimates. Comparing the ITC soybean own-commodity results for the one event model to the two event model results show that three two event coefficients are smaller and one is coefficient larger.

The ITC results are consistent with the OLS results in that the cross-commodity effect is stronger in soybeans than in corn. As expected after correcting for measurement error, all significant coefficients are larger in corn and in soybeans, except for the soybean cross-commodity corn coefficient in November, which is positive. The positive ITC coefficient of 0.81 is not consistent in sign with the -0.52 from the OLS regression. Table 5 also displays the $\sigma^2_{\eta_1}/\sigma^2_{z_1}$ ratio representing the percentage of corn measured surprise due to noise, and $\sigma^2_{\eta_2}/\sigma^2_{z_2}$ ratio represents the percentage of soybean measured surprise due to noise. For corn the percentage error ranges from 54 to 70 percent, and for soybeans the percentage error ranges from 14 to 47 percent. The large percentage errors indicates the noise in the measured variables is substantial. Comparing the corn ratio results for the one event model to the two event model results in no clear pattern (two larger and two smaller); the soybean ratio comparison results in three smaller ratios and one larger (November).

Summary and Conclusions

Crop reports prepared by the U.S. Department of Agriculture (USDA) provide important and widely-disseminated production forecasts for various crops. The traditional approach to measuring market impact is to regress the futures price change immediately following release of reports on the market "surprise," where the surprise is measured as the difference between the announced USDA forecast and market expectations prior to release of the reports. An average of private firm forecasts typically is used to measure market expectations before the announcement. Previous studies using this traditional approach find significant futures price reaction following USDA announcements but the explanatory power of price reaction regressions is surprisingly low, with few R^2 estimates above 40%. The low explanatory power may not be a mystery if one considers the problem of measurement error in estimating price reaction regressions. Proxies must be employed to measure the surprise which permits sources of measurement error to exist. The consequence is that a classic errors-in-variables problem is created in past event studies, and therefore, estimated price reaction coefficients are likely biased downward.

The objective of this paper is to estimate the impact of USDA crop reports on corn and soybean futures prices after adjusting for measurement error in market surprises. USDA crop reports released in August, September, October, and November over 1970-2006 are analyzed. The first part of the analysis estimates conventional OLS price reaction regressions. The second part of the analysis estimates price reaction coefficients produced by Rigobon and Sack's ITC method and compares them to the OLS estimates.

One event OLS coefficient estimates for corn range from -0.58 to -1.55 and for soybeans from -0.55 to -0.90. Diagnostic test results reveal mis-specification in the one-event models. It is hypothesized that the missing variables in the OLS test are the soybean surprise in the corn regression and the corn surprise in the soybean regression. Two event OLS results indicate that both soybean and corn surprises should be present in the corn and soybean regression models. Corn own-commodity coefficients range from -0.73 to -1.05 and cross-commodity coefficients range from -0.07 to -0.19. Soybean own-commodity coefficients range from -0.95 to -0.34 and cross-commodity coefficients range from -0.14 to -0.70.

The OLS results are informative, but measurement error in the regressions likley causes attenuation bias. The ITC approach accounts for error-in-variables by using an identification procedure through moment conditions. ITC coefficient estimates consistently show greater sensitivity to market surprises than OLS coefficients. The two event own-commodity ITC coefficients in corn are 1.76 to 2.49 times larger than OLS coefficients and in soybeans 1.18 to 6.84 times as large. The cross commodity significant coefficients are 1.63 to 5.45 times as large for the corn regression and 0.91 to 1.21 times as large for the soybean regression. The results suggest the noise in the measurement of the data surprises causes a substantial downward bias in OLS coefficients measuring sensitivity of futures prices to new information.

In conclusion, the actual sensitivity of futures prices to surprises associated with USDA crop production report is likely much greater after adjusting for measurement error than the sensitivity found in OLS coefficients. Futures prices are more strongly influenced by surprises in USDA reports than previously believed. Econometrically, the OLS procedure suffers from a large amount of noise in the surprise measure. Future research could expand the ITC analysis to additional commodity markets such as beef or pork to discover if increased sensitivity is also evident.

Notes

[1]Censoring intuition comes from Goldberger (1991), who argues that the variance of the error-in-variables in survey data depends on the size of the announcement. He uses the following example: If you ask how may cigarettes a person smokes in a day, a non-smoker will answer zero and that reply has no error-in variables whatsoever. But someone who smokes a pack and a half a day will probably have a sizable error. In other words, the magnitude of the error depends on the magnitude of the reply, with complete censoring of the error at zero.

[2]A detailed description of methods forecasting methods employed by Leslie and Sparks can be found in Egelkraut et al. (2003)

[3]The change in average of forecasts was made because Conrad Leslie discontinued his service after 2000.

[4]The corn 1993 observation is 9.16 standard deviations from the expected value, and soybean 1993 observation is 5 standard deviations from the expected value.

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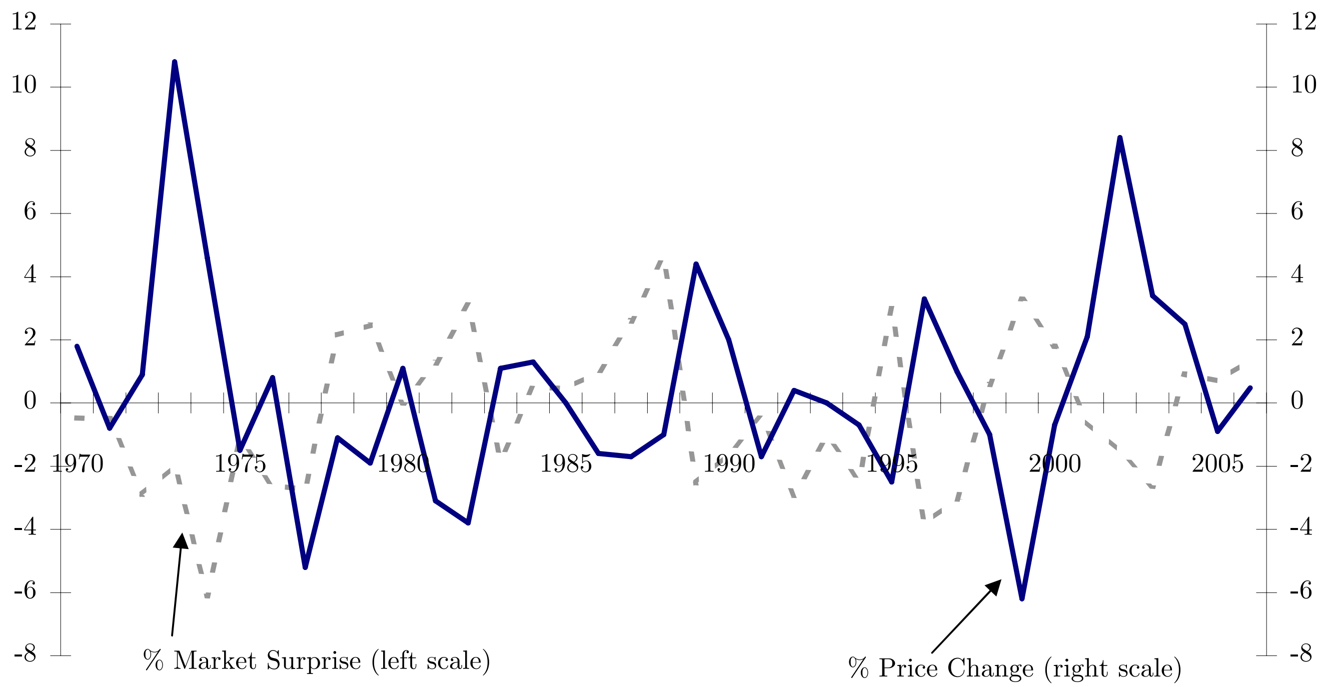

Figure 1. Market surprise and price change in corn following release of USDA August production forecasts, 1970-2006

Table 1. Reaction of Corn and Soybean Futures Prices to USDA Crop Production Reports over 1970-2006, Traditional OLS Estimates with One Event

Commodity/ Announcement Month	Estimated Price Reaction Coefficient	R^2	Breusch-Pagan Test for Heteroskedasticity	Breusch-Godfrey LM Test for Autocorrelation	Ramsey Reset Test for Mis-specification $\Delta\hat{S}_t^2$	Ramsey Reset Test for Mis-specification $\Delta\hat{S}_t^3$
Corn						
August	-1.08 ***	0.46	0.09	9.76	2.20 **	-1.77 *
	(0.20)					
September	-0.58 ***	0.39	0.33	9.96	-1.76 *	-2.02 *
	(0.12)					
October	-1.07 ***	0.46	2.64	14.23	-0.04	-0.98
	(0.19)					
November	-1.55 ***	0.54	19.44 ***	4.93	4.96 ***	1.89 *
	(0.24)					
Soybeans						
August	-0.69 ***	0.20	1.65	15.59 **	0.74	-0.13
	(0.23)					
September	-0.55 ***	0.33	3.10 *	3.13	2.20 **	-0.28
	(0.13)					
October	-0.90 ***	0.29	0.23	5.41	-0.16	-0.05
	(0.24)					
November	-0.67 ***	0.27	2.51	8.16	2.05 **	1.19
	(0.19)					

Notes: One star indicates 10% significance, two stars 5% significance, and three stars 1% significance.. Figures in parenthesis are standard errors. The Breusch-Pagan and Breusch-Godfrey LM test statistics follow chi-square distributions with 36 degrees of freedom. The Ramsey Reset test statistic follows a t-distribution with N-1 degrees of freedom. The intercept in price reaction regressions is forced through the origin to allow direct comparison with later ITC coefficient estimates. N is 37 for all regressions.

Table 2. Reaction of Corn and Soybean Futures Prices to USDA Crop Production Reports over 1970-2006, Traditional OLS Estimates with Two Events

Commodity/ Announcement Month	Estimated Price Reaction Coefficients			Breusch-Pagan Test for	Breusch-Godfrey LM Test for	Ramsey Reset Test for Mis-specification	
	Corn Surprise	Soybeans Surprise	R^2	Heteroskedasticity	Autocorrelation	$\Delta\hat{S}_t^2$	$\Delta\hat{S}_t^3$
Corn							
August	-1.05 ***	-0.18	0.46	0.01	31.36 **	2.06 **	-1.71
	(0.20)	(0.23)					
September	-0.57 ***	-0.07	0.40	0.99	21.75	-0.77	-1.12
	(0.12)	(0.09)					
October	-1.01 ***	-0.33 **	0.54	3.33 *	11.80	0.69	-0.52
	(0.18)	(0.14)					
November	-0.73 ***	-0.19	0.42	2.30	16.29	1.25	0.44
	(0.18)	(0.14)					
Soybeans							
August	-0.63 ***	-0.53 **	0.40	3.38 *	22.78	0.81	-1.36
	(0.19)	(0.21)					
September	-0.14	-0.53 ***	0.34	2.40	21.83	-0.34	-0.50
	(0.17)	(0.13)					
October	-0.70 **	-0.95 ***	0.43	0.74	28.46 *	0.10	-0.39
	(0.30)	(0.23)					
November	-0.52 **	-0.34 **	0.36	0.00	27.60 *	0.81	0.74
	(0.19)	(0.15)					

Notes: One star indicates 10% significance, two stars 5% significance, and three stars 1% significance. Figures in parenthesis are standard errors. The Breusch-Pagan and Breusch-Godfrey LM test statistics follow chi-square distributions with 35 degrees of freedom. The Ramsey Reset test statistic follows a t-distribution with N-1 degrees of freedom. The intercept in price reaction regressions is forced through the origin to allow direct comparison with later ITC coefficient estimates. N is 37 for all regressions except November; when N is 36 because November 1993 observations are excluded.

Table 3. Reaction of Corn and Soybean Futures Prices to USDA Crop Reports over 1970-2006, Identification-Through-Censoring (ITC) with One Event Compared to Traditional OLS Estimates with One Event

Commodity/ Announcement Month	Estimated ITC Price Reaction Coefficient	Estimated OLS Price Reaction Coefficient	Ratio ITC/OLS	Proportion of Measured Surprise Due to Noise $\left(\sigma_\eta^2 / \sigma_Z^2\right)$
Corn				
August	-2.09 ***	-1.08 ***	1.93	49%
	(0.05)	(0.20)		
September	-0.99 ***	-0.58 ***	1.71	45%
	(0.03)	(0.12)		
October	-1.71 ***	-1.07 ***	1.61	36%
	(0.03)	(0.19)		
November	-1.77 ***	-0.82 ***	2.17	51%
	(0.05)	(0.24)		
Soybeans				
August	-3.09 ***	-0.69 ***	4.45	78%
	(0.03)	(0.23)		
September	-1.17 ***	-0.55 ***	2.13	54%
	(0.02)	(0.13)		
October	-2.88 ***	-0.90 ***	3.20	69%
	(0.17)	(0.24)		
November	-1.37 ***	-0.49 ***	2.81	65%
	(0.05)	(0.19)		

Notes: One star indicates 10% significance, two stars 5% significance, and three stars 1% significance. The ITC results are estimated using GMM with day -3 used for identification. Figures in parentheses are standard errors. N is 37 for all regressions except November; where N is 36 because November 1993 observations are excluded.

Table 4. Sensitivity of Identification-through-Censoring (ITC) Estimates to Alternative Identification Days

Days Before Crop	Corn Announcement Months				Soybean Announcement Months			
Report Release	August	September	October	November	August	September	October	November
Panel A: ITC Price Reaction Coefficients								
Day -1	-2.33	-1.13	-2.10	-1.73	-3.28	-1.56	-2.93	-1.66
Day -2	-2.29	-0.81	-2.04	-1.91	-3.25	-1.51	-3.00	-1.57
Day -3	-2.09	-0.99	-1.71	-1.77	-3.09	-1.17	-2.88	-1.37
Day -4	-2.22	-0.72	-1.56	-2.65	-3.01	-1.48	-2.94	-1.89
Day -5	-2.25	-0.61	-1.52	-2.27	-2.99	-1.31	-2.97	-1.72
Panel B: Proportion of Measured Surprise Due to Noise								
Day-1	54%	52%	47%	50%	79%	65%	65%	71%
Day-2	53%	33%	46%	54%	79%	64%	70%	70%
Day-3	49%	45%	36%	51%	78%	54%	69%	65%
Day-4	52%	25%	29%	40%	77%	64%	69%	65%
Day-5	53%	12%	27%	30%	77%	59%	70%	61%

Notes: All parameters are estimated using GMM.

Table 5. Reaction of Corn and Soybean Futures Prices to USDA Crop Reports over 1970-2006, Identification through Censoring (ITC) Estimates with Two Events Compared to Traditional OLS Estimates with Two Events

Commodity/ Announcement Month	Estimated ITC Price Reaction Coefficients		Estimated OLS Price Reaction Coefficients				Proportion of Own-Commodity Measured
	Corn Surprise	Soybeans Surprise	Corn Surprise	Soybeans Surprise	Ratio Corn ITC/OLS	Ratio Soybeans ITC/OLS	Surprise Due to Noise $(\sigma_\eta^2 / \sigma_Z^2)$
Corn							
August	-1.84 ***	-0.98 ***	-1.05 ***	-0.18	1.76	5.45	70%
	(0.01)	(0.02)	(0.20)	(0.23)			
September	-1.16 ***	-0.03	-0.57 ***	-0.07	2.06	0.38	54%
	(0.02)	(0.03)	(0.12)	(0.09)			
October	-2.52 ***	-0.54 ***	-1.01 ***	-0.33 **	2.49	1.63	61%
	(0.01)	(0.01)	(0.18)	(0.14)			
November	-1.43 ***	0.11	-0.73 ***	-0.19	1.96	NA	65%
	(0.47)	(0.51)	(0.18)	(0.14)			
Soybeans							
August	-0.58 ***	-1.89 ***	-0.63 ***	-0.53 **	0.91	3.56	47%
	(0.03)	(0.02)	(0.19)	(0.21)			
September	-0.01	-0.99 ***	-0.14	-0.53 ***	0.05	1.85	45%
	(0.03)	(0.03)	(0.17)	(0.13)			
October	-0.84 ***	-1.12 ***	-0.70 **	-0.95 ***	1.20	1.18	14%
	(0.03)	(0.03)	(0.30)	(0.23)			
November	0.81 ***	-2.35 ***	-0.52 **	-0.34 **	NA	6.84	47%
	(0.10)	(0.07)	(0.19)	(0.15)			

Notes: One star indicates 10% significance, two stars 5% significance, and three stars 1% significance. The ITC results are estimated using GMM estimation with day -3 used for identification. Figures in parentheses are standard errors. N is 37 for all regressions except November; where N is 36 because November 1993 observations are excluded.