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**Fundamentals and Grain Futures Markets**

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**Fundamentals and Grain Futures Markets**


**Practitioner's Abstract**

*A long-standing puzzle in commodity markets is the low explanatory power of supply and demand fundamentals for explaining the variability of prices in these markets. We apply an instrumental variables correction for measurement errors to investigate how noise in the surprise component of USDA Crop Production reports affects estimated price responses in corn, soybeans, and wheat futures markets from 1970 to 2016. Our findings demonstrate that after correcting for measurement error in market surprises, the explanatory power of fundamentals increases about three-fold and often exceeds 70%. This is compelling evidence that fundamentals are the main driver of price movements in grain futures markets.*



**Key words:** announcement effects, crop production, futures price reaction, identification-through-censoring, measurement error


## Introduction

A central question in commodity markets is the relationship between prices and information. The efficient market hypothesis (Fama 1970) predicts that market prices always fully reflect fundamental supply and demand information. However, it has often been difficult to demonstrate this link empirically. One of the most famous examples is the "orange juice puzzle" found in the seminal paper by Roll (1984). This paper uses weather information as an identifiable and exogenous fundamental factor. Surprisingly, Roll (1984, p. 879) found that "…weather surprises explain only a small fraction of the observed variability in futures prices…there is a large amount of inexplicable price volatility." Subsequent studies focus on identification of alternative fundamental signals, such as temperature variation around freezing (Boudoukh et al. 2007; Chou, Hsieh, and Shen 2016) and USDA production reports that more precisely identify changing fundamental information (Baur and Orazem 1994). However, these efforts resulted in a similar outcome. Baur and Orazem's (1994, p. 694) reported that little more than one-third of the announcement-day variation in FCOJ (frozen concentrated orange juice) prices could be explained by USDA announcements, and the recent Chou, Hsieh, and Shen (2016) study found that only about 20% of the FCOJ return variation could be explained by fundamentals. Hence, the "orange juice puzzle" remains largely unresolved.

The apparent failure of fundamentals to fully explain commodity price movements is not limited to the orange juice market. There is an extensive literature that examines the reaction of agricultural futures prices to unanticipated fundamental information contained in USDA crop and livestock reports (e.g., Colling and Irwin 1990; Grunewald, McNulty, and Biere 1993; Garcia et al. 1997; and McKenzie 2008). However, as Carter (1999) and Garcia and Leuthold (2004) note, the explanatory power of the price reaction regressions reported in these studies is surprisingly low, with few R-squared estimates above 40% and most between 10% and 30%. Similar problems have been observed in energy markets where, despite using intraday returns, fundamental information contained in market announcements explains only between 20% and

35% of variability in oil, natural gas, gasoline, and distillate fuel oil prices (Halova, Kurov and Kucher 2014). In the macroeconomic literature, "…the estimated effects of data releases on monetary policy expectations and asset prices are found to be relatively small" (Rigobon and Sack 2008, p. 335).

The lack of strong empirical linkages between commodity prices and fundamental supply and demand information suggests that "non-fundamentals" may be an important driver of price movements. Non-fundamental factors can be rational in the form of non-informational liquidity trading (Grossman and Miller 1988) or irrational in the form of noise trading (Black 1986). There is an extensive body of literature in finance that cites the difficulty of explaining price movements with public information as support for models of asset prices that include non-fundamental "behavioral" factors (e.g., Shleifer 2000; Hirshleifer 2001; Daniel, Hirshleifer, and Teoh 2002). This issue is also related to the debate about the role of speculative trading in commodity futures markets that erupted during the price spike of 2007-2008. A common argument was that supply and demand fundamentals simply could not explain observed price movements, and it therefore followed that non-fundamental speculative trading was an important, if not dominant, driver of prices during the spike (e.g., Lagi et al. 2015).

Rigobon and Sack (2008, p. 336) provide an interesting potential approach to addressing the "fundamentals puzzle" in commodity markets, arguing that, "…the puzzle of the 'detachment' of monetary policy expectations and asset prices from the incoming economic news is partly related to the difficulties associated with measuring the surprise component of that news." In the context of scheduled government announcements, Rigobon and Sack (2008) note that difficulties in measuring economic news may be due to challenges in correctly measuring market expectations and noise in the released government information. To solve this problem, they propose an instrumental variable method, called identification-through-censoring (ITC) to correct for the measurement error in fundamental economic news variables. The key is that measurement error is exactly equal to zero on non-announcement days. This censoring of the measurement error provides the identification needed for estimation. Rigobon and Sack (2008) demonstrate that the link between asset prices and monetary policy expectations and macroeconomic conditions is much stronger using the ITC method than in previous studies.

The goal of our study is to analyze the "fundamentals puzzle" in the grain futures markets by applying the ITC approach to estimating corn, soybean, and wheat futures price reaction to unexpected fundamental news contained in USDA Crop Production reports. Unexpected fundamental news is measured using market surprises, which is the difference between the USDA announcement and an extensive proprietary dataset containing industry expectations for these announcements that spans the 47 years from 1970 through 2016. We apply both the traditional ordinary least squares (OLS) regression and the ITC approach to measuring market reaction to USDA Crop Production reports in order to determine if measurement error in the market surprises dilutes the price impact and results in downward biased estimates of explained variation.[1] We also measure the magnitude of the bias due to measurement error problems. Furthermore, our study investigates possible asymmetric price responses to positive versus negative surprises and potential changes in the ability of commodity fundamentals to explain variation in grain futures prices over time.

[1] In the agricultural commodity space, the ITC approach has only been used in Aulerich, Irwin, and Nelson (2007).

We find that after correcting for measurement error the explanatory power of fundamentals in grain futures markets increases about three-fold. For example, the OLS regression for pooled production surprises in corn explains only 27% of futures return variance in our sample, while the same fundamentals explain 75% of the return variance with the ITC method. Furthermore, price response estimates from traditional OLS models are biased downward by two to six times for corn, three to four times for soybeans, and about eight times for wheat. This is compelling evidence that fundamentals are the main driver of price movements in grain futures markets.

**Measurement Errors and their Econometric Consequences**

In a perfect setting, the market surprise (or "news") associated with a USDA Crop Production report should equal the announced USDA estimate minus the true market expectation of final production just prior to release of the USDA estimate (Orazem and Falk 1989). It is a given that it is not possible to obtain the true weighted-average market expectation due to the potentially large number of market participants and incentives to protect private information. As a result, there are several potential sources of measurement error in the survey expectations used as proxies for true market expectations in previous studies of market reaction to USDA Crop Production reports. First, expectations for only a small and potentially unrepresentative sample of private firms may be available. For example, the widely-followed Reuters "poll" of private expectations in advance of USDA corn and soybean Crop Production reports generally includes at most only about 40 firms. The responses are typically unweighted and the mean or median of responses is used to represent market expectations. Second, survey respondents may have an incentive to report more extreme expectations in order to maximize the chance of being the most accurate forecaster in winner-take-all contests (Ottaviani and Sorensen 2006). Third, survey expectations are released several days before USDA reports, and therefore, may not reflect the latest information about crop conditions and prospects. Fourth, it is unclear if private forecasts reflect expectations of announced USDA forecasts or final USDA production estimates. The aforementioned Reuters poll has included two sets of expectations for several years now, one set for the USDA announcement and another for the final USDA estimate. Fifth, there is evidence that announced USDA crop forecasts themselves 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." While recent research indicates that private forecasters tend to incorporate expectations of systematic errors in USDA forecasts (Isengildina-Massa, Karali, and Irwin 2017), there is still ample room for this to be at least occasionally another source of measurement error in news surprises.

Similar problems with measurement errors in the survey data on market expectations has been highlighted in the macroeconomic literature, where it is argued that the error-in-variables problem results in biased parameter estimates (e.g., Figlewski and Wachtel 1983; Dietrich and Joines 1983) and a rejection of the rationality hypothesis (e.g., Jeong and Maddala 1991). Measurement errors violate the assumption of independence between the regression error term and regressors in an OLS framework, and thereby resulting in a smaller R-squared value as well as biased coefficient estimates. Additionally, when the regressors are contemporaneously correlated with the error term, then the OLS estimator is even asymptotically biased. Kennedy (2003, p. 158) explains that "…This is because the OLS procedure, in assigning 'credit' to regressors for explaining variation in the dependent variable, assigns, in error, some of the disturbance-generated variation of the dependent variable to the regressor with which that disturbance is contemporaneously correlated." He argues that the OLS regression leads to an underestimated variance of the error term in the case of positive simultaneous correlation, and an overestimated error variance in the case of negative correlation.

To see the impact of measurement error on the R-squared and the OLS coefficient estimate, consider the following regression equation:

(1) $y = \beta x + \varepsilon,$

where the regressor $x$ is measured with some error, $\eta$,

(2) $x^m = x + \eta.$

Substituting $x^m - \eta$ for $x$ in (1) yields:

(3) $y = \beta(x^m - \eta) + \varepsilon = \beta x^m + (\varepsilon - \beta\eta)$

$= \beta x^m + \omega,$

where the new error term $\omega = \varepsilon - \beta\eta$ is negatively correlated with $x^m$. Assume that the measurement error has a zero mean ($E[\eta] = 0$), a variance of $\sigma_\eta^2$, and it is uncorrelated with $\varepsilon$, $x$, and $y$ ($cov[\eta, \varepsilon] = 0$, $cov[\eta, x] = 0$, and $cov[\eta, y] = 0$). Further, suppose the random disturbance term has a zero mean ($E[\varepsilon] = 0$) and a variance of $\sigma_\varepsilon^2$, and denote the variances of $x$ and $y$ as $\sigma_x^2$ and $\sigma_y^2$, respectively. Under these assumptions, the OLS estimate of $\beta$ in (3) is:

(4) $$\hat{\beta}_{OLS} = \frac{cov(y, x^m)}{var(x^m)} = \frac{cov(\beta x + \varepsilon, x + \eta)}{var(x + \eta)},$$

and

(5) $$plim\ \hat{\beta}_{OLS} = \frac{\beta var(x)}{var(x) + var(\eta)} = \beta \frac{\sigma_x^2}{\sigma_x^2 + \sigma_\eta^2} = \beta\lambda.$$

Because $0 < \lambda < 1$, $plim\ \hat{\beta}_{OLS}$ is smaller than the true value of $\beta$ by the amount:

(6) $$plim\ \hat{\beta}_{OLS} - \beta = \beta\lambda - \beta = \beta(\lambda - 1) = -\beta \frac{\sigma_\eta^2}{\sigma_S^2 + \sigma_\eta^2}.$$

Next, consider the residual from OLS estimation of equation (3):

(7) $\hat{\omega} = y - \hat{\beta}_{OLS} x^m = y - \hat{\beta}_{OLS}(x + \eta).$

Adding and subtracting the true error from equation (1), $\varepsilon = y - \beta x$, to the above equation yields:

(8) $\hat{\omega} = \varepsilon - (y - \beta x) + y - \hat{\beta}_{OLS}(x + \eta) = \varepsilon + (\beta - \hat{\beta}_{OLS})x - \hat{\beta}_{OLS}\eta.$

Thus, the residual from estimating equation (3) contains two additional sources of variation due to measurement error. The estimated variance of the equation error, $\hat{\sigma}_\omega^2$, is then obtained as:

(9) $$plim\ \hat{\sigma}_\omega^2 = \sigma_\varepsilon^2 + (1 - \lambda)^2 \beta^2 \sigma_x^2 + \lambda^2 \beta^2 \sigma_\eta^2.$$

Consider the R-squared value from regression of (3):

(10)
$$plim\ \hat{R}^2 = 1 - \frac{\sigma_\varepsilon^2 + (1-\lambda)^2\beta^2\sigma_x^2 + \lambda^2\beta^2\sigma_\eta^2}{\sigma_y^2} = 1 - \frac{\sigma_\varepsilon^2}{\sigma_y^2} - \frac{(1-\lambda)^2\beta^2\sigma_x^2 + \lambda^2\beta^2\sigma_\eta^2}{\sigma_y^2}$$
$$= R^2 - \frac{(1-\lambda)^2\beta^2\sigma_x^2 + \lambda^2\beta^2\sigma_\eta^2}{\sigma_y^2} = R^2\frac{\sigma_x^2}{\sigma_x^2 + \sigma_\eta^2}$$
$$= R^2\lambda.$$

As $0 < \lambda < 1$, the estimated R-squared value from the regression with mis-measured regressor is lower than the true value of R-squared.

Traditional approaches of dealing with error-in-variables problem include weighted regression, instrumental variables, and linear structural relations (Kennedy 2003). The main drawback of the weighted regression procedure is that the ratio of the error variables is not usually known and cannot usually be estimated. While the instrumental variable estimator tends to be the most common approach of dealing with measurement error problem, finding an appropriate instrument is often very challenging. Linear structural models are not popular in economics because the variance of the measurement error is not known and the assumption of normal distribution of the regressors is often violated.

A straightforward special case within the weighted regression framework is the reverse least squares (RLS) regression, where the independent variable with the measurement error is regressed on the dependent variable. In this approach, the response coefficient is then calculated as the inverse of the estimated coefficient on the dependent variable. However, Jacobs (1982) argues that OLS and RLS methods can provide parameter bounds only for large samples, and the parameter bounds for small samples are random variables. In addition, Kennedy (2003) notes that the RLS method is appropriate when the variance of the measurement error is extremely large relative to the variance of the regression error term. However, both of these variances are usually unknown. Furthermore, even though the RLS regression method can provide parameter bounds in large samples, the explanatory power of the model remains unchanged.

## The ITC Estimator

The ITC method is proposed by Rigobon and Sack (2008) as a remedy in addressing potential measurement errors in the survey data on market expectations for scheduled macroeconomic announcements. A major advantage of this method is that it does not require researchers to search for appropriate instruments or improve survey data, both of which are very difficult to accomplish in practice. The key to the ITC method is that both the true surprise, $x$, and the measurement error, $\eta$, are zero on days without report releases. This censoring provides the identification needed for estimation.

The ITC model can be represented as:

(11)
$$y_t = \begin{cases} \beta x_t + \varepsilon_t & t \in D, \\ \varepsilon_t & t \notin D, \end{cases}$$

where $D$ is the set of report-release days. If variance of $y$ on the day prior to the report release is used as additional information for identification, this model leads to the following moment conditions:

(12)
$$var(y_{t-1}) = \sigma_\varepsilon^2,$$
$$var(y_t) = \beta^2\sigma_x^2 + \sigma_\varepsilon^2,$$
$$var(x_t^m) = \sigma_x^2 + \sigma_\eta^2,$$
$$cov(y_t, x_t^m) = \beta\sigma_x^2,$$

with four unknown parameters $(\beta, \sigma_x^2, \sigma_\eta^2, \sigma_\varepsilon^2)$ that can be estimated via generalized method of moments (GMM). The estimate $\hat{\beta}_{ITC}$ can then be solved as:

(13)
$$\hat{\beta}_{ITC} = \frac{var(y_t) - var(y_{t-1})}{cov(y_t, x_t^m)},$$

and a pseudo R-squared statistic, showing the fraction of the variance of the dependent variable explained by the model, can be computed as (Halova, Kurov, and Kucher 2014):

(14)
$$\text{pseudo-}\hat{R}^2 = 1 - \frac{\hat{\sigma}_\varepsilon^2}{var(y_t)},$$

where $\hat{\sigma}_\varepsilon^2$ is the estimated variance of the error term through GMM. The ITC method, therefore, allows the analyst to compute a statistic to measure the explanatory power of the fundamentals.

## Data

In their attempt to solve the orange juice puzzle, Baur and Orazem (1994) used the USDA's Crop Production reports as information reflecting commodity fundamentals and analyzed how much of the variation in futures prices can be explained by these fundamentals. A significant advantage of this specification is that the variation in fundamentals can be precisely identified so long as no other announcements consistently occur during the same time window. We maintain the view that Crop Production reports provide information related to commodity fundamentals in our study, but argue that the variables used in previous studies to represent the new information contained in these reports is likely to have been subject to measurement errors.

The Crop Production report is one of the USDA's key reports that is prepared and issued monthly by their National Agricultural Statistics Service (NASS) agency. These reports include information from survey-based estimates of yield and production estimates for major crops consistent with their growth cycles: August through November for corn and soybeans, and May through August for winter wheat. All forecasts are finalized in January in the Crop Production Annual Summary report.[2] The reports typically have been published between the 9th and the 12th of each month and released at 3pm EST until April 1994, at 8:30am EST from May 1994 to December 2012, and at 12pm EST from January 2013 to present.

[2] For more information on the preparation of USDA Crop Production reports, see Good and Irwin (2011).

The news component of these reports, or "market surprise," is typically computed as the difference between the actual announcement and the market's expectation of the announcement before the release: $S_t^m = A_t - E_{t-\tau}[A_t]$. Since it is impossible to obtain the true belief of numerous market participants, the average or the median of industry analysts' estimates have been generally used as a proxy for $E_{t-\tau}[A_t]$ (e.g., Colling and Irwin 1990; Grunewald, McNulty, and Biere 1993; Garcia et al. 1997; Egelkraut et al. 2003). We follow the same approach to construct private expectations in this study. For corn and soybeans, we use the average of forecasts by Conrad Leslie and Informa Economics (formerly Sparks Companies, Inc.) during 1970-2000; the average between the Informa Economics estimate and the average analyst estimate reported by the Dow Jones Newswire survey for 2001-2005; the average of the Dow Jones survey for 2006-2012; the average of the Bloomberg survey during 2013-2015; and the average of the Reuters survey for 2016. Private expectations for wheat are based on the average production forecasts by Informa Economics for the period 1970-1983, and the average analysts' forecasts reported by Knight-Ridder/Dow Jones Newswire for 1983-2017. The surprise component of Crop Production reports is defined as the percentage difference between the USDA's crop production estimate, $q_t^U$, and the average private analysts' production estimate, $q_t^P$, on day $t$ as $S_t^m = 100 \times (\ln q_t^U - \ln q_t^P)$. Potential errors in this surprise variable may stem from either using the mean of survey expectations, or inefficiencies in government announcements, or both. In this study, we demonstrate how having a surprise variable plagued by measurement error could diminish the role of commodity fundamentals in explaining price movements.

Market prices are represented with prices of new crop futures contracts. Corn, soybean, and soft red winter wheat futures contracts are traded at the Chicago Board of Trade (CBOT). The primary new crop futures contracts are December for corn, November for soybeans, and July for wheat. Table 1 lists the specific contract maturities used in each calendar month for these new crop futures price series. Close-to-close returns on report release days are calculated as $R_t = 100 \times (\ln P_t - \ln P_{t-1})$, where $P_t$ is the settlement price of new crop futures contract on day $t$.[3] In order to isolate the impact of Crop Production surprises on futures prices, we exclude the report day if there was another report release on the same day, or on the previous day.[4] Table 2 presents the summary statistics of the surprise variables. Over the entire sample period, average production surprise is 0.08% for corn, 0.12% for soybeans, and 0.41% for wheat. For all commodities, market surprises are more volatile in the month when the Crop Production report contains the USDA's first production forecast for the marketing year: August for corn and soybeans, and May for wheat. Production surprises are depicted in figure 1 in two ways. In panel (a), annual surprises are calculated averaging the surprises in different report months for a given marketing year. All three commodities exhibit both positive and negative surprises, fluctuating from one year to the next. However, there is no clear pattern in either of the surprises. In panel (b), production surprises and their absolute values are averaged throughout

[3] Some have argued that close-to-open returns provides a better measure of price reaction than close-to-close returns since the open reflects the market's instantaneous assessment of the unanticipated information in USDA reports (e.g., Isengildina-Massa et al. 2008). However, due to the changes in Crop Production report release times and futures market trading hours in the latter part our sample (see Adjemian and Irwin 2018), we use close-to-close returns to ensure consistency of our measure of grain futures returns throughout.

[4] Based on this criteria, three report days are excluded for corn and soybeans, and two report days for wheat. In addition due to missing data on private expectations, one report day for corn and two report days for wheat are excluded.

the sample period for a given report month. Similar to the higher variability found in table 2, the magnitude of the surprises is the largest in the first report month for the marketing year (August for corn and soybeans, and May for wheat). Furthermore, the magnitude of wheat surprises is greater than those for corn and soybeans. Several things may lead to this outcome: 1) the wheat market consists of multiple types of winter and spring wheat, which may be difficult to aggregate; and/or 2) the U.S. wheat market is much smaller than corn or soybean market, which may result in less information available for market analysts.

## Results

To demonstrate the impact of errors-in-variables on estimation results, we estimate equation (3) for each commodity separately using the OLS approach, and the set of equations in (12) via GMM using the ITC method.[5] All reported results for the ITC method use the day before release of USDA Crop Production reports as the non-report day. The ITC estimator eliminates the bias arising from measurement error so long as the error-in-variables is classical (i.e. the measurement error is additive) and the random disturbance term, $\varepsilon_t$, is homoskedastic. We compute robust standard errors to relax the homoskedasticity assumption, which is well-known to be violated for commodity prices.

The pooled estimates for corn in table 3 are obtained using all the report months. Comparing the R-squared values from OLS and ITC methods reveals a striking difference in their explanatory power. While the OLS regression explains only 27% of the corn futures return variance with the production surprises, the same fundamentals explain 75% of the return variance with the ITC approach. Removing those additional components in the regression error term due to measurement error leads to a better model fit, indicating a much more important role for the fundamentals in corn. Turning our attention to the response coefficient, the price sensitivity to a 1% surprise is estimated as -0.8 percentage points with the OLS and as -2.25 percentage points with the ITC model, about three times larger price response. The table also shows that the estimated percentage of the variance of the measured surprise due to noise, $\hat{\sigma}_\eta^2/\sigma_{S^m}^2$, is substantial at 64%.

To investigate the possibility of asymmetric price response, we repeat the analysis separately for negative- and positive-surprise days. The model's explanatory power improves from 29% to 63% with negative-surprise days, and from 24% to 77% with positive surprises. We also find that positive surprises (indicating larger than expected production) lead to a larger price response in magnitude when the attenuation bias is removed with the ITC method. Specifically, the ITC results indicate a drop in futures return by 6.32 percentage points for a 1% positive (bearish) surprise, and a 3.43 percentage point increase for a 1% negative (bullish) surprise. In this sense, "bad" news has a larger market impact than "good" news.

When the models are estimated for each report month separately, a similar pattern is observed. The larger explanatory power of the ITC method compared to the OLS regression is clearly

[5] For brevity, we present selected parameters estimated with the ITC model in tables 3-5. Full estimation results are available from the authors upon request.

evident for each report month as well. While the R-squared values range from 15% to 40% in the OLS model, they range from 64% to 85% in the ITC method. This large difference provides compelling evidence that measurement errors in surprise variables largely explains the low power of the fundamentals found in earlier studies of commodity price changes.

Our results also show that different report months are affected by noise to a different degree, with September being most affected (82%) and August being least affected (52%). This leads to a striking difference between the OLS and the ITC results in assessing the largest price response. The OLS model suggests that the largest price reaction occurs in response to November surprises (1.14 percentage points), followed by October, August, and September reactions. On the other hand, the ITC model indicates that September surprises have the largest effect (3.73 percentage points), and November is only the third in magnitude. This difference further demonstrates the bias in the OLS estimates that don't take into account the error-in-variables problem and how it unevenly affects the estimates based on the proportion of measured surprises due to noise.

Table 4 presents our results for the soybean market. Production surprises can explain the return variance about three and a half times larger with the pooled ITC approach (R-squared of 74%) compared to the OLS regression (R-squared of 21%). The OLS R-squared value is 16% for positive and 27% for negative surprises, whereas the ITC R-squared is 76% for positive and 65% for negative surprises. Response coefficient is estimated as -0.64 percentage points with the pooled OLS and -2.21 percentage points with the ITC model, indicating a ratio of 3.44. The bias in the price response is more pronounced for the positive-surprise days, with the ITC to OLS coefficient ratio of 10.57.

Focusing on each report month separately, the pseudo R-squared values from the ITC estimations demonstrate that the production surprises explain from about 67% to 82% of soybean return variance, which is much higher than the OLS R-squared values that range from 21% to 27%. Similar to corn results, the percentage of the measured surprise variance due to noise, $\hat{\sigma}_{\eta}^{2}/\sigma_{S^m}^{2}$, is the largest for September report (74%), which yields the weakest price reaction according to the OLS results (-0.53 percentage points) and the second weakest according to ITC estimates (-2.19 percentage points). More specifically, the OLS response coefficient estimates range in magnitude from 0.53 to 0.95 percentage points, whereas the magnitude of ITC estimates ranges between 1.79 and 2.72 percentage points. The largest ITC response coefficient estimate is for October report, indicating that a 1% surprise in soybean production results in a 2.72 percentage point decrease in returns. However, OLS estimates suggest that the November report leads to the strongest reaction in the market.

Table 5 shows that the explanatory power of both OLS and ITC methods for wheat are lower compared to corn and soybean markets. The R-squared for the pooled sample is only 5% with OLS and 38% with ITC. While the OLS R-squared becomes 15% for May reports, the response coefficient is statistically insignificant with the ITC method, resulting in a poor model performance. In addition, while all the price responses in corn and soybean futures markets are statistically significant, there is limited evidence of significant market reaction to winter wheat production surprises. Except for the pooled report months, all ITC estimates are statistically insignificant, with the variance of the noise contributing to 89% of the positive measured surprise variance, and to 91% of the negative surprise variance.[6] This result demonstrates that the ITC approach does not automatically result in a good model fit after correcting for measurement error. It appears that because of the challenges associated with multiple types of wheat and the size of the market mentioned in the data section, the quality of fundamental information contained in the wheat market surprises is less likely to lead to a market price reaction.

Finally, similar to Rigobon and Sack (2008), we find high noise ratios for measured surprise variables. For example, the noise ratio for pooled ITC regressions is 64%, 70%, and 86% for corn, soybeans, and wheat, respectively. One explanation is simply that the surprises contain measurement errors of this magnitude. This is consistent with the multiple sources of measurement error discussed earlier. Another possibility is that the variance of returns on non-report days, which is required for identification in the ITC model, is underestimated. This would cause the ITC parameters to be overestimated and result in a higher noise percentage in measured surprises. Since we employ the return variance on the day prior to Crop Production report release, it is possible that the anticipation of the report release on the next day itself reduces uncertainty, thereby resulting in smaller measured non-report return variance. Consequently, we checked whether ITC estimation results are sensitive to the choice of non-report day. Estimation results are similar if non-report day lagged variance is defined as two days or three days before the release date of USDA Crop Reports. We also investigated whether lagged return variances used for identification in the ITC method are underestimated by comparing one-day lagged return variances to the variance for all non-report days for each commodity. The day before report release variance is modestly smaller than on all other non-report days for corn and soybeans but approximately the same for wheat.[7] The differences are not nearly large enough to account for the noise in measured surprises.

Another possible explanation for the high noise ratios is additional USDA information released simultaneously with Crop Reports for corn, soybeans, and wheat. Starting in January 1985, USDA Crop Production reports and World Agricultural Supply and Demand Estimates (WASDE) reports were released simultaneously, with updated WASDE supply and demand balance sheets reflecting the latest estimates in the Crop Production report. This means that USDA crop production estimates for the U.S. since 1985 have been released simultaneously with international crop production estimates, U.S. and international demand estimates, and U.S. and international ending stock estimates. If grain futures markets consistently react to the unanticipated component of the additional information, this may result in a higher variance of report day futures returns. Since we only utilize Crop Production reports, any additional price

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[6] Similar findings are obtained using hard red winter wheat futures contracts that are traded at the Kansas City Board of Trade (KCBT).

[7] Days with any of the following USDA report releases were excluded from the "all days" sample: WASDE, Prospective Plantings, Acreage, Grain Stocks, Small Grains Annual Summary, Crop Production Annual Summary, Cattle on Feed, Hogs and Pigs, and Crop Production in other months of the year. In addition, we excluded both five days before and five days after the Crop Production report releases incorporated in our study. For corn and soybeans, we find that our lagged return variance measure is modestly underestimated when compared to the return variance obtained with the elimination process described: 1.40 versus 1.86 for corn and 1.60 versus 1.89 for soybeans. For wheat, on the other hand, our lagged return variance measure of 2.53 is slightly higher than the variance of 2.47 calculated using all days without other major USDA report releases.

volatility associated with other USDA information may be attributed to the production surprises, which could bias ITC estimates upward and inflate the noise ratio.

There is evidence on the market impact of the other USDA information in the literature. Isengildina-Massa et al. (2008) examined the volatility of corn and soybean futures returns on days when Crop Production and WASDE reports are released simultaneously and on days when only WASDE reports are released. They found no evidence of significant price reaction on WASDE only release days in corn and a small price reaction in soybeans. These findings indicate that the high noise ratios estimated in our study are unlikely to be due to additional USDA information released on Crop Production report days.

*Changes in Explanatory Power of Fundamentals over Time*

In order to test if the improved explanatory power of Crop Production surprises with the ITC approach relative to the OLS method is robust throughout our sample period, we estimate each model with a 25-year rolling window. Specifically, all the models are first estimated for the sample period of 1970-1994, then for 1971-1995, and so on, until the last 25-year window of 1992-2016. The plots of the R-squared values from OLS regressions and the pseudo R-squared values from ITC estimations are presented in figure 2 for corn and soybeans, and in figure 3 for wheat.

Figure 2(a) shows that the ITC approach consistently has higher explanatory power compared to the OLS over the entire sample period for both corn and soybeans. The R-squared values are relatively stable for both methods and commodities, with the OLS ranging between 10% and 40% and the ITC ranging from 70% to 90%. A similar pattern is observed in figure 2(b) for August and September reports. However, the results for October report show a notable variation in the explanatory power of the production surprises over time. Specifically, the OLS R-squared values show an increase over time, ranging between 4% and 53% for corn and between 6% and 55% for soybeans. The pseudo R-squared from the ITC estimation, on the other hand, is fairly stable for both crops. For the November report, the explanatory power of the OLS model shows a steady decline in the soybean market. For the corn market, there is a drop in the explanatory power of the ITC method in the 1985-2009 sub-period from 89% to 63%.

Figure 3(a) shows that once again the ITC approach outperforms the OLS method throughout the sample period. Interestingly, there is a clear reduction in the explanatory power of fundamentals in the wheat market for both pooled OLS and ITC, with the R-squared for pooled regressions dropping from around 10% to 0% for OLS and dropping from around 50% to 30% for ITC. Figure 3(b) reveals that this drop is due declines in the explanatory power of July and August reports. Explanatory power for the May and June reports, on the other hand, exhibits a decline in the ITC R-squared in the very earliest sample sub-periods, followed by increases after mid-1970s.[8] Overall, there is little change in the explanatory power of the May and June reports, with

[8] For May reports starting with the sample period of 1979-2003, convergence in ITC method is achieved using the variance of returns three days before the release date as the non-report day. For July reports, the ITC approach failed to converge for sample periods containing the 1980s except for 1987-2011 period using several alternatives for non-report day returns, and therefore the R-squared values from ITC for those sample periods are not included in

R-squared around 60% for later samples. This indicates that the earlier Crop Production reports for wheat retain substantial informational value.

The ITC results in this section show that the relatively high explanatory power of fundamental information, as represented by USDA Crop Production reports, in corn and soybean futures markets has been remarkably stable from the 1970s through the 2010s. This holds for both pooled regressions and for individual report month regressions. The results are mixed for wheat, with consistently high explanatory power for May and June report months and declining explanatory power for July and August. Overall, these results indicate a surprising consistency in the importance of fundamental supply and demand information, despite large structural changes in market participation and trading technology (Irwin and Sanders 2012).

*Cross-Commodity Effects*

The ITC model can also be extended to include multiple markets and multiple surprises. Since surprises in corn production could affect soybean prices, and surprises in soybean production could affect corn prices, we study these possible cross-commodity effects of the surprises contained in Crop Production reports. The model with two markets and two surprises becomes:

$$
\begin{aligned}
(15)\quad R_{1,t} &= \beta_{1,1}S_{1,t} + \beta_{1,2}S_{2,t} + \varepsilon_{1,t}, \\
R_{2,t} &= \beta_{2,1}S_{1,t} + \beta_{2,2}S_{2,t} + \varepsilon_{2,t}, \\
S_{1,t}^{m} &= S_{1,t} + \eta_{1,t}, \\
S_{2,t}^{m} &= S_{2,t} + \eta_{2,t},
\end{aligned}
$$

where the subscripts on $R_t$ refer to markets and the subscripts on $S_t^m$ and $S_t$ refer to different surprises, possibly affecting both markets. This model leads to 13 moment conditions and 13 parameters that can be estimated via GMM.[9]

Results are shown in table 6. To allow for possible correlations in the structural error terms $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ we estimate the model through seemingly unrelated regression (SUR) model. While the SUR model yields identical results to OLS when both equations have exactly the same regressors, the standard errors of the estimates differ in the case of correlated error terms across the equations. Similar to the results presented above, the ITC method for pooled report months leads to an R-squared value that is about three times larger than the OLS for both corn and soybean equations. The improvement in the explanatory power of the fundamentals with the ITC method is most obvious for the September report, which has the highest estimated noise percentage in the measured surprises for both corn (74%) and soybeans (69%).

Our findings suggest that soybean production surprises do not have any impact on corn futures prices, whereas corn surprises result in soybean price reactions except for September report. Response coefficients for corn are similar to those in table 3, with ITC/SUR ratios ranging from 2.14 to 5.74. On the other hand, the response coefficients for soybeans to their own surprises are smaller compared to table 4, but ITC estimates are still larger relative to SUR. The magnitude ranges between 0.42 and 0.73 percentage points with the SUR results, and between 0.98 and 2.40

the graph for July wheat reports. Note that convergence did occur for the pooled wheat ITC regressions for all sample periods.

[9] The moment equations from this model are provided in the appendix.

percentage points with the ITC results, resulting in the ITC/SUR ratio of about 1.33 to 4.28. An unexpected result is found with the ITC model for August reports, with soybean futures prices not responding to their own-commodity production surprises but to corn surprises, accompanied by the weakest reaction and the lowest pseudo R-squared compared to other monthly reports.

## Conclusions

A long-standing puzzle in commodity markets is the low explanatory power of supply and demand fundamentals for explaining the variability of prices in these markets. We analyze the "fundamentals puzzle" in grain futures markets by applying an instrumental variables correction for measurement errors when estimating corn, soybean, and wheat futures price reaction to release of USDA Crop Production reports. Specifically, the ITC method developed by Rigobon and Sack (2008) is used to account for potential measurement errors in the surprise components of USDA Crop Production reports and explanatory power and market price sensitivity is compared for OLS and ITC methods. Unexpected fundamental information is measured using market news surprises, which is the difference between the USDA announcement and an extensive proprietary dataset containing industry expectations for these announcements that spans the 47 years from 1970 through 2016.

We demonstrate that fundamentals, as represented by USDA Crop Production report surprises, explain a limited amount of the variation in grain futures price movements within a traditional OLS framework. After adjusting for measurement error with the ITC method, the explanatory power of fundamentals increases dramatically. For example, the pooled OLS regression for all Crop Production report months in corn explains only 27% of the futures return variance, while the same fundamentals explain 75% of the return variance with the ITC approach. Our findings also demonstrate that traditional OLS estimates are biased downward by two to six times for corn, three to four times for soybeans, and about eight times for wheat. Furthermore, noise in surprises across different reports resulted in different rankings of price impacts in magnitude between OLS and ITC estimates. Finally, we find no evidence that the explanatory power of USDA surprises has diminished over time in corn and soybeans but some decline for wheat surprises in the second half of the forecast cycle.

In sum, the results of this study provide compelling evidence that fundamentals are the main driver of price movements in grain futures markets. Previous studies that ignore the problem of measurement error could incorrectly suggest that fundamental supply and demand information is a poor indicator of movements in grain futures prices and that non-fundamental factors, such as noise trading, dominate. Our findings indicate that measurement errors largely explain the "fundamentals puzzle" in agricultural futures markets.

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**Table 1. New Crop Futures Contracts**

| Calendar Month | Corn | Soybeans | Wheat |
|---|---|---|---|
| January$_t$ | Mar$_t$ | Mar$_t$ | Mar$_t$ |
| February$_t$ | Dec$_t$ | Nov$_t$ | Jul$_t$ |
| March$_t$ | Dec$_t$ | Nov$_t$ | Jul$_t$ |
| April$_t$ | Dec$_t$ | Nov$_t$ | Jul$_t$ |
| May$_t$ | Dec$_t$ | Nov$_t$ | Jul$_t$ |
| June$_t$ | Dec$_t$ | Nov$_t$ | Jul$_t$ |
| July$_t$ | Dec$_t$ | Nov$_t$ | Sep$_t$ |
| August$_t$ | Dec$_t$ | Nov$_t$ | Sep$_t$ |
| September$_t$ | Dec$_t$ | Nov$_t$ | Dec$_t$ |
| October$_t$ | Dec$_t$ | Nov$_t$ | Dec$_t$ |
| November$_t$ | Dec$_t$ | Jan$_{t+1}$ | Dec$_t$ |
| December$_t$ | Mar$_{t+1}$ | Jan$_{t+1}$ | Mar$_{t+1}$ |

*Note* : The subscript, t or t + 1, refers to the year of the futures contract expiration date relative to the year t of the daily price being computed. The primary new crop futures contracts are December for corn, November for soybeans, and July for wheat.

**Table 2. Summary Statistics of Surprises in Crop Production Reports**

| | Corn (1970-2016) | | | Soybeans (1970-2016) | | | Wheat (1971-2016) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | No. of obs. | Mean | Std. Dev. | No. of obs. | Mean | Std. Dev. | No. of obs. |
| Pooled | 0.08 | 1.52 | 183 | 0.12 | 1.76 | 184 | 0.41 | 2.37 | 180 |
| 1 | -0.18 | 2.29 | 47 | -0.10 | 2.28 | 47 | -0.04 | 3.11 | 45 |
| 2 | 0.32 | 1.33 | 45 | 0.40 | 1.75 | 45 | 0.25 | 2.09 | 46 |
| 3 | 0.13 | 1.19 | 45 | -0.01 | 1.71 | 46 | 1.13 | 2.56 | 45 |
| 4 | 0.07 | 0.86 | 46 | 0.18 | 1.10 | 46 | 0.31 | 1.15 | 44 |

*Note* : Suprises are measured in percentage. Full sample periods for each commodity are given in parentheses. Crop Production reports for corn and soybeans are released in 1=August, 2=September, 3=October, and 4=November. Crop Production reports for wheat are released in 1=May, 2=June, 3=July, and 4=August.

**Table 3. Price Response to Crop Production Report Surprise for Corn, 1970/71-2016/17 Marketing Years**

| | R-squared | | | Response coefficient | | | Noise percentage |
|---|---|---|---|---|---|---|---|
| Report month | OLS | ITC | Ratio (ITC/OLS) | OLS | ITC | Ratio (ITC/OLS) | $\hat{\sigma}_{\eta}^{2}/\sigma_{S^m}^{2}$ |
| Pooled | 0.27 | 0.75 | 2.82 | -0.80 *** | -2.25 *** | 2.82 | 64% |
| ($N$=183) | | | | (0.10) | (0.33) | | |
| Negative surprise | 0.29 | 0.63 | 2.14 | -0.82 *** | -3.43 *** | 4.16 | 78% |
| ($N$=89) | | | | (0.15) | (1.20) | | |
| Positive surprise | 0.24 | 0.77 | 3.15 | -0.78 *** | -6.32 *** | 8.14 | 89% |
| ($N$=94) | | | | (0.14) | (2.24) | | |
| August | 0.40 | 0.85 | 2.14 | -0.76 *** | -1.63 *** | 2.14 | 52% |
| ($N$=47) | | | | (0.13) | (0.25) | | |
| September | 0.15 | 0.81 | 5.45 | -0.64 *** | -3.73 *** | 5.86 | 82% |
| ($N$=45) | | | | (0.17) | (1.07) | | |
| October | 0.22 | 0.64 | 2.98 | -0.98 *** | -2.91 *** | 2.97 | 65% |
| ($N$=45) | | | | (0.31) | (1.16) | | |
| November | 0.28 | 0.70 | 2.51 | -1.14 *** | -2.82 *** | 2.48 | 58% |
| ($N$=46) | | | | (0.27) | (0.84) | | |

*Note* : Robust standard errors are given in parentheses. Coefficient ratio and noise percentage are given only for the cases with statistically significant parameter estimates. The asterisks *, **, *** represent statitical significance at the 10%, 5%, and 1% level, respectively.

**Table 4. Price Response to Crop Production Report Surprise for Soybeans, 1970/71-2016/17 Marketing Years**

| | R-squared | | | Response coefficient | | | Noise percentage |
|---|---|---|---|---|---|---|---|
| Report month | OLS | ITC | Ratio (ITC/OLS) | OLS | ITC | Ratio (ITC/OLS) | $\hat{\sigma}_{\eta}^{2}/\sigma_{Sm}^{2}$ |
| Pooled | 0.21 | 0.74 | 3.46 | -0.64 *** | -2.21 *** | 3.44 | 70% |
| ($N$=184) | | | | (0.09) | (0.33) | | |
| Negative surprise | 0.27 | 0.65 | 2.37 | -0.75 *** | -3.48 *** | 4.63 | 75% |
| ($N$=86) | | | | (0.13) | (0.96) | | |
| Positive surprise | 0.16 | 0.76 | 4.63 | -0.55 *** | -5.80 *** | 10.57 | 88% |
| ($N$=98) | | | | (0.13) | (2.07) | | |
| August | 0.21 | 0.67 | 3.24 | -0.56 *** | -1.79 *** | 3.18 | 68% |
| ($N$=47) | | | | (0.15) | (0.58) | | |
| September | 0.21 | 0.82 | 3.99 | -0.53 *** | -2.19 *** | 4.10 | 74% |
| ($N$=45) | | | | (0.14) | (0.68) | | |
| October | 0.22 | 0.78 | 3.51 | -0.78 *** | -2.72 *** | 3.48 | 70% |
| ($N$=46) | | | | (0.22) | (0.68) | | |
| November | 0.27 | 0.70 | 2.54 | -0.95 *** | -2.44 *** | 2.57 | 60% |
| ($N$=46) | | | | (0.22) | (0.64) | | |

*Note* : Robust standard errors are given in parentheses. Coefficient ratio and noise percentage are given only for the cases with statistically significant parameter estimates. The asterisks *, **, *** represent statitical significance at the 10%, 5%, and 1% level, respectively.

**Table 5. Price Response to Crop Production Report Surprise for Wheat, 1971/72-2016/17 Marketing Years**

| | R-squared | | | Response coefficient | | | Noise percentage |
|---|---|---|---|---|---|---|---|
| Report month | OLS | ITC | Ratio (ITC/OLS) | OLS | ITC | Ratio (ITC/OLS) | $\hat{\sigma}_{\eta}^{2}/\sigma_{S^m}^{2}$ |
| Pooled | 0.05 | 0.38 | 7.28 | -0.19 *** | -1.45 ** | 7.50 | 86% |
| ($N$=180) | | | | (0.06) | (0.65) | | |
| Negative surprise | 0.04 | 0.51 | 11.35 | -0.20 *** | -3.87 * | 19.01 | 91% |
| ($N$=76) | | | | (0.08) | (2.38) | | |
| Positive surprise | 0.06 | 0.24 | 3.95 | -0.19 ** | -1.91 | | 89% |
| ($N$=104) | | | | (0.09) | (1.90) | | |
| May | 0.15 | 0.07 | 0.49 | -0.25 *** | -0.08 | | |
| ($N$=45) | | | | (0.08) | (0.49) | | |
| June | 0.05 | 0.51 | 10.77 | -0.22 | -2.42 | | 90% |
| ($N$=46) | | | | (0.17) | (2.03) | | |
| July | 0.02 | 0.38 | 17.38 | -0.11 | -1.32 | | 84% |
| ($N$=45) | | | | (0.11) | (1.12) | | |
| August | 0.01 | 0.52 | 55.76 | -0.16 | -7.41 | | 95% |
| ($N$=44) | | | | (0.25) | (9.90) | | |

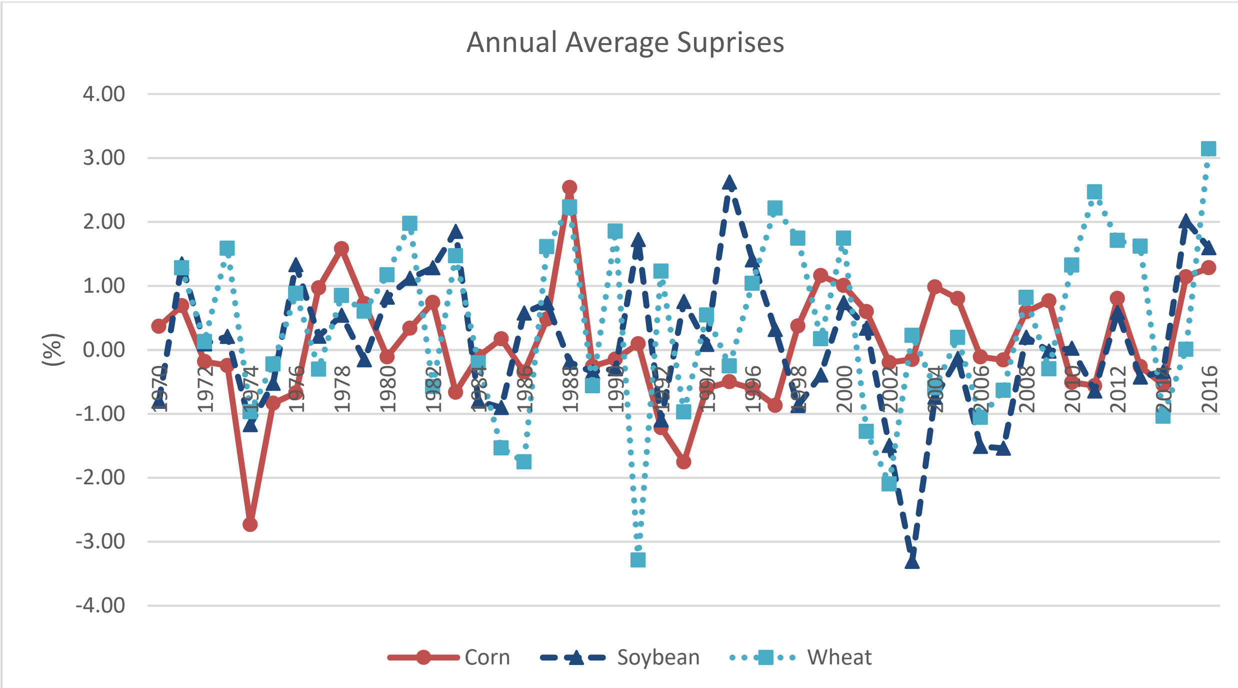
*Note* : Robust standard errors are given in parentheses. Coefficient ratio and noise percentage are given only for the cases with statistically significant parameter estimates. The asterisks *, **, *** represent statitical significance at the 10%, 5%, and 1% level, respectively.

**Table 6. Price Response to Crop Production Report Surprise in Corn and Soybean Markets, 1970/71-2016/17 Marketing Years**

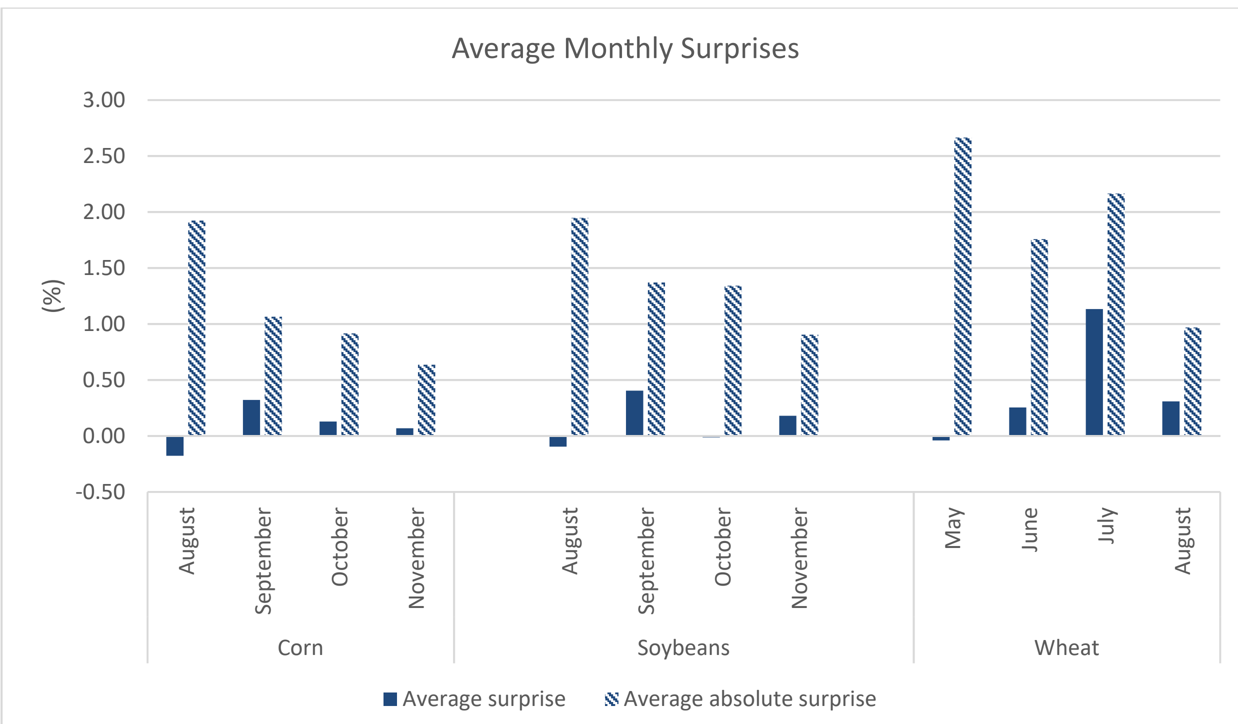
| | R-squared | | | Response coefficient | | | | | | Noise percentage |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | *Corn* | | | *Soybeans* | | | |
| Report month | SUR | ITC | Ratio (ITC/SUR) | SUR | ITC | Ratio (ITC/SUR) | SUR | ITC | Ratio (ITC/SUR) | $\hat{\sigma}_{\eta}^2/\sigma_{S^m}^2$ |
| *Corn* | | | | | | | | | | |
| Pooled | 0.27 | 0.75 | 2.81 | -0.81 *** | -2.22 *** | 2.76 | 0.02 | -0.10 | | 64% |
| | | | | (0.10) | (0.34) | | (0.09) | (0.25) | | |
| August | 0.40 | 0.85 | 2.14 | -0.77 *** | -1.65 *** | 2.14 | 0.04 | 0.10 | | 52% |
| | | | | (0.14) | (0.28) | | (0.15) | (0.40) | | |
| September | 0.15 | 0.81 | 5.45 | -0.64 *** | -3.67 *** | 5.74 | 0.01 | -1.49 | | 74% |
| | | | | (0.23) | (1.44) | | (0.17) | (1.14) | | |
| October | 0.22 | 0.64 | 2.94 | -1.01 *** | -2.93 *** | 2.90 | 0.08 | 0.13 | | 64% |
| | | | | (0.29) | (1.20) | | (0.21) | (0.55) | | |
| November[a] | 0.28 | | | -1.10 *** | N/A | | -0.07 | N/A | | |
| | | | | (0.30) | | | (0.23) | | | |
| *Soybeans* | | | | | | | | | | |
| Pooled | 0.27 | 0.74 | 2.77 | -0.36 *** | -1.21 *** | 3.39 | -0.58 *** | -1.44 *** | 2.50 | 58% |
| | | | | (0.11) | (0.33) | | (0.09) | (0.28) | | |
| August | 0.32 | 0.67 | 2.09 | -0.44 *** | -0.92 *** | 2.11 | -0.42 *** | -0.85 | | 50% |
| | | | | (0.16) | (0.32) | | (0.16) | (0.57) | | |
| September | 0.23 | 0.82 | 3.65 | 0.22 | -1.35 | | -0.56 *** | -2.40 ** | 4.28 | 69% |
| | | | | (0.21) | (1.24) | | (0.16) | (0.99) | | |
| October | 0.35 | 0.78 | 2.24 | -0.75 *** | -2.68 ** | 3.59 | -0.73 *** | -0.98 ** | 1.33 | 28% |
| | | | | (0.30) | (1.15) | | (0.21) | (0.50) | | |
| November[a] | 0.33 | | | -0.63 ** | N/A | | -0.73 *** | N/A | | |
| | | | | (0.32) | | | (0.24) | | | |

*Note* : Robust standard errors are given in parentheses. Coefficient ratio and noise percentage are given only for the cases with statistically significant parameter estimates. The asterisks *, **, *** represent statitical significance at the 10%, 5%, and 1% level, respectively.

[a] Convergence is not achieved in ITC method.

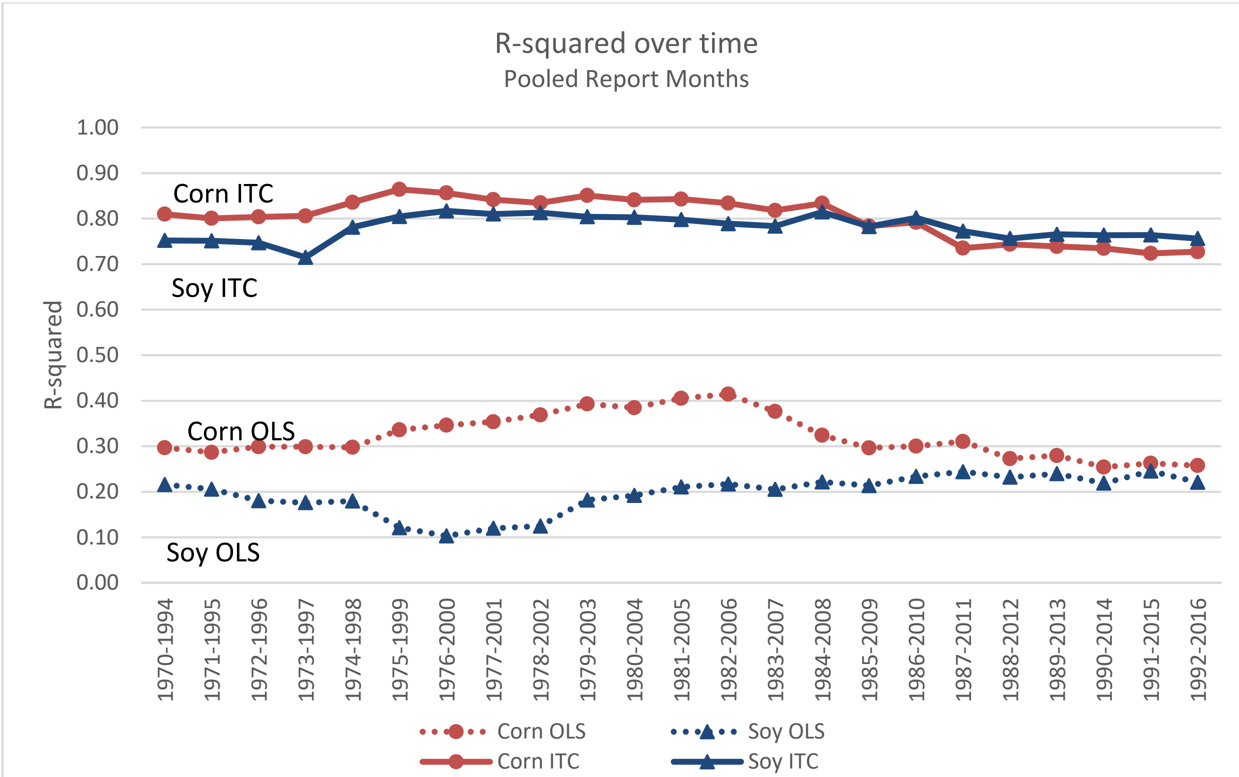



(a) Annual average surprises

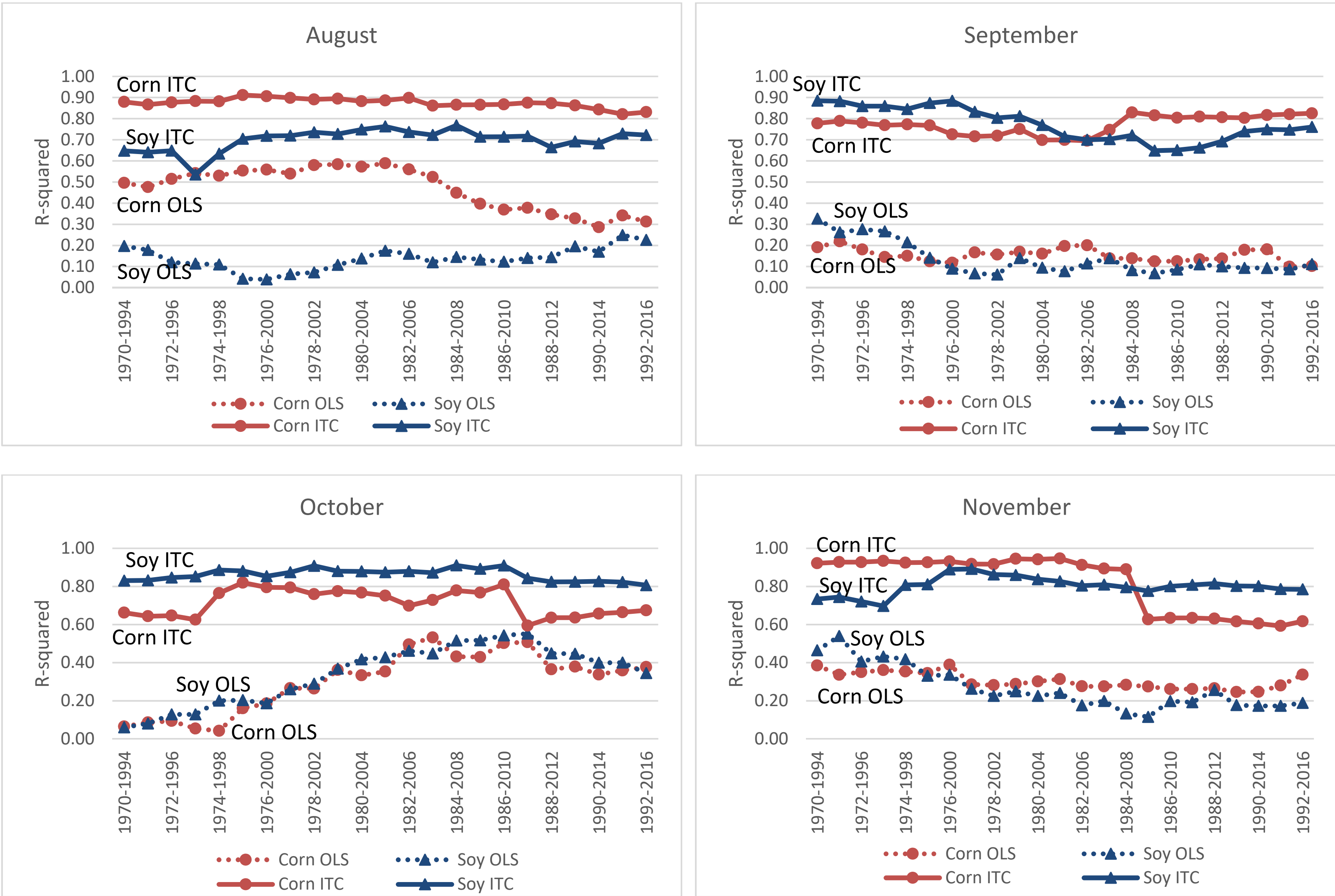



(b) Average surprises by report month

**Figure 1. Surprises in Crop Production reports for corn, soybeans, and wheat, 1970/71-2016/17 marketing years**

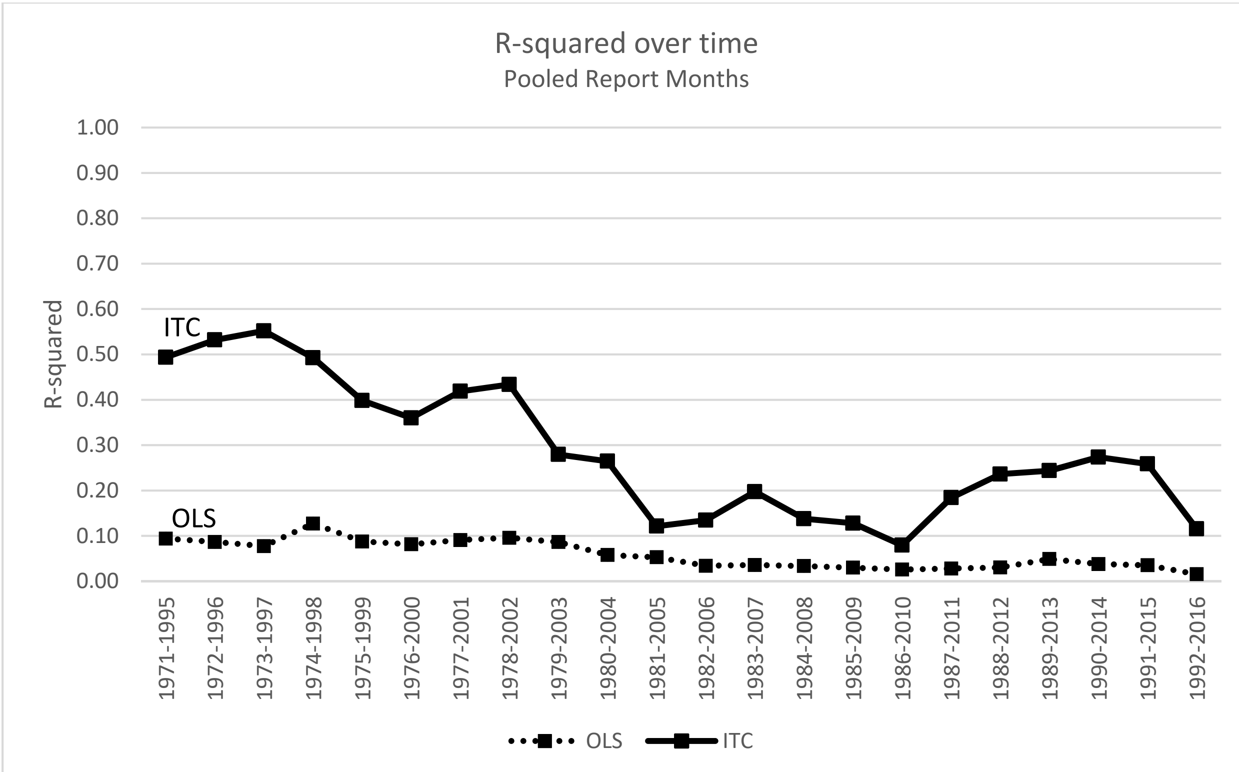



(a) Pooled report months

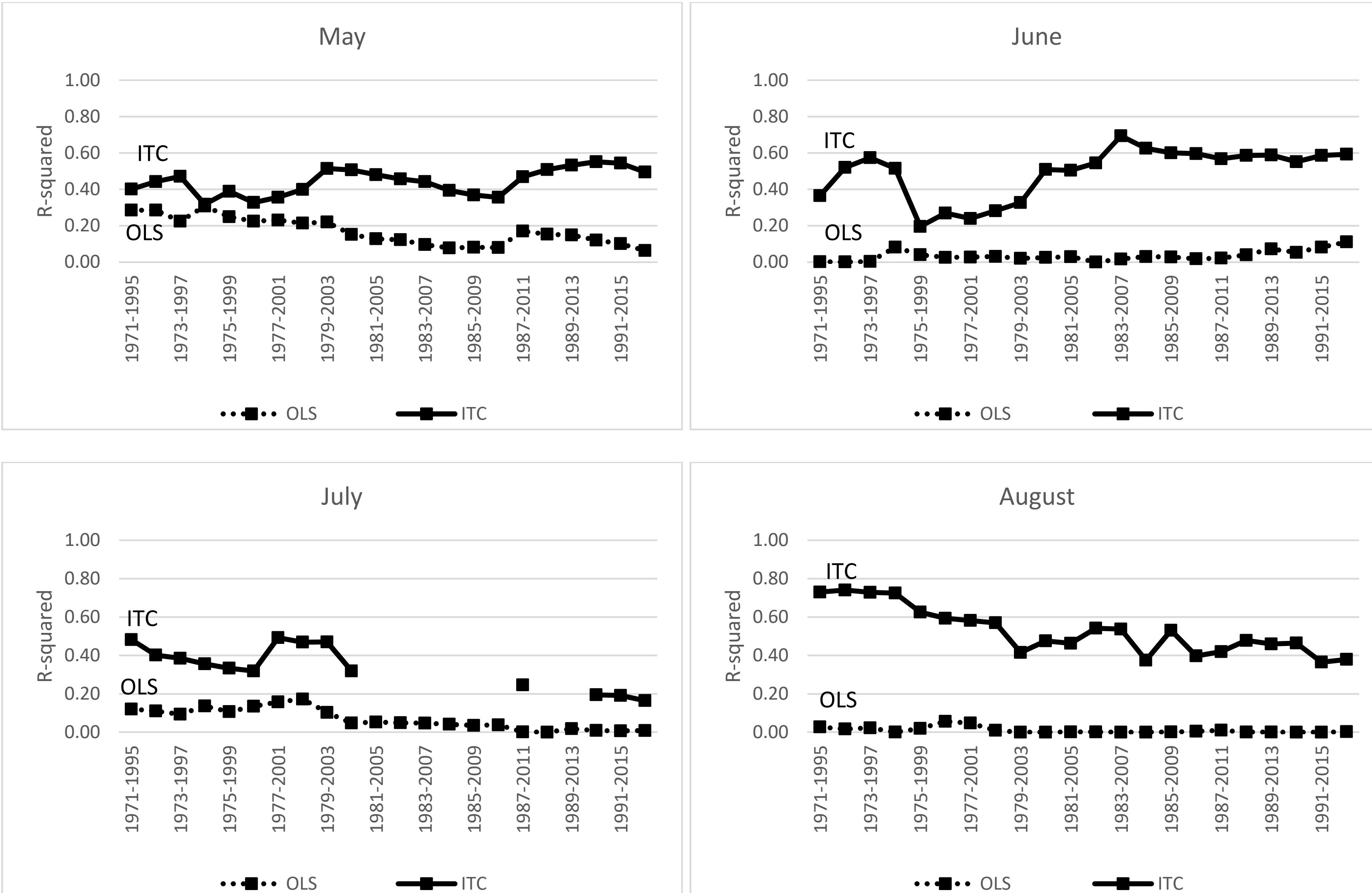



(b) Separate report months

**Figure 2. Explained variation in corn and soybean futures return changes over time on Crop Production report release days**



(a) Pooled report months




(b) Separate report months

**Figure 3. Explained variation in wheat futures return changes over time on Crop Production report release days**

## Appendix

### Moment Conditions for the ITC Estimation with Two Markets and Two Surprises

The ITC estimation of a model with two markets and two surprises leads to the following 13 moment conditions with 13 unknown parameters to be estimated through GMM.

(1) $var(R_{1,t-1}) = \sigma_{\varepsilon 1}^2$

(2) $var(R_{2,t-1}) = \sigma_{\varepsilon 2}^2$

(3) $var(R_{1,t}) = \beta_{1,1}^2 \sigma_{S1}^2 + \beta_{1,2}^2 \sigma_{S2}^2 + \sigma_{\varepsilon 1}^2 + 2\beta_{1,1}\beta_{1,2} cov(S_{1,t}, S_{2,t})$

(4) $var(R_{2,t}) = \beta_{2,1}^2 \sigma_{S1}^2 + \beta_{2,2}^2 \sigma_{S2}^2 + \sigma_{\varepsilon 2}^2 + 2\beta_{2,1}\beta_{2,2} cov(S_{1,t}, S_{2,t})$

(5) $var(S_{1,t}^m) = \sigma_{S1}^2 + \sigma_{\eta 1}^2$

(6) $\mathrm{var}(S_{2,t}^m) = \sigma_{S2^*}^2 + \sigma_{\eta 2}^2$

(7) $cov\left(R_{1,t}, S_{1,t}^m\right) = \beta_{1,1}\sigma_{S1}^2 + \beta_{1,2} cov(S_{1,t}, S_{2,t})$

(8) $cov\left(R_{1,t}, S_{2,t}^m\right) = \beta_{1,2}\sigma_{S2}^2 + \beta_{1,1} cov(S_{1,t}, S_{2,t})$

(9) $cov\left(R_{2,t}, S_{1,t}^m\right) = \beta_{2,1}\sigma_{S1}^2 + \beta_{2,2} cov(S_{1,t}, S_{2,t})$

(10) $cov\left(R_{2,t}, S_{2,t}^m\right) = \beta_{2,2}\sigma_{S2}^2 + \beta_{2,1} cov(S_{1,t}, S_{2,t})$

(11) $cov\left(R_{1,t}, R_{2,t}\right) = \beta_{1,1}\beta_{2,1}\sigma_{S1}^2 + \beta_{1,2}\beta_{2,2}\sigma_{S2}^2 + \beta_{1,1}\beta_{2,2} cov\left(S_{1,t}, S_{2,t}\right) +$
$\beta_{1,2}\beta_{2,1} cov\left(S_{1,t}, S_{2,t}\right) + cov(\varepsilon_{1,t}, \varepsilon_{2,t})$

(12) $cov\left(R_{1,t-1}, R_{2,t-1}\right) = cov(\varepsilon_{1,t}, \varepsilon_{2,t})$

(13) $cov\left(S_{1,t}^m, S_{2,t}^m\right) = cov\left(S_{1,t}, S_{12t}\right) + cov(\eta_{1,t}, \eta_{2,t})$