Conditional Information: When Are Pork Belly Cold Storage Reports Informative?

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INTRODUCTION

It is well known that agricultural supply and demand are quite variable. The variability includes seasonal patterns of production and consumption as well as longer-term production cycles extending over several years. By implication, the impact of information from public and private sources released into agricultural markets may also be quite variable over the production cycle. That is, similar information may change investor beliefs in substantially different ways, depending on where the market is in its cycle.

Only recently have event studies begun to analyze the impact of information flows in a conditional framework [McQueen and Roley (1993), Colling and Irwin (1996)]. Information released to the public from either public or private sources may have an impact only under certain economic or time-specific conditions. Further, the magnitude and direction of im-

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pact may also be conditioned by economic or time-specific states. Economic states include the general business cycle as well as specific market cycles. Time-specific states focus on seasonality issues and simultaneous release of information from closely related markets.

The purpose of this study is to establish whether or not the arrival of unexpected information in *Cold Storage Reports* (CSR) has a differential impact on prices depending on the point in the market cycle when the information is released. That is, is the market reaction conditioned on market cycle? Specifically, this study extends previous research by examining conditionality of information flows in pork futures. Three issues of the impact of USDA pork belly cold storage releases on pork futures are examined: the seasonal impact, the market cycle impact, and the cross impact of seasonality and market cycle.

LITERATURE REVIEW

Three areas of literature are important to review. First, there is considerable research that focuses on the impact of USDA *Hog and Pig Reports* (HPR) on live hog and pork belly futures. These studies find that the live hog futures market is reasonably efficient and prices adjust quickly to new information contained in these reports. Miller (1979), Hoffman (1980), and Hudson, Koontz, and Purcell (1984) find live hog futures generally react quickly to the new information contained in HPR. Colling and Irwin (1990), using methodology that separates the response into anticipated and unanticipated components, find live hog futures react sharply and quickly to the unanticipated information contained in an HPR. Schroeder, Blair, and Mintert (1990) find no significant abnormal returns in live hog, live cattle, and feeder cattle markets following quarterly inventory releases. Mann and Dowen (1996) find increased price variance and trading volume after release of an HPR indicating new information arriving in both live hog futures and frozen pork belly futures markets.

One study seems to contradict this body of work. Carter and Galopin (1993) find that HPRs do not contain new information. They find that a trader with advance knowledge of the report could not make statistically significant risk-adjusted profits. However, Colling and Irwin (1995), with a different risk-adjustment approach, find that a trader could make statistically significant profits over the same period. With the exception of the Carter and Galopin study, the question of a response of live hog and pork belly futures to the information contained in HPRs is seemingly well established.

Second, several recent event studies find that seasonality, market cycle, and business cycle may play an important role in determining informational impact. In an analysis of macroeconomic news, McQueen and Roley (1993) analyze the impact of these fundamental information flows over stages of the business cycle. They find that the stock market's response to macroeconomic news does depend on the stage of the business cycle. Generally, when the economy is strong, good economic news leads to lower stock prices, whereas when the economy is weak, good economic news leads to higher stock prices. Colling and Irwin (1996) analyze the impact of export inspections reports on corn, wheat, and soybean futures for the period 1988–1991. Without accounting for any market or seasonal conditions, they find no evidence of informational impact on corn and wheat futures. They do find support for general informational impact for soybeans. However, when conditioning variables are introduced, they find evidence of informational impact on soybean futures when soybean stocks are low relative to use, as well as during the June–August quarter. Corn futures respond to a seasonal impact during the December–February quarter.

Third, Colling and Irwin (1994) study the impact of CSRs on pork belly and live hog futures over the period January 1989 to December 1992. Survey data from Knight-Ridder News Service are used to develop an unanticipated component of the pork belly cold storage estimate released by the USDA. They find that pork belly and live hog futures respond to the unanticipated component contained in the USDA release. They also find that the impact is most pronounced at opening the day following the release, with some impact measurable by closing. No statistical impact is detectable on the second day after release.

DATA

The period of analysis is January 1988–July 1995. Pork belly cold storage estimates are contained in the USDA *Cold Storage Report,* which is issued monthly, typically between the 19th and 23rd of the month. Estimates of the report are collected by Knight-Ridder News Service two days prior to the USDA release. These estimates are then disseminated over their wire service after the close of the market.[1] Of the 91 possible events to be studied, complete data are available for 88 events.

Price impact is determined by the logarithmic change in live hog and frozen pork belly futures prices from the closing price on day t (release

[1]The Knight–Ridder Chicago office permitted the authors access to their history files.

TABLE I

Impact of Cold Storage Reports on Pork Futures

Month of Cold Storage Report Release	*Nearby Live Hog Futures*	*Nearby Frozen Pork Belly Futures*
January	February	February
February	April	May
March	April	May
April	June	May
May	June	July
June	July	July
July	August	August
August	October	February
September	October	February
October	December	February
November	December	February
December	February	February

day) to the opening and closing prices of day $t + 1$ (the next trading day). Presumably, changes in pork belly cold storage reflect current supply/demand issues; therefore, changes in nearby futures are analyzed. Nearby futures are defined in Table I.

MODELS AND METHODOLOGY

The rational expectations model of Muth (1961) provides the theoretical basis of this study. Pearce and Roley (1983, 1985) use the model to analyze the impact of macroeconomic news on stock prices. Because Colling and Irwin (1990, 1994, 1996) and Gruenwald, McNulty, and Biere (1993) demonstrate the applicability of this method to agricultural announcements, the rational expectations model is utilized, rather than the more traditional excess return model. However, before the model can be applied, the expectations data must first be examined for unbiasedness and efficiency.

Are the Expectations Data Unbiased?

For the linear rational expectations model to work, the expectations data of the survey participants should fairly represent the market expectations. This implies testing the survey data for unbiasedness and efficiency. To examine the KR CSR survey data for unbiasedness, the model is specified as

$$\mathrm{CSR}^a(t) = \beta_0 + \beta_1\,\mathrm{CSR}^e(t) + z(t) \tag{1}$$

where CSR^a is the actual CSR value released by the USDA, CSR^e is the estimated CSR from the KR survey data, t is the time period, β_0 and β_1 are the model coefficients, and $z(t)$ is the error term for time period t. The model is estimated by ordinary least squares. The KR survey expectations are deemed to be unbiased estimates if $\beta_0 = 0$ and $\beta_1 = 1$, and the forecast errors are uncorrelated. The null and alternative hypotheses are specified as

$$\mathrm{H_0}:\ \beta_0 = 0, \qquad \mathrm{H_0}:\ \beta_1 = 1$$

and

$$\mathrm{H_a}:\ \beta_0 \neq 0, \qquad \mathrm{H_a}:\ \beta_1 \neq 1$$

A two-tailed t-test decides statistical significance.

To determine if new information crept into the market after the release of the KR CSR survey data but prior to the release of the USDA CSR, a second test of unbiasedness is performed. Roley (1983) suggests that new information entering the market can be modeled by the percentage change in closing futures prices from the day (t-2) the KR data are released to the day (t) the HPR data are released. In effect, this variable represents the cumulative rate of return over the period t-2 to 0. This variable is added to eq. (1) to produce the following model:

$$\mathrm{CSR}^a(t) = \beta_0 + \beta_1\,\mathrm{CSR}^e(t) + \beta_2\,\mathrm{DFP}(t - 2, t) + z(t) \tag{2}$$

where $\mathrm{DFP}(t\text{-}2,0) = \{\ln(\mathrm{FP}(t\text{-}2) - \ln[\mathrm{FP}(0)]\}*100$ and ln is the natural logarithm. Nearby pork belly futures capture the influence of additional information entering the market. If β_2 is not statistically significant, then no new information entered the market.

Finally, to test for efficiency of the survey data, the following model is specified:

$$\mathrm{CSR}^u(t) = \beta_0 + \beta_1\,\mathrm{CSR}^a(t - 1) + z(t), \tag{3}$$

where $\mathrm{CSR}^u(t)$ is the unexpected information component of the actual market hog inventory contained in the official HPR data and is defined as $\mathrm{CSR}^a(t) - \mathrm{CSR}^e(t)$. If the KR survey data are efficient, one should not be able to forecast the unexpected component from lagged actual data. Therefore, the coefficient on lagged actual data should not be statistically different from zero. In all three models, the Durbin–Watson statistic tests for first-order correlation in the error terms. A variant of White's (1980) test examines the squared residuals for heteroscedasticity.[2]

A Linear Rational Expectations Model

The rational expectations hypothesis asserts that market participants use available and relevant information to develop a rational probabilistic expectation concerning the future value of a variable. The average of the market participants' expectation of the variable becomes the market expectation. The market's expectation of the USDA cold storage value is proxied with the KR survey data. Following Pearce and Roley (1983), only the impact of unanticipated information on price is examined. Again, unanticipated information is modeled as the USDA CSR value minus the KR survey estimate of the CSR. The general model is specified as

$$[\ln \mathrm{FP}(t + 1, \mathrm{O}) - \ln \mathrm{FP}(t, \mathrm{C})] = \beta_0 + \beta_1 [\ln \mathrm{CSR}^u(t)] + z(t), \quad (4)$$

where FP is the futures price of either pork belly futures or live hog futures, t is the time period, with $t = 0$ designated the USDA release day, O refers to the opening futures price, C refers to the closing futures price, β_0 and β_1 are the model coefficients to be estimated, and $z(t)$ is the error term. The null and alternative hypotheses for information arrival in Eq. 4 is

$$\mathrm{H}_0\colon\ \beta_1 = 0$$
$$\mathrm{H}_1\colon\ \beta_1 < 0$$

If the null hypothesis is rejected, then it is assumed that the market reacted to the unanticipated information contained in the USDA CSR. Specifically, if the CSR is larger than expected, prices will fall, and if the CSR is smaller than expected, prices will rise. Because hogs are a food and food is a necessity, it is anticipated that the price response to the new information will be inelastic. That is, the absolute value of β_1 will be less than 1. Out of 88 events, only three involve limit moves in pork belly futures on a close to next day open basis. There are no limit moves in live hog futures.[3] As a result, standard OLS regression is employed.

[2]Lee suggests regressing the squared residuals on the yhats of the fitted equation. Then construct the statistic (as in White) of N^*R^2 which will be distributed chi-square with degrees of freedom equal to number of independent variables.

[3]Chicago Mercantile Exchange rules permit prices to change during a day's trading session from the previous day's close only by a given maximum amount. For live hog futures, this change is $1\frac{1}{2}$ cents per pound and for pork belly futures it is 2 cents per pound.

Seasonal Analysis

Dummy variables, accounting for both intercept and slope interactions, model the impact of seasonality. Dummy variables for changes in the intercept follow the standard 0,1 convention and dummy variables for differing slopes are constructed as the dummy intercept term times the independent variable. A seasonal intercept model can be specified as

$$[\ln FP(t+1, O) - \ln FP(t, C)] = \beta_0 + \beta_1 [\ln CSR^u(t)] + \beta_i Mi(t) + z(t) \tag{5a}$$

A seasonal slope model can be specified as

$$[\ln FP(t+1, O) - \ln FP(t, C)] = \beta_0 + \beta_1 [\ln CSR^u(t)] + \beta_i [\ln CSR^u(t)] + z(t) \tag{5b}$$

In both models, β_i represents the coefficient for the dummy variable. In Eq. 5(a), it represents the coefficient on the seasonal intercept terms, where Mi represents differing intercepts for each calendar month ($i = 2 \cdots 12$, February = 2, etc.). In eq. 5(b), β_i represents the seasonal slope for CSR for each calendar month ($i = 2 \cdots 12$, February = 2, etc). Other terms are as previously defined.

Market Cycle

The general and seasonal models are then extended to account for the market cycle. Here, actual cold storage stocks, defined as the ratio to year-ago levels and denoted in the model as PBSYA, are used as an explanatory variable and act as a proxy for the market cycle.[4] Market cycle in the pork industry generally refers to those extended periods of time when production exceeds year-ago levels and prices are less than year-ago levels and then reverse. Differing slopes are added to examine for a possible interaction between market cycle and seasonality. Seasonal intercepts are not added due to the problems of interpretation. The first seasonal/market cycle is specified as

$$[\ln FP(t+1, O) - \ln FP(t, C) = \beta_0 + \beta_1 [\ln CSR^u(t)] + \beta_i [\ln CSR^u(t)] + \gamma_1 \, PBSYA(t) + \gamma_i \, PBSYA(t) + z(t), \tag{6a}$$

[4]The variable is defined as ln PBS(t)-ln PBS(t-12). In all regressions, its explanatory power is less than defining the variable as a percent of a year ago. Therefore it is not used.

where γ_1 represents the impact of actual pork belly stocks (which is the proxy for the market cycle) and γ_i represents the seasonal impact of actual pork belly stocks, $i = 2, \ldots, 12$. To account for market reactions at different points in the market cycle, McQueen and Roley (1993) and Colling and Irwin (1996) are followed and the range of the PBSYA variable is examined. The PBSYA variable is reconstructed to examine the largest 25% (PBSYA^h) and smallest 25% (PBSYA^l) of observations. The second seasonal/market-cycle model is specified as

$$[\ln \text{FP}(t + 1, \text{O}) - \ln \text{FP}(t, \text{C})] = \beta_0 + \beta_1 [\ln \text{CSR}^u(t)] + \beta_i [\ln \text{CSR}^u(t)] + \delta_1 \text{PBSYA}^h(t) + \delta_2 \text{PBSYA}(t) + z(t) \quad (6b)$$

where δ_1 represents the impact of the largest 25% of observations of PBSYA and δ_2 represents the impact of the smallest 25% of observations of PBSYA.

RESULTS AND DISCUSSION

Are the Expectations Data Unbiased?

Panel A of Table II presents the test results of regressing actual CSR (CSR^a) on the estimated CSR (CSR^e) from the KR survey data. The coefficient on CSR^e is highly significant and within two standard errors of 1. However, the constant term is positive and statistically significant at the 10% level. This suggests that the survey participants underestimate the pork belly cold storage values issued by USDA. Colling and Irwin (1994), in a detailed analysis of individual survey participants, also find a tendency for some of the participants to underestimate actual pork belly cold storage stocks.

The test for information arrival between survey release and USDA release rejects the null hypothesis of statistical significance of DFP (Table II, Panel B). Also, the test for efficiency indicates that past CSRs cannot be used to forecast the unanticipated component of a CSR (CSR^u, Table II, Panel C). The results of the Durbin–Watson tests do not point to first-order serial correlation in eqs. (1)–(3). Application of White's test does not reject the null hypothesis of homoskedasticity. From these results, the data appear sufficiently unbiased and efficient for use in the linear expectations model.

Heteroskedasticity is an important issue in analysis of futures prices. Two methods are employed. First, we use the Goldfeld–Quandt test is used.[5] Specifically, it is applied to models A.1–A.4 (Table II), B.1 (Table

[5]See Pindyck and Rubinfeld (1991, p. 134).

TABLE II

Testing for Unbiasedness and Efficiency of Knight–Ridder Survey Estimates of Cold Storage Stocks

Panel A: Testing for Unbiasedness

$CSR^{a}(t) = \beta_0 + \beta_1 \, CSR^{e}(t) + z(t)$

Constant β_0	CSR^{e} β_1	ADJ R^2	DW	F
1.085*	0.983**	99.4%	2.12	>100**
(0.606)	(0.0083)			

Panel B: Testing for Information Arrival between Release of Knight-Ridder Survey Estimates and USDA Cold Storage Release

$CSR^{a}(t) = \beta_0 + \beta'_1 \, CSR^{e}(t) + \beta_2^{*} \, DFP + z(t)$

Constant β_0	CSR^{e} β_1	DFP β_2	ADJ R^2	DW	F
1.07*	0.983**	0.174	99.4%	2.17	>100**
(.61)	(0.0083)	(0.18)			

Panel C: Testing for Efficiency

$CSR^{u}(t) = \beta_0 + \beta_1 \, CSR^{a}(t) + z(t)$

Constant β_0	CSR^{a} β_1	ADJ R^2	DW	F
3.24	−0.027	0.0%	2.15	0.71
(2.32)	(−0.027)			

Note: Standard error in parentheses under coefficient estimate.
*Significant at the 10% level or less.
**Significant at the 1% level or less.

III), and C.3 (Table IV). Second, following a suggestion of Lee (1993, pp. 677–680) a variant of White's (1980) test examines the squared residuals for heteroskedasticity.[6] This variant only examines the linear functional form. Other functional forms are not examined because of the use of seasonal slope variables. All tests fail to reject the null hypothesis of homoskedasticity.

Results of Linear Expectations Model

If all variables, seasonals, and interactions are to be analyzed at one time, a specified model with over 30 explanatory variables could be constructed. The interpretation, let alone statistical issues, would be quite fuzzy. Therefore, a sequential approach examining each issue is employed, beginning with Eq. (4) (Table III). With the use of Eq. (4), the general impact on pork belly futures and live hog futures in two time spans is first examined: close-to-open (close of release day to the open of the next

[6]See Pindyck and Rubinfeld (1991, pp. 110–113).

TABLE III

Results of General Linear Expectations Model

Model Number	*Dependent Variable*	*Time Span of Reaction*	*Constant* β_0	CSR[u] β_1	ADJ R^2	DW	F
A.1	Pork belly future	Close to Next Day Open	−0.0008 (0.001)	−0.221* (0.03)	44.7%	1.83	71.2*
A.2	Pork belly future	Close to Next Day Close	0.0016 (0.0024)	0.189* (0.049)	13.7%	1.86	14.8*
A.3	Live hog future	Close to Next Day Open	−0.0072 (0.0075)	−0.07 (0.15)	0.0%	2.00	0.22
A.4	Live hog future	Close to Next Day Close	−0.0059 (0.0076)	−0.051 (0.15)	0.0%	2.05	0.11

Note: Standard error in parentheses under coefficient estimate.
*Significant at the 1% level or less.

TABLE IV

Results of Seasonal Linear Expectations Model. Model B.1 Uses Seasonal Slopes; Dependent Variable is Futures Price Close to Next Day Open. Model B.2 Uses Seasonal Intercepts; Dependent Variable is Futures Price Close to Next Day Open. Model B.3 Uses Seasonal Slopes; Dependent Variable is Futures Price Close to Next Day Close.

Model Number	*Dependent Variable*	*Time Span of Reaction*	*Constant* β_0	$CSR^u\beta_1$	β_2	β_3	β_4	β_5	β_6	β_7	$\beta_8\beta$	β_9	β_{10}	β_{11}	β_{12}	*ADJ* R^2	*DW*	*F*
B.1	Pork belly future	Close to next day open	−0.065 (0.095)	−0.306 (0.06)	0.039 (0.129)	0.051 (0.103)	−0.268* (0.117)	−0.435* (0.113)	−0.239* (0.096)	0.284* (0.153)	0.062 (0.1)	0.268* (0.098)	0.235* (0.069)	0.198* (0.073)	0.01 (0.083)	73.7%	1.79	21.3*
B.2	Pork belly future	Close to next day open	−0.0006 (0.004)	−0.231* (0.029)	−0.0005 (0.006)	−0.001 (0.006)	−0.004 (0.006)	−0.009 (0.006)	−0.005 (0.006)	−0.003 (0.006)	0.001 (0.006)	0.005 (0.007)	−0.005 (0.006)	0.007 (0.007)	0.001 (0.006)	44.1%	1.67	6.72*
B.3	Pork belly future	Close to next day close	−0.17 (0.23)	−0.24*** (0.15)	−0.23 (0.32)	−0.39 (0.25)	−0.04 (0.29)	−0.27 (0.28)	−0.46** (0.24)	−0.53 (0.38)	−0.15 (0.25)	0.14 (0.24)	0.28*** (0.17)	0.23 (0.18)	−0.01 (0.2)	29.4%	1.95	4.0*

Note: Standard error in parentheses under coefficient estimate.
*Significant at the 1% level or less.
**Signicant at the 1% level or less.
***Significant at the 1% level.

trading day) and close-to-close. Finding an impact only on the close-to-open time span, evaluation of a close-to-close time span is discontinued in further analysis. Seasonal intercept terms and slope seasonals for the CSR variable are added to the general model, and results are examined (Table IV).[7] Next, the explanatory variable for market cycle, PBSYA, is examined (Table V).

Consistent with Colling and Irwin (1994), CSRs do have an impact on frozen pork belly futures, with a p value less than 1% (Table III, models A.1 and A.2). As expected, the sign of the coefficient is negative and the absolute value is less than 1, indicating price inelasticity. These are simple models with no other variables except the unanticipated expectations component as the independent variable. The impact measured on a close-to-open basis (model A.1) is considerably greater than the impact on a close-to-close basis (model A.2). However, contrary to Colling and Irwin, live hog futures do not respond to the release of the USDA CSR (Table III, models A.3 and A.4). Apparently, their result is dependent on their sample period and the unique market conditions of that sample period. Because no response in live hog futures was found, further analysis examines pork belly futures only.

Impact of Seasonality

Results with a reaction span of close to open for the dependent variable and differing seasonal slopes are highly significant for certain months, and are presented in Table IV as model B.1. In the months of April, May, and June, the negative reaction to the arrival of unexpected information is particularly strong. However, in September, October, and November, the season reaction works to significantly dampen the overall negative effect.

These results indicate that traders react strongly to the information contained in cold storage reports for the period April–July, and that they act in the predicted direction. This is the major accumulation in stocks for the summer consumption season and for delivery on the May, July, and August contracts. Hog slaughter is seasonally large in the spring and fall. For pork bellies, spring is the primary accumulation period so that sufficient product is available for summer consumption. Additionally, the futures contract specifies that only those pork bellies placed in storage from the previous November to present may be delivered up to the August

[7]All of the equations estimated for pork belly futures were also estimated for live hogs. The results are not reported in the tables because there were no significant coefficients. These results are available from the authors on request.

TABLE V

Results of Seasonal-Market-Cycle Model. Model C.1 is Seasonal Model with Variables to Account for Extremes in Market Cycle. Model C.2 is Seasonal Model with Variables to Account for Market Cycle. Model C.3 is Seasonal Model with Variables to Account for Seasonality of Market Cycle Impact.

Model Number	*Dependent Variable*	*Time Span of Reaction*	*Constant* β_0	*CSR*[a] β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	β_{11}	β_{12}	*HIGH 25%* β_1	*LOW 25%* β_2	*ADJ* R^2	*DW*	*F*
C.1	Pork	Close to	−0.0006	−0.308***	0.048	0.07	0.236**	−0.425***	−0.244**	−0.291**	0.064	0.279***	0.242***	0.199***	0.013	−0.001	0.003	73.9%	1.8	18.61***
	belly	next day	(0.001)	(0.061)	(0.133)	(0.103)	(0.119)	(0.116)	(0.097)	(0.152)	0.099	(0.098)	(0.07)	(0.074)	(0.084)	(0.001)	(0.0037)		4	
	future	open																		
C.2	Pork	Close to	0.0014	0.312**	0.057	0.065	0.255***	−0.424***	−0.237**	−0.288**	0.065	0.274***	0.246***	0.196***	0.016	0.00169		73.9%	1.8	20***
	belly	next-day	(0.0018)	(0.06)	(0.13)	(0.10)	(0.12)	(0.11)	(0.096)	(0.15)	(0.10)	(0.098)	(0.069)	(0.073)	(0.083)	(0.0012)			4	
	future	open																		
C.3	Pork	Close to	0.0018	−0.313***	0.05	0.064	0.251**	−0.417***	−0.224**	0.296**	0.069	0.27***	0.248***	0.193***	0.018	−0.0016	−0.011***	76.6%	1.7	21***
	belly	next-day	(0.0012)	(0.057)	(0.12)	(0.097)	(0.11)	(0.11)	(0.09)	(0.14)	(0.094)	(0.092)	(0.066)	(0.069)	(0.078)	(0.0012)	(0.0037)		8	
	future	open																		

Note: Standard error in parentheses under coefficient estimate.
*Significant at the 10% level or less.
**Significant at the 5% level or less.
***Significant at the 1% level or less.

contract. Any cold storage stocks carried over may not be delivered on the next year's contracts. Theoretically, all stocks, except for a small pipeline supply, should be consumed by the end of the current crop year (September 30). Traders and hedgers must monitor stocks quite closely to reach the delicate balance of meeting summer demand but not carrying more than required pipeline supplies. Thus, results indicating the importance of knowledge of cold storage levels from April through July fit with known market forces.

The seasonal slope coefficients for the months of September–November are also statistically important but positive. The overall impact of the unexpected information is still in the anticipated direction, but is of a smaller magnitude. This indicates a sharply reduced reliance upon the information contained in the reports. In effect, the information impact in these months is reduced. The frozen pork belly contract of the Chicago Mercantile Exchange specifies that only bellies placed in cold storage after November 1 are eligible for delivery during the pork belly cold storage season, which extends to the August contract of the next year. Apparently, traders are very rational in ignoring the information contained in reports that do not directly impact them.

The informational impact is clearly seen in the magnitude of the slope coefficients. April, June, and July are approximately 80% of the value of CSR^u whereas May exceeds it. As these variables are measured in logarithms, determining magnitude of impact is straightforward. For the month of May, the impact of a 1% underestimation produces nearly a 0.74% increase in price. This impact is over three times greater than expected with a nonseasonal model (Table III, model A.1), and results of Colling, Irwin, and Zulauf (1995) (Open Day 1, Table II). Magnitude is also important for the months of September–November. For example, in September the large positive coefficient implies that a 1% underestimation results in only a 0.04% increase in price. This is significantly less than a nonseasonal model response, and could almost be considered a nonresponse.

Results based on a close-to-close basis suggest much less impact. The CSR^u variable is only significant at the 11% level, and only two slope seasonals are somewhat important (Table IV, model B.3). These results suggest that the impact of the CSR release is nearly absorbed by the close of the market.

The differences between the close-to-open and close-to-close results are consistent with the finding of Berry and Howe (1994). In explaining the difference between close-to-open and open-to-close market volatility, they demonstrated that the amount of public information arriving when the market is open is substantially greater than when the market is closed. Hence, changes in prices while the market is open are much noisier than the change in price from market close to market open. Any test of the impact of a specific piece of information will have a weaker result when tested during a period when markets are open than when they are closed.

Results that have dummy intercepts on a close-to-open basis indicate no statistical significance for seasonal intercepts. CSR^u is significant at the 1% level. However, with an adjusted R^2 of 44.1%, this model is clearly inferior to the seasonal slope model. The lack of importance of monthly intercepts suggests that month alone is not the dominant issue. Instead, the informational impact is both highly seasonal and intimately tied to the information contained in the USDA *Cold Storage Reports*.

Impact of Market Cycle

The seasonal model is then extended to account for market cycle with the addition of the variable constructed as the ratio of pork belly cold storage stocks in the current time period to year-ago levels (PBSYA). For model C.1, two variables represent the highest and lowest 25% of values of the cold storage ratio. Although the coefficients have the correct sign, t tests on coefficients δ_1 and δ_2 are not significant.

The seasonal model is extended to account for the interaction of seasonality and market cycle. Only one seasonal slope coefficient, the June coefficient, is significant (Table V, model C.2). Even though highly significant, the impact of the June market cycle seasonal is quite small in relation to the other explanatory variables. At best, the market cycle plays only a minor role in market response.

CONCLUSIONS

Similarly to Colling and Irwin (1994), this study finds that USDA *Cold Storage Reports* add information to the market as measured by the response of pork belly futures to the unanticipated component of the USDA announcement. The response is significantly greater on a close-to-open basis than on a close-to-close basis. However, and contrary to Colling and Irwin, no response in live hog futures is detected. This is most likely due to the difference in sample periods.

This study finds that the futures response is highly seasonal with respect to the information contained in the USDA *Cold Storage Reports*. The impact in the months of April–July is highly negative, with the coefficient for May greater than the coefficient for the major explanatory variable (CSR"). The impact in these months is several times greater than the impact measured with a nonseasonal model. Further, the seasonal slope coefficients for September–November are statistically important and positive. The magnitude of the coefficients point to almost no impact for these months. No seasonal impact is measured for the months of February, March, August, and December. These results are consistent with the cold storage cycle for frozen pork bellies.

This study also finds that market cycle is not statistically important. The lack of impact of these variables strongly suggests the seasonal impact of cold storage information.

Given that agricultural commodities are highly seasonal in production and consumption, it would appear that the impact of information might also be seasonal. Further analysis of the seasonality of public and private information entering markets would seem appropriate future research.

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