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Information Transmission between Hog Futures and Expert Price Forecasts

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We evaluate the interactions in four markets among expert forecasts, futures prices, and realized cash hog prices. Vector autoregression findings indicate a dynamic interaction among futures and cash markets, with some past forecasts affecting cash prices. Contemporaneous causal analysis reveals causation of cash prices by futures prices and by some expert forecasts, and is consistent with the causal ordering of prior-day futures, subsequent forecasts, and cash prices realized one quarter later. Forecast error decompositions indicate expert forecasts are substantially influenced by futures prices, but have more influence on futures and cash hog prices than previously identified.

Key words: Causality, Efficient market hypothesis, Forecasts, Futures markets, Information transmission

With few exceptions, researchers find it difficult for publicly available forecasts to outperform the accuracy of the gold-standard benchmark of futures prices, lending support to the efficient market hypothesis and contributing to a perception that public forecasts are unnecessary (e.g., Just and Rausser, 1981; Irwin, Gerlow, and Liu, 1994; Bowman and Husain, 2004; Sanders and Manfredo, 2004, 2005). Recent studies delving beyond relative accuracy, however, identify that futures markets do not entirely encompass expert forecasts which offer additional (possibly private) information (e.g., Colino and Irwin, 2010; Colino, Irwin, and Garcia, 2011; Colino et al., 2012). An aspect of this line of research which has received far less attention is the dynamic transmission of information between futures and expert forecasts. Only Bessler and Brandt (1992) examine this question focusing on one extension outlook program at the University of Missouri. Using live cattle and hog markets, they identify cases in which both futures and expert forecasts respond to information provided by the other, supporting the information content of public forecasts.

Much has changed in agricultural markets, both futures and cash, as well as in outlook programs since the late 1980s—the end of Bessler's and Brandt's (1992) sample. Nearly 80% of livestock futures trade is now electronic. Trader composition has also changed,

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reflecting the growth of exchange-traded products and long-only commodity index traders as well as a decline in smaller, non-reporting traders (Irwin and Sanders, 2012). Livestock cash markets have become more vertically coordinated and concentrated, but their linkages to global and highly volatile feedstuff markets make prices difficult to predict. Of the major commodities, the hog sector has experienced both the greatest consolidation of production and increase in the use of contracts in recent times (Key, 2004; Franken, Pennings, and Garcia, 2009). While outlook experts have retired—and one hog outlook program has even terminated its service—information systems and technology have become pervasive throughout the marketing channel. Related increases in information availability may influence the value of outlook programs as sources of information. Does enhanced information availability erode reliance on experts' opinions or does information overload increase the value of outlook reports as summaries of relevant market information? Could changes in forecast procedures employed impact their effectiveness? In this setting, confirmation and replication studies are valuable contributions to a body of research (Tomek, 1993). Furthermore, the informational content or value of public forecasts remains a relevant issue, particularly in recent times of declining budgets and volatile prices.

Our objective is to assess the transmission of information between futures and expert price forecasts in hog markets. Using a current and richer dataset than analyzed by Bessler and Brandt (1992), we examine expert forecasts for hog prices from the University of Missouri, Iowa State University, Purdue University/University of Illinois, and the U.S. Department of Agriculture (USDA) for a more recent 20-year period. We focus on this period in order to assess information transmission in light of the aforementioned industry changes. Following Bessler and Brandt (1992), we evaluate the interaction between expert forecasts, futures prices, and subsequent cash prices. Using a three-variable vector autoregression (VAR), we identify the lag structure and error decompositions which indicate the degree of dynamic interaction that exists. As in Haigh and Bessler (2004), we assess contemporaneous relationships and causality by applying a directed acyclic graph (DAG) framework to residuals filtered from the VAR, the results of which also inform the ordering of variables in error decompositions. Filtering the series through VARs permits estimation of causal relationships among contemporaneous variables without specifying an explicit identification structure (Moneta et al., 2011) and ensures contemporaneous causality is tested, accounting for correlation between contemporaneous and lagged observations (Demiralp and Hoover, 2003; Haigh and Bessler, 2004; Moneta, 2004; Reale and Wilson, 2001; Swanson and Granger, 1997).

Consistent with Bessler and Brandt's (1992) study, our VAR results indicate dynamic interaction of information in futures and cash markets but also an influence of past expert forecasts on cash prices not previously observed. Causal analysis finds that the University of Missouri outlook program, in particular, exerts a contemporaneous causal influence on cash hog prices. However, cash market innovations are more commonly caused by innovations in futures prices, with a chronological ordering of futures followed by expert forecasts and then realized cash prices. This ordering is employed in error decompositions, which indicate that some hog price forecasts account for more of the error variance in cash and futures prices than indicated in the prior study. Whereas one might expect the value of expert forecasts to decline over time with increased information availability associated with technological advancements, the value of such forecasts appears to have increased possibly due to structural changes and growth of alternative marketing arrangements in the hog industry.

Previous Research

Most studies on price forecast performance compare relative accuracy with that of futures markets (e.g., Just and Rausser, 1981; Irwin, Gerlow, and Liu, 1994; Bowman and Husain, 2004; Sanders and Manfredo, 2004, 2005). Findings are fairly consistent across commodities, as summarized by Colino and Irwin (2010, p.1): “the weight of the existing evidence indicates that outlook forecasts cannot beat futures prices in terms of forecasting accuracy.” Bessler and Brandt (1992) extend the analysis to dynamic transmission of information using VAR and Cholesky decomposition, and find that cattle futures do not capture all inherent information in expert forecasts, while hog price forecasts are no more accurate than the futures market. Recent studies of these livestock markets find that futures do not entirely encompass the (possibly private) information content of expert forecasts (e.g., Colino and Irwin, 2010; Colino, Irwin, and Garcia, 2011; Colino et al., 2012). As we investigate these issues for hog markets, the literature review emphasizes studies of livestock markets.

Bessler and Brandt (1992) compare the accuracy of University of Missouri Extension economist Glenn Grimes’ one-quarter-ahead cash price forecasts for fed cattle and hogs to prior day futures contract prices using quarterly data from quarter one of 1972 to quarter two of 1986. Statistical tests suggest that the mean squared error (MSE) of Grimes’ forecasts is not significantly different than that of futures for hogs, but is significantly lower than that of futures for cattle. Based on VAR analysis of the interrelationships between Grimes’ forecasts and futures and cash prices, Grimes appears to draw on past futures and cash prices to forecast cash cattle prices but only the latter to forecast cash hog prices. While cattle futures appear to respond to Grimes’ forecasts, this does not appear to be the case for hog futures or cattle and hog cash prices. Subsequent forecast error decompositions indicate that Grimes' forecasts account for about 10% while futures account for none of the error variance in cash cattle prices for each horizon considered. Conversely, one-third to half of the variation in cash hog prices is attributable to futures, depending on horizon, with only 1% attributable to Grimes' forecasts. Thus, the authors conclude that futures for cattle are not as efficient as those for hogs.

While no study since Bessler and Brandt (1992) directly addresses information transmission between expert forecasts, futures markets, and cash prices, a few recent studies investigate whether futures markets encompass all pertinent information contained in expert forecasts of cash prices. Sanders and Manfredo (2004) consider this issue for USDA and Purdue University/University of Illinois one- and two-quarter-ahead forecasts of hog prices and find that neither forecast is as accurate as the futures market nor do they add incremental information relative to the futures market. Colino and Irwin (2010) consider the relative accuracy and information encompassment issues for a broader set of outlook programs for hogs and cattle, including University of Missouri, Iowa State University, Purdue University/University of Illinois, and USDA forecasts up to three quarters out. Though expert forecasts outperform futures prices in only two out of the 11 cases for hogs and one out of the seven cases for cattle, futures do not encompass outlook forecasts in five cases for hogs and four cases for cattle, implying that these forecasts offer additional information beyond futures prices. Other studies using similar data and forecast-encompassing frameworks consider whether existing public forecasts of hog prices can be improved with composite forecasts. Colino, Irwin, and Garcia (2011) show that composites of time-series models (e.g., VAR) add incremental information to the Iowa State University forecast. Colino et al. (2012) show that the finding holds more generally for the other hog price outlook programs noted above. The only known application of the forecast-encompassing framework to analyze outlook programs outside of hogs finds that milk futures do not encompass all information contained in two-quarter-ahead USDA forecasts (Sanders and Manfredo, 2005).

Data

We examine an updated version of Colino's and Irwin's (2010) data of one-quarter-ahead expert forecasts of hog prices by the University of Missouri, Iowa State University, Purdue University/University of Illinois, and the USDA; prior day futures prices; basis adjustments; and realized cash prices (Tables 1 and 2). Data for some forecasts are available as far back as the mid-1970s. However, in each case, VAR analysis of the full sample shows evidence of parameter instability, as indicated by cumulative sum of square plots (Brown, Durbin, and Evans, 1975); and structural breaks around the late

1980s identified by Chow-type tests. Given these findings and our objective of analyzing information transmission in hog markets in light of industry changes that materialized predominately after the end of Bessler's and Brandt's (1992) period, we begin the analysis in 1990. With a sample period of 20 years, the dataset still offers greater statistical power than commonly available in previous studies of price forecast performance. Although it is possible that forecasting methods changed over the period of analysis, we are not able to account for these changes in a reliable manner. Hence, our analysis is based on the notion that experts use their most reliable forecast procedures, which could change over time.

As shown in Table 1, each outlook program targets different cash markets, which vary over time as the experts adjusted them to coincide with changes in widely reported cash price series that reflect changes in market structure. Point forecasts are computed as the midpoint if forecasts are reported as price ranges (Irwin, Gerlow, and Liu, 1994; Sanders and Manfredo, 2003); and, if given as qualitative statements, a consistent set of rules is applied (e.g., "upper 40s"=$47.50/cwt). Less than 2% of the observations in each dataset contain missing values for forecasts corresponding to gaps in outlook publications, which are replaced with the average of the preceding and following values. Release dates differ across outlook programs, requiring forecasts from the respective programs to be aligned with futures quotes on different dates and preventing direct comparisons of forecasts due to differences in information availability on the release dates. Specifically, while Iowa State and Missouri are on average released on the same date, Purdue/Illinois are released eight days after, and the USDA forecasts are released 45 days prior (Table 1).

Table 1. Outlook Program Forecast Data.

Outlook Program	Forecast Sample Period	Quarters	Missing Observations	Average Timing of Release	Forecast Cash Price Series	Source Publication
Illinois/Purdue	1990.1-2007.4	72	1 -1.39%	10 days after start of each calendar quarter	1990.1-1994.1: Barrows & Gilts (Omaha) 1994.2-2007.4: Barrows & Gilts (6mkts)	*Livestock Price Outlook*
Iowa	1990.1-2010.4	84	1 -1.19%	2 days after start of each calendar quarter	1990.1-2010.4: Barrows & Gilts (Iowa-S.MN.)	*Iowa Farm Outlook*
Missouri	1990.1-2010.4	84	0 0.00%	2 days after start of each calendar quarter	1990.1-1991.4: Barrows & Gilts (7mkts) 1992.1-1994.2: Barrows& Gilts (6mkts) 1994.3-2010.4: Barrows & Gilts (Terminal mkt)	*Livestock Outlook Letter* *Quarterly Hog* *Outlook-AgEBB*
USDA	1990.1-2010.4	84	0 0.00%	43 days before start of each calendar quarter	1990.1-1991.4: Barrows & Gilts (7mkts) 1992.1-1992.2: Barrows & Gilts (6mkts) 1992.3-1999.3: Barrows& Gilts (Iowa-S.MN.) 1999.4-2010.4: Barrows& Gilts (Nat. Base)	*Livestock Situation & Outlook* *LDPO*

Note: Figures in parentheses are the percentage of missing observations. AgEBB: Agricultural Electronic Bulletin Board. LDPO: Livestock, Dairy, and Poultry Outlook. Outlook forecasts are obtained from respective outlook publications. Settlement prices for live/lean hog futures contracts are obtained from the Chicago Mercantile Exchange. An estimated ratio of 0.73673 is applied to lean-hog futures prices to adjust for the shift in Chicago Mercantile Exchange delivery terms from a live weight to carcass weight basis, beginning with the February 1997 contract. This ratio is obtained by dividing an average weight for lean hogs (180.5) by an average weight for live hogs (245). Cash prices are obtained from various USDA reports.

Futures-based forecasts are constructed following Hoffman's (2005) model, which has been in use at the USDA for over a decade, and univariate autoregressive moving average models with seasonal (quarterly) dummy variables are used to forecast basis following Garcia and Sanders (1996). Cash price is the quarterly average of the expert's target listed in the outlook publication. As shown in Figure 1, forecasts and futures prices track relatively similar patterns as realized cash prices but miss some extreme cash price values (e.g., 1998 crash). Significant mean differences in futures prices and realized cash prices typically dissipate once adjusted for expected basis, with the exception of the basis-adjusted futures price series corresponding to the Purdue/Illinois forecasts (Table 2). With this exception, no other significant difference exists between realized cash prices and expert- and basis-adjusted futures forecasts.

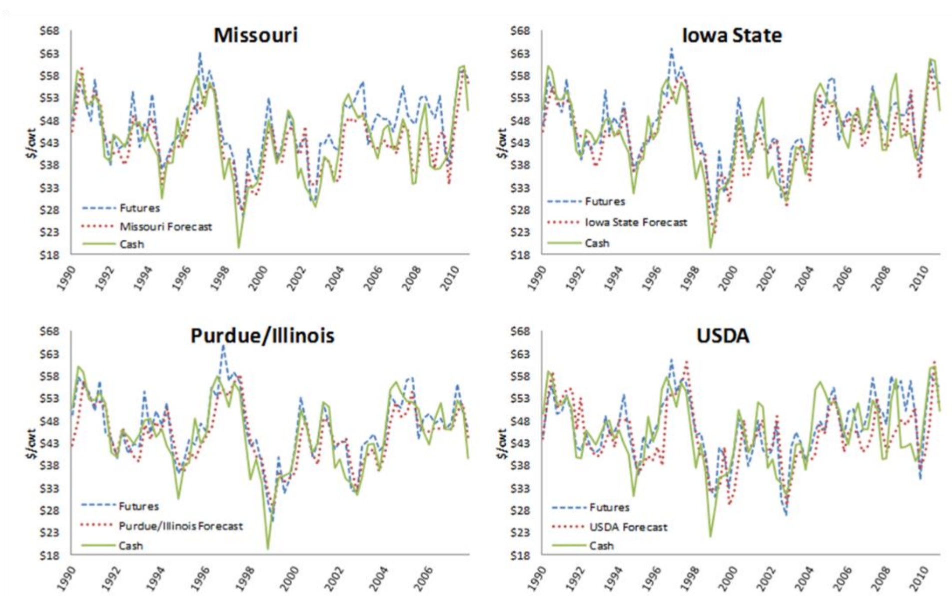

Figure 1. One-Quarter-Ahead Forecasts, Prior Day Futures, and Realized Cash Hog Prices

Table 2. Summary Statistics for Quarterly Data.

Variable	*N*	Mean	Standard Deviation	Minimum	Maximum
Missouri – 1990.1-2010.4					
Expert	84	43.44	6.76	27.50	59.50
Futures	84	46.60***	7.17	26.15	63.06
Basis adj. Futures	84	43.84	7.65	22.33	60.48
Cash	84	43.46	8.25	19.49	60.13
Iowa State – 1990.1-2010.4					
Expert	84	44.72	7.24	22.50	59.50
Futures	84	46.78***	7.40	26.43	64.04
Basis adj. Futures	84	45.46	8.15	22.24	61.05
Cash	84	45.25	8.51	19.49	61.59
Purdue/Illinois – 1990.1-2007.4					
Expert	72	44.63	6.31	28.27	58.33
Futures	72	46.25***	7.52	25.29	65.02
Basis adj. Futures	72	45.80**	8.00	20.86	64.64
Cash	72	44.96	8.09	19.30	60.02
USDA – 1990.1-2010.4					
Expert	84	44.65	6.92	29.00	61.00
Futures	84	46.55*	7.05	26.89	61.55
Basis adj. Futures	84	45.57	7.30	25.47	59.31
Cash	84	45.47	7.76	22.06	60.13

Note: All statistics are reported as $/cwt. Single, double, and triple asterisks (*,**,***) indicate the mean is statistically different from that of the corresponding cash series at the 10%, 5%, and 1% levels. Sample periods are 1990.1-2010.4 for Missouri, Iowa, and USDA, and 1990.1-2007.4 for Illinois/Purdue.

The MSE of expert forecasts is significantly larger than that of basis-adjusted futures, with the exception of the insignificantly larger MSE of the Missouri outlook program (Table 3), which is largely consistent with prior findings (e.g., Just and Rausser, 1981; Irwin, Gerlow, and Liu, 1994; Bowman and Husain, 2004; Sanders and Manfredo, 2004, 2005) and the proposition that it is difficult to outperform the futures market (i.e., the efficient market hypothesis). Furthermore, the MSE of basis-adjusted futures is significantly smaller than that of unadjusted futures in each case (Table 3), offering further evidence that futures should be adjusted for basis prior to comparison with realized cash prices and competing expert forecasts. Hence, we report results using basis-adjusted futures for the remainder of the analysis, noting that qualitatively similar findings are obtained using unadjusted futures.[1] Dickey-Fuller (DF) tests indicate that the null hypothesis of non-stationarity is rejected at the 5% confidence level for each series. Thus, the price series can be viewed as stationary, and the analysis proceeds in levels.

Table 3. Diebold-Mariano Test of Differences in MSE of Outlook and Futures Forecasts.

	Missouri			Iowa State			Purdue/Illinois			USDA		
Futures	33.50	33.50		20.49	20.49		17.90	17.90		29.58	29.58	
Basis Adj. Futures	15.77		15.77	12.66		12.66	12.57		12.57	25.44		25.44
Expert		16.95	16.95		21.81	21.81		20.37	20.37		39.53	39.53
Difference	17.73***	16.55**	-1.18	7.82***	-1.32	-9.15***	5.33***	-2.47	-7.80***	4.142*	-9.949***	-14.09***

Note: Single, double, and triple asterisks (*,**,***) indicate the mean is statistically different from that of the corresponding cash series at the 10%, 5%, and 1% levels.

Empirical Methods and Procedures

Following Bessler and Brandt (1992), dynamic transmission of information between cash hog prices and expert and futures forecasts is evaluated using a VAR model

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + e_t, \tag{1}$$

where y_t is a vector of i endogenous variables (e.g., expert forecasts and cash and futures prices) at time t that are a function of their lagged values up to t-p with error e_t, and A_p are regression coefficients (i suppressed in notation for sake of simplicity). Model selection procedures, similar to those used by Bessler and Brandt (1992), are employed to identify parsimonious models with optimal lag structures and residuals free of autocorrelation. Specifically, we use the system sequential elimination of regressors (SER) procedure (Lütkepohl and Krätzig, 2004), which sequentially deletes those regressors in an equation which lead to the largest reduction in Akaike information criterion (AIC).

To perform innovation accounting, it is important to identify the model. Since the error terms e_t in general are not independent (i.e., off-diagonal elements of the covariance matrix of error terms may be nonzero), one variable may not be shocked through its corresponding error term without simultaneously delivering correlated shocks to other

[1] Bessler and Brandt (1992) examined information transmission between expert forecasts, unadjusted futures prices, and realized cash prices for cattle and hogs.

variables, thereby complicating economic interpretation (Demirlap and Hoover, 2003). A transformation remedies the situation by identifying the contemporaneous relationships among the variables and organizing them in a well-defined causal order to arrive at a structural VAR model (Reale and Wilson, 2001; Moneta et al., 2011)

$$\text{(2)} \qquad \Gamma_0 y_t = B + \Gamma_1 y_{t-1} + \Gamma_2 y_{t-2} + \ldots + \Gamma_p y_{t-p} + \varepsilon_t,$$

where $B = \Gamma_0 c$, $\Gamma_i = \Gamma_0 A_i$, and Γ_0 is a particular rotation matrix that both is compatible with the contemporaneous causal structure of the variables and yields independent errors $\varepsilon_t = \Gamma_0 u_t$. One common approach to achieve such orthogonal transformations is to use theory to inform ordering of variables in Choleski decomposition and trace out the effects of a shock using economically interpretable impulse response functions (Demiralp and Hoover, 2003; Moneta et al., 2011).

Alternatively, a data-driven approach is possible, as all information on contemporaneous causal dependence is captured by the innovations e_t in the standard VAR (Reale and Wilson, 2001; Demiralp and Hoover, 2003; Moneta et al., 2011). Innovations e_t for each series in the VAR are subjected to causal analysis using mathematical models building on counterfactual logic to investigate causal relationships (Salmon, 1998; Spirtes, Glymour, and Scheines, 2000; Pearl, 1986, 1995, 2000). This practice is common in studies applying causal inference methods to time series data, as testing causal hypotheses on VAR innovations ensures that contemporaneous causality is assessed and that results are not confounded by correlation between contemporaneous and lagged observations (Demiralp and Hoover, 2003; Haigh and Bessler, 2004; Moneta, 2004; Reale and Wilson, 2001; Swanson and Granger, 1997). Furthermore, the approach allows estimation of causal relationships among contemporaneous variables without specifying an explicit identification structure (Moneta et al., 2011). Such models are depicted as directed graphs designed to represent conditional independence as implied by the recursive production decomposition (Chong, Zey, and Bessler, 2010):

$$\text{(3)} \qquad pr(v_1, v_2, \ldots v_m) = \prod_{j=1}^{m} pr(v_j \mid \pi_j)\,,$$

where pr is the probability of variables v_1, v_2,…, v_m; π_j refers to a realized subset of variables that precede (in a causal sense) v_j in order (j = 1, 2,…,m); and $\prod$ is the multiplication operator. Pearl, (1986, 1995) suggested d-separation for graphical characterization of independence relations. As a simple example, in a directed acyclic graph (DAG) with variables X, Y, and Z in variable set V, the correlation between X and Y

conditional on Z equals zero ($X \perp Y \mid Z$) if, and only if, X and Y are d-separated given Z (Chong, Zey, and Bessler, 2010).[2]

Haigh and Bessler (2004) apply DAGs to infer causation among innovations (i.e., residuals) of an error correction model (ECM), thereby informing subsequent error decompositions and impulse response functions that characterize dynamic patterns of price discovery between Illinois and Gulf of Mexico soybean markets and barge freight markets. Bryant, Bessler, and Haigh (2006) also apply DAGs to innovations of a VAR to test causal hypotheses from theories of futures market behavior.

Here, VAR analysis and subsequent error decompositions are conducted using JMulTi software (Lütkepohl and Krätzig, 2004) available online (http://www.jmulti.de/). Various algorithms are available for searching observational data for causal structure in this manner, including Pearl's (2000) IC algorithm and Spirtes, Glymour and Scheines's (2000) PC algorithm. We use the PC algorithm which is freely available online through TETRAD IV software (http://www.phil.cmu.edu/projects/tetrad/).[3]

Results

Vector Autoregression

Results for VAR models using outlook programs' expert forecasts, prior day basis-adjusted futures prices, and cash prices realized one quarter later are reported in Table 4. Following Bessler and Brandt (1992), we also performed the analysis using unadjusted futures prices, and found results that are largely similar to those reported here. Bessler and Brandt (1992, p. 256) argued that "lags beyond one year will probably not be important." By starting with five lags of each series and using similar model selection procedures as Bessler and Brandt (1992), we arrive at parsimonious models with optimal lag structures and residuals free of autocorrelation. Specifically, we use the system SER procedure in JMulTi (Lütkepohl and Krätzig, 2004), which sequentially deletes those regressors in an equation which lead to the largest reduction in AIC. Other procedures available in JMulTi yield fairly similar model specifications.

[2] In a directed acyclic graph or DAG, one cannot return to a starting variable by following arrows leading away from it, meaning that chain relationships such as X→Y→X are not allowed.

[3] See Chong, Zey, and Bessler (2010) for a more complete description of d-separation. Also, see Bryant, Bessler, and Haigh (2009) for a simplified three-variable example (i.e., variables *A*, *B*, and *C*) applying a subset of Spirtes, Glymour and Scheines's (2000) PC algorithm to evaluate the null hypothesis H_0: *A* causes *B* based on unconditional correlations.

Table 4. Vector Autoregression Results.

	Missouri			Iowa State			Purdue/Illinois			USDA		
Variable	Futures	Expert	Cash	Futures	Expert	Cash	Futures	Expert	Cash	Futures	Expert	Cash
$Futures_{t-1}$	-0.20**	–	-0.38***	-0.31***	–	-0.46***	–	0.20***	–	0.23***	–	–
	-0.09		-0.11	-0.09		-0.15		-0.07		-0.09		
$Futures_{t-2}$	-0.27***	-0.32***	–	-0.14**	–	–	–	–	–	–	–	-0.40***
	-0.09	-0.08		-0.07								-0.10
$Futures_{t-3}$	–	–	–	–	0.25***	–	0.21**	–	–	0.10	-0.23***	–
					-0.06		-0.09			-0.07	-0.08	
$Futures_{t-4}$	0.33***	0.12	0.44***	0.40***	0.60***	0.72***	0.31***	0.32***	0.38***	0.55***	0.45***	0.45***
	-0.11	-0.08	-0.14	-0.11	-0.09	-0.12	-0.11	-0.08	-0.13	-0.08	-0.09	-0.10
$Futures_{t-5}$	0.26***	0.15**	–	–	0.17**	–	0.17*	0.17**	–	–	–	0.28*
	-0.08	-0.06			-0.08		-0.09	-0.09				-0.15
$Expert_{t-1}$	–	0.24***	–	–	–	–	–	–	–	-0.24**	0.22**	–
		-0.09								-0.10	-0.09	
$Expert_{t-2}$	–	0.15	–	–	–	–	-0.61***	-0.15	-0.77***	-0.12*	–	–
		-0.10					-0.14	-0.10	-0.17	-0.07		
$Expert_{t-3}$	–	–	–	–	–	–	–	–	–	–	–	–
$Expert_{t-4}$	–	–	0.36**	–	–	–	–	–	–	–	–	–
			-0.15									
$Expert_{t-5}$	–	–	–	0.10	–	–	–	-0.19**	–	0.07	–	-0.31**
				-0.06				-0.09		-0.05		-0.12
$Cash_{t-1}$	1.00***	0.66***	1.10***	1.12***	0.79***	1.16***	0.92***	0.51***	0.84***	0.70***	0.38***	0.77***
	-0.08	-0.06	-0.11	-0.09	-0.05	-0.14	-0.06	-0.06	-0.07	-0.06	-0.07	-0.07
$Cash_{t-2}$	–	-0.24***	–	–	-0.19***	–	–	-0.14**	–	–	0.21***	–
		-0.08			-0.06			-0.07			-0.08	
$Cash_{t-3}$	0.20**	0.35***	–	0.17**	–	–	0.24*	0.17**	0.47***	–	–	0.28***
	-0.09	-0.08		-0.07			-0.12	-0.08	-0.13			-0.10
$Cash_{t-4}$	0.22*	0.21*	–	0.15*	–	–	–	0.12*	–	0.29***	0.41***	–
	-0.09	-0.08		-0.08				-0.07		-0.08	-0.09	
$Cash_{t-5}$	-0.79***	-0.58***	-0.79***	-0.65***	-0.82***	-0.74***	-0.60***	-0.40***	-0.48***	-0.66***	-0.52***	-0.54***
	-0.11	-0.09	-0.10	-0.10	-0.10	-0.11	-0.13	-0.09	-0.12	-0.08	-0.08	-0.12
Constant	11.33***	11.61***	11.69***	8.06***	7.83***	13.94***	15.90***	16.50***	23.86***	3.71	3.24	21.26***
	-2.67	-2.23	-3.68	-2.66	-2.38	-3.61	-3.01	-2.67	-3.61	-3.09	-3.00	-4.54

Note: Standard errors are reported in parentheses. Single, double, and triple asterisks (*,**,***) denote statistical significance at the 10%, 5%, and 1% levels. A dash ("–") denotes exclusion of lags to arrive at parsimonious models based on a system sequential elimination of regressors (SER) selection procedure, which sequentially deletes those regressors that lead to the largest reduction in the Akaike information criterion (AIC) until no further reduction is possible. AIC, FPE, and SC are 6.40, 603.18, and 7.18 for Missouri, 6.67, 790.21, and 7.30 for Iowa State, 6.11, 451.86, and 6.93 for Purdue/Illinois, and 7.19, 1329.80, and 7.97 for the USDA model.

Several findings are fairly consistent in regard to the frequency with which lagged values enter into the respective equations and the magnitude and statistical significance of the effects (Table 4). For instance, lagged cash prices are highly influential on each series—a result that likely reflects reoccurring patterns in the hog market. That is, if forecasts accurately reflect such patterns, then the forecasts should appear to be influenced by past cash values. In general, lags of futures prices, and expert forecasts in particular, appear less regularly. The importance of past cash prices for Missouri forecasts is also apparent in Bessler and Brandt's (1992) results, as is that of past futures market prices (at lag one) in the cash price equation. In contrast to Bessler and Brandt (1992), where lags of Missouri forecasts do not enter into the cash price equation, we observe a significant effect at lag four. Purdue/Illinois forecasts also enter the associated cash equation at lag two, but no lags of the other two forecasts appear in the respective cash equations. In unreported results using futures prices without adjusting for basis, significant lags of each expert's forecast appear at least once in the respective cash equations, albeit less frequently than lags of the other variables. Bessler and Brandt (1992) interpreted the lack of such effects as evidence that cash markets for hogs do not rely explicitly on expert forecasts.

In most cases, there seems to be a one-way interaction between futures and expert forecasts. That is, lags of futures prices appear in expert forecast equations more often than lags of expert forecasts appear in futures price equations. This partly contrasts Bessler's and Brandt's (1992) hog market findings, where futures prices were driven only by past futures and cash prices and forecasts were driven by only past cash prices. Here, we find evidence that experts may rely more explicitly on the futures market than Bessler and Brandt (1992) observed. The results also seem to suggest that the futures market pays relatively more attention to the USDA outlook than other outlook programs.

Contemporaneous Causal Analysis

Innovations (i.e., residuals) for each of the VAR models are retained and used in the causal analysis conditional on the prior knowledge that our futures prices are reported the day before the forecast is released and cash prices are realized one quarter later.[4] Given this chronological ordering, illogical causal relations are precluded in the causal search (i.e., cash cannot cause futures or expert forecasts, and forecasts cannot cause futures). With this information, causal inference is detected, as represented graphically in Figure 2.

In each case, innovations in futures prices exert contemporaneous causal influences on innovations in forecasts. Only the Missouri forecast, in turn, exerts a contemporaneous causal influence on cash hog prices. Otherwise, cash market innovations are generally caused by innovations in futures prices, with the exception of data associated with the USDA forecast for which no causal influence on cash prices can be determined. In the absence of prior knowledge, similar patterns of undirected edges (i.e., without arrows) emerge, indicating the presence of relationships for which causality could not otherwise be determined. Further searches for superior alternatives (i.e., structures with lower Bayesian Information Criteria) cannot reject the hypothesized causal chronological ordering described above. Hence, we adopt the chronological ordering of futures followed by forecasts and then realized cash prices in error decompositions, which is consistent with the sequence used previously by Bessler and Brandt (1992).

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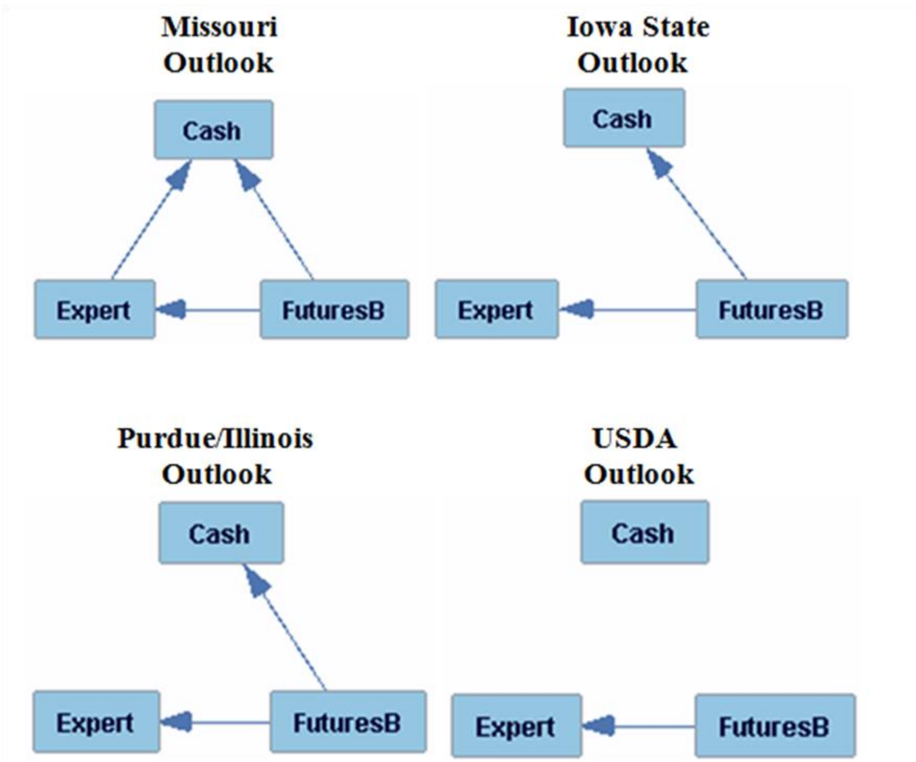
[4] Exploratory searches for causal relationships can be performed over a full set of possible relationships or a reduced set conditioned by prior knowledge (Franken, Pennings, and Garcia, 2012).



Note: Directed edges (arrows) indicate the contemporaneous causal influences of one series of innovations on another. Omitted edges indicate a lack of a causal relationship.

Figure 2. Causal Analysis Results of Pc Algorithm Search over Vector Autoregression Innovations Conditional on Prior Knowledge

Forecast Error Decomposition

Table 5 contains forecast error decompositions corresponding to the separate VAR models. The procedure partitions errors in each series at successive horizons into parts due to past innovations in each alternative series. The relative proportions of the error variance attributable to innovations in each series sums horizontally to 100%. As is commonly the case, the forecast error variances are explained predominately by their own innovations at shorter horizons, and stronger "true" relationships with other variables emerge at longer horizons.

Table 5. Forecast Error Variance Decompositions from Vector Autoregressions.

		Variables' Proportional Contributions to Innovation Standard Error (%)											
		Missouri			Iowa State			Purdue/Illinois			USDA		
Equation	Horizon	Futures	Expert	Cash	Futures	Expert	Cash	Futures	Expert	Cash	Futures	Expert	Cash
Futures	0												
	1	100%	0%	0%	100%	0%	0%	100%	0%	0%	100%	0%	0%
	2	39%	10%	51%	51%	0%	49%	62%	1%	37%	48%	6%	46%
	3	26%	13%	61%	39%	0%	61%	50%	2%	48%	35%	8%	57%
	4	24%	13%	63%	37%	0%	63%	45%	4%	51%	32%	8%	60%
	5	27%	12%	61%	41%	0%	59%	42%	4%	54%	30%	7%	63%
	6	30%	13%	57%	44%	0%	56%	44%	4%	52%	32%	7%	61%
	7	29%	13%	57%	44%	0%	55%	43%	5%	52%	32%	9%	60%
	8	29%	14%	57%	44%	0%	56%	44%	6%	51%	31%	11%	59%
	9	30%	13%	57%	45%	0%	55%	43%	6%	51%	33%	11%	55%
	10	29%	13%	57%	45%	0%	55%	43%	6%	51%	35%	13%	52%
Expert	0												
	1	18%	82%	0%	41%	59%	0%	34%	66%	0%	15%	85%	0%
	2	19%	44%	37%	42%	22%	35%	46%	27%	27%	14%	68%	19%
	3	13%	39%	48%	35%	16%	48%	41%	21%	38%	11%	46%	43%
	4	11%	35%	53%	37%	14%	49%	34%	19%	47%	10%	37%	53%
	5	14%	30%	56%	46%	10%	43%	37%	14%	48%	10%	27%	63%
	6	17%	30%	53%	49%	9%	41%	40%	13%	47%	10%	26%	64%
	7	17%	30%	53%	50%	9%	41%	38%	15%	47%	10%	26%	64%
	8	17%	30%	53%	50%	9%	41%	38%	16%	46%	10%	27%	64%
	9	17%	29%	53%	52%	9%	39%	38%	16%	46%	12%	27%	61%
	10	17%	29%	54%	51%	9%	40%	38%	16%	46%	14%	28%	59%
Cash	0												
	1	17%	14%	69%	43%	0%	57%	32%	1%	67%	3%	2%	96%
	2	10%	15%	75%	32%	0%	68%	32%	1%	67%	3%	2%	96%
	3	8%	16%	76%	29%	0%	71%	27%	4%	69%	4%	2%	95%
	4	8%	16%	76%	29%	0%	71%	23%	5%	72%	5%	1%	94%
	5	14%	17%	70%	37%	0%	63%	26%	4%	70%	6%	2%	93%
	6	15%	18%	67%	39%	0%	61%	27%	4%	68%	8%	3%	89%
	7	15%	18%	67%	39%	0%	61%	28%	6%	67%	7%	6%	87%
	8	15%	18%	67%	39%	0%	61%	29%	6%	65%	7%	8%	85%
	9	16%	18%	67%	40%	0%	60%	29%	6%	65%	10%	9%	82%
	10	15%	17%	67%	39%	0%	61%	28%	6%	66%	11%	9%	80%

Note: Decompositions are derived under the following ordering of contemporaneous correlation: Futures, Expert, and Cash. Statistics are the percentage of the innovation standard error which is attributable to each series in the moving average representation and sum to 100% horizontally (with rounding error).

Again, similarities to Bessler and Brandt's 1992 study are apparent. Innovations in futures and cash prices generally explain most of the error variance of futures prices, with much smaller amounts attributable to expert forecasts—ranging from 0% for Iowa State to 13% for Missouri and USDA at the most distant horizon. It may be that futures market participants follow the USDA and Missouri outlook programs somewhat more closely. Also, as in Bessler and Brandt's 1992 study, notable proportions of the error variance of each of the expert forecasts are attributable to cash and futures prices. Futures account for somewhat lower proportions of the error variance of Missouri and USDA forecasts than for Iowa State and Purdue/Illinois forecasts, which may indicate that the former two outlook programs rely on futures markets relatively less when preparing their forecasts.

In contrast to Bessler and Brandt, where the Missouri forecast accounted for only 1% of the error variance of cash hog prices, we observe larger proportions at distant horizons for forecasts by Missouri (17%) and, to a lesser extent, USDA (9%) and Purdue/Illinois (6%). These levels are closer to Bessler and Brandt's 1992 finding of 10% of the error variance in cash cattle prices attributable to the Missouri forecast. Based on this result and a 0% contribution of futures prices to the error variance of cash cattle prices, the authors concluded that cattle futures do not capture all public information relevant to subsequent cash prices. Applying this logic, the information content of the Missouri hog price forecast, in particular, appears to have improved with time. Overall, these results mirror those of the contemporaneous causal analysis and the VAR model. Missouri provides the only expert forecast to exert a causal influence on cash hog prices (Figure 2) and, of the four expert forecasts, it accounts for the largest proportion of cash price error variance (Table 5). For the three expert forecasts that account for some portion of the cash price error variance (Table 5), at least one lag of the forecast appears in the respective cash price equation in the VAR model (Table 4). As a check on these findings, we generated the same tables using futures prices unadjusted for basis as Bessler and Brandt did in their 1992 study. Each forecast has at least one lag appearing in the respective cash price equation in the VAR model. However, the implications of forecast error decomposition remain similar, with proportions of cash price error variance attributable to forecasts by Missouri at 17%, Iowa State at 6%, Purdue/Illinois at 6%, and the USDA at 12% at later horizons.[5]

Conclusions

We assess the dynamic interaction among futures markets, expert forecasts, and realized cash prices for hogs using data for four outlook programs spanning 1990 through 2010. The results corroborate several of Bessler and Brandt's (1992) findings for one of the forecasts examined here—University of Missouri's outlook program—but also contrast with other findings in important ways. VAR analysis reveals lag structures that reflect dynamic interaction of information in futures and cash markets consistent with prior

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[5] Expert forecasts have a more muted effect on futures and cash prices using the data set beginning in the mid-1970s, the proportions of futures (cash) error variance attributed to Missouri is 2% (4%), Iowa State 3% (4%), Purdue/Illinois 0% (0%), and USDA 4% (1%). These findings are more in line with Bessler and Brandt who used a large portion of this early data in their analysis, and highlight the importance of allowing for a structural break as the structure of the industry changed dramatically.

findings, but also an influence of past expert forecasts on cash prices not previously observed.

VAR model residuals are analyzed using causal inference procedures to generate graphical depictions of contemporaneous causation. Results indicate contemporaneous causal flows from the Missouri forecast to realized cash prices, but no such effects are found for other expert forecasts. In most cases, futures prices exert causal influences on cash prices, and graphs correspond to the chronological ordering of our data with futures prices recorded the day prior to forecast release and cash prices realized one quarter later. Hence, this ordering is adopted in subsequent forecast error decompositions.

The results of forecast error decompositions corroborate prior findings that much of the variation in futures prices is attributable to past innovations in cash and futures prices. In contrast, and consistent with the causal analysis, the University of Missouri forecast accounts for larger portions of cash price error variance than observed by Bessler and Brandt (1992) for hogs but similar to that for cattle. In fact, similar to Bessler and Brandt's (1992) previous findings for cattle, the portion of cash hog price error variance attributable to the Missouri forecast exceeds that attributable to futures prices in our results. USDA forecasts also account for slightly more of the cash price error variance than other expert forecasts.

In regard to the likely reason for a larger expert influence in cattle than hog prices, Bessler and Brandt (1992) report personal communication with Grimes at Missouri. Grimes indicated that accumulation of information from several cattle industry sources (packers, producers, etc.) may confer his forecast informational advantages over other market participants, and his judgment sometimes enables him to adjust to changing market conditions quicker than other analysts and the futures market. We contacted Professor Ron Plain, who is currently in charge of the University of Missouri outlook program, for further comment. Plain notes that Grimes continued to lead the program throughout most of our sample period, retiring in 2009. Over Grime's career, a vast network of industry contacts was accumulated, partly through surveys involving phone conversations with larger producers in particular. These initial contacts evolved into ongoing information trading with major producers sharing their plans and perspectives in return for an accumulated view.

The comments by Grimes and Plain are striking and particularly enlightening in regard to our own results. Forecast error decompositions indicate that Missouri and USDA forecasts are slightly more important to futures market participants than other expert forecasts. Furthermore, although sizable portions of the error variance of each expert forecast are attributable to past innovations in forecasts and cash and future prices, the futures market accounts for markedly smaller proportions for the Missouri and USDA forecasts. If these forecasts are driven by information not otherwise available to futures market participants, it makes sense that the futures market reacts more strongly to them. Moreover, such information may be of increasing importance. Bessler and Brandt (1992) indicate that Grimes considered the cattle market relatively more difficult to forecast than the hog market. Recent structural changes and growth of alternative marketing arrangements in the hog industry call into question the accuracy and representativeness of some cash market information, leading to mandatory price reporting to combat reduced information availability (Franken, Parcell, and Tonsor, 2011; Franken and Parcell, 2012). If these changes make predicting cash hog prices more difficult, then the industry sourced fundamental (e.g., supply) information content of the Missouri forecasts may be of greater importance now than previously. Furthermore, the program's access to supply-side information from large hog producers, in particular, may be even more beneficial, given the transition to fewer small farms and greater numbers of large ones.

In a larger context, what are the implications of these differences in information or asymmetry? It re-emphasizes the importance of measuring futures market efficiency by assessing the degree to which futures prices encompass other competing forecasts (Sanders and Manfredo, 2004, 2005). Consistent with Colino and Irwin (2010), our findings support the notion that expert forecasts can offer additional information beyond futures prices which may be useful in effective market decision-making. The findings also point to the difficulty and cost/value in acquiring, obtaining, and interpreting relevant market information, and emphasize that most market participants make choices in an environment restricted by limited information.

Overall, the results suggest that futures and cash markets now rely somewhat more on expert forecasts than would be inferred from Bessler's and Brandt's 1992 study. Both their study and this one considers one-quarter-ahead forecasts. If it is relatively easier to predict cash prices just a short time into the future, then it may be that experts can more easily provide additional information beyond that conveyed by futures markets at more distant horizons. Furthermore, if updated one-quarter-ahead forecasts change little from earlier forecasts at more distant horizons, our results may understate the impact of expert forecasts. Hence, future research may investigate issues of dynamic information transmission among futures, expert forecasts, and cash prices over longer horizons than considered here.

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