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We evaluate dynamic interaction between four expert forecasts, futures prices, and realized cash hog prices. Lag structures of three variable vector autoregression indicate dynamic interaction among futures and cash markets and that past forecasts impact cash prices. Causal analysis of model residuals reveals contemporaneous causation of cash prices by futures prices and by some forecasts, and in all cases indicates causal structures consistent with the chronological ordering of prior day futures, subsequent forecasts, and cash prices realized one quarter later. Error decompositions following this ordering indicate expert forecasts are somewhat more important to futures and cash markets than previously believed.

Keywords: causality, efficient market hypothesis, forecasts, futures, information transmission

Introduction

With few exceptions, researchers evaluating publicly available forecasts find it difficult 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, Irwin, Garcia, and Etienne 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 outlook program. 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 and Brandt's (1992) sample. Nearly 80 percent of livestock futures trade is now electronic. Trader composition has also changed reflecting the growth of exchange traded products and long-only commodity index traders and 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. Outlook experts have retired, and one outlook program has even terminated its service. Information systems and technology are pervasive throughout the marketing channel. In this setting, the informational content of public forecasts continues to be relevant 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, University of Illinois/Purdue University, and the U.S. Department of Agriculture (USDA) for over a 30 year period. 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 ensures contemporaneous causality is tested and the 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).

The paper is organized as follows. The next section presents a brief review of the relevant literature, informing the choice of empirical procedures, which are discussed subsequently and are followed by a description of the data. Then the results are presented, followed by a discussion of their implications in the concluding section of the paper.

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). Bessler and Brandt (1992) extend the analysis to dynamic transmission of information using vector autoregression (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, Irwin, Garcia, and Etienne 2012). As we investigate these issues for livestock markets, the literature reviewed herein emphasizes studies of livestock markets.

Bessler and Brandt (1992) compare 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. Grimes' forecasts are superior to futures in terms of simple measures, e.g., mean squared error (MSE), mean absolute percentage error (MAPE), and the number of years in which he outperforms the futures market. Statistical tests suggest that the MSE of forecasts is not significantly different than that of futures for hogs, but is significantly lower than that of futures for cattle. Based on vector autoregression (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. Whereas cattle futures appear to respond to Grimes' forecasts, this does not appear to be the case for hog futures nor cattle or hog cash prices. Subsequent Choleski decomposition of innovations (i.e., errors) in VAR equations indicate that Grime's 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 are not as efficient for cattle as they are for hogs.

Colino and Irwin (2010) revisit the relative accuracy of Grimes' forecasts and forecasts derived from futures for cattle and hogs in addition to that of Iowa State, Illinois/Purdue, and USDA forecasts with an updated set of quarterly data spanning 1974 to 2007. Availability of multiple outlook programs with variation in forecast horizons up to three-quarter-ahead provides seven cattle and eleven hog outlook series for analysis. Differences in root mean squared error (RMSE) between outlook and futures are generally small and statistically insignificant for all but three cases in cattle (i.e., one- and two-quarter-ahead Illinois/Purdue and one-quarter-ahead USDA forecasts) but statistically significant for all cases in hogs except two- and three-quarter-ahead forecasts for Iowa and three-quarter-ahead forecasts for Missouri. Though expert forecasts outperform futures prices in only two out of the eleven cases for hogs and one out of the seven cases for cattle, futures are found to not encompass these forecasts in five cases for hogs and four cases for cattle, implying that these forecasts offer additional information beyond futures prices.

Data

We examine an updated version of Colino and Irwin's (2010) dataset of one quarter ahead expert forecasts of hog prices by the University of Missouri, Iowa State University, University of Illinois/Purdue University, and the USDA, prior day futures prices, basis adjustments, and realized cash prices (Table 1). With a sample period exceeding 30 years, the dataset offers greater statistical power than commonly available in previous studies of price forecast performance. 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 four percent 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 comparison of forecasts due to differences in information availability on the release dates.

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 (ARMA) 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). Only futures prices unadjusted for basis differ significantly from realized cash prices on average (Table 1). No significant difference exists between realized cash prices and expert and basis adjusted futures forecasts. Though not reported here in tabular form, there is also no significant difference in the forecast error of experts and basis adjusted futures, which is 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).

Dickey-Fuller (DF) tests indicate that the null hypothesis of nonstationarity (i.e., a unit root) is rejected at the five percent confidence level for each series, as the absolute values of the DF test statistics are between zero and the DF absolute critical value (Table 2). Thus, the price series are stationary (i.e., differencing is unwarranted), and the analysis proceeds in 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 the standard vector autoregression (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). VAR analysis and subsequent error decompositions are conducted using JMulTi software (Lütkepohl and Krätzig 2004) freely available online (http://www.jmulti.de/).

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 conducting tests of 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). Such models are depicted as directed graphs designed to represent conditional independence as implied by the recursive production decomposition (Chong, Zey, and Bessler 2010):

$$pr(v_1, v_2, \ldots v_m) = \prod_{j=1}^{m} pr(v_j \mid \pi_j), \tag{2}$$

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).[1]

Haigh and Bessler (2004) apply directed acyclic graphs (DAG) 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.

Various algorithms are available for searching observational data for causal structure in this manner, including Pearl's (2000) IC algorithm and Spirtes et al.'s (2000) PC algorithm. Here we use the PC algorithm which is freely available online through TETRAD IV software (http://www.phil.cmu.edu/projects/tetrad/).[2]

Results

Vector Autoregression

As established in Table 1, basis adjusted futures should be used to make equitable comparisons with realized cash prices when assessing forecast accuracy, but when considering information transmission in a Vector Autoregression (VAR) framework, the need to adjust futures prices is less clear.[3] Cash markets may react to changes in actual futures contract prices, but then again market participants may build in some basis adjustment, through experience if not formal modeling, when evaluating such changes. Thus, we run separate VAR models with futures prices and basis adjusted futures prices to assess sensitivity to this modeling choice (Tables 3 and 4).

Following Bessler and Brandt's (1992, p .256) argument that "lags beyond one year will probably not be important" we start with a maximum of four lags of each series and use similar model selection procedures to arrive at parsimonious models with optimal lag structure chosen based on minimizing Akaike information criterion (AIC). Specifically, we use the top-down procedure in JMulTi (Lütkepohl and Krätzig 2004), which deletes the last regressor in an equation if doing so improves the AIC and then proceeds to the second to last regressor and so on. Other procedures for sequential elimination of regressors available in JMulTi yield fairly similar model specifications. Notably, R^2 values are similar to or better than those obtained by Bessler and Brandt (1992).

Several findings are consistent across both sets of results (Tables 3 and 4), though apparent to a lesser extent for results using basis adjusted futures. For instance, lagged cash prices are highly influential on each series—a result that likely reflects quarterly patterns in the hog market. If forecasts are relatively accurate, then it should look like they are influenced by past cash values. 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 price (often with lag one) in the representation of cash prices. In contrast to the prior study, where lags of Missouri forecasts do not enter into the cash price equation, a few significant effects are detected here. Overall, the results suggest that cash markets for hogs now show somewhat more explicit reliance on the information content of experts' public forecasts than indicated by Bessler and Brandt (1992). As an exception, the now discontinued Illinois/Purdue forecast never enters into the cash equation. Futures markets also now appear to respond more to experts' forecasts, and given that lagged futures enter into the cash equation, experts' forecasts may indirectly influence cash prices.

Causal Analysis

Innovations (i.e., residuals) for each series in 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 forecasts and forecasts cannot cause futures). With this information, causal inference is detected, as represented graphically in Figure 2. Interesting, only innovations from the Missouri forecast, and perhaps the Iowa State forecast, exert contemporaneous causal influences on innovations in cash hog prices. Otherwise, cash market innovations are caused by innovations in futures, particularly in the case of Illinois/Purdue and USDA forecast innovations, which have no relation to cash innovations. In the absence of prior knowledge, identical patterns of undirected edges (i.e., without arrows) emerge, indicating the presence of relationships for which causality could not otherwise be determined. Furthermore, searches for superior alternatives (i.e., structures with lower Bayesian Information Criteria) cannot reject hypothesized causal structures consistent with the 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, p .256):

> "The variables are ordered as follows: Futures prices, Grimes' forecasts, and actual cash price. This allows current futures price and Grimes' forecast to influence current cash price; but current cash price cannot influence current futures price or Grimes' forecast. As these latter two variables occur in real time before cash prices this assumption appears appropriate. So too, the assumption allows current futures prices to influence Grimes' forecast but not vice versa."

Error Accounting

Tables 5 and 6 contain Choleski error decompositions corresponding to the separate VAR models using futures and basis adjusted futures forecasts, respectively. 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 should sum horizontally to roughly 100%, given rounding error. As is commonly the case, the error variances of variables are explained predominately by their own innovations at shorter horizons, and stronger "true" relationships with other variables emerge at longer horizons.

Again, several similarities to Bessler and Brandt's (1992) study are apparent. Since Bessler and Brandt (1992) used unadjusted futures prices, results presented in Table 5 provide the most direct comparison. Still, the results presented in Table 6 are fairly similar. As in the previous study, innovations in futures and cash prices generally explain most of the error variance of futures prices, with smaller amounts attributable to experts' forecasts. Futures market participants may follow the USDA outlook program somewhat more closely. Up to 8% of the error variance of futures prices (Table 5) and 4% of that of basis adjusted futures (Table 6) is attributable to the USDA forecast. Also as in Bessler and Brandt's (1992) study, past innovations in each series account for notable proportions of the error variance of forecasts.

In contrast to the prior study, where the University of Missouri hog price forecast accounted for only 1% of the error variance of cash prices, notably larger proportions are observed at longer horizons here for University of Missouri and perhaps Iowa State University forecasts. In the Table 5 results, which are directly comparable to Bessler and Brandt's (1992), the respective of cash price error variance attributable to innovations in these outlook programs reach 10% and 5%, respectively. In Table 6 results using basis adjusted futures, the proportion attributable to the Missouri forecast is smaller, though still apparent, while that of the Iowa State forecast diminishes to 1%. Hence, it appears that the value of the University of Missouri hog price forecast, in particular, has been improving with time. By these measures, direct influences of the other forecasts on cash prices are almost nonexistent, with the discontinued University of Illinois/Purdue University forecast exhibiting the smallest impact. Recall, that this forecast program did not enter into the cash equation at any lag in VARs. Notably, these results are consistent with the causal inferences of DAGs reported in Figure 2.

Conclusions

We assess the dynamic interaction among futures markets, expert forecasts, and realized cash prices for hogs using a current and richer dataset covering more forecast programs than examined previously by Bessler and Brandt (1992). As in the past work, the lag structure of vector autoregressions reflects dynamic interaction of information in futures and cash markets but also an influence of past forecasts on cash prices not observed previously. Model residuals are analyzed using causal inference procedures to generate graphical depictions of contemporaneous causation. Results imply contemporaneous causal flows from University of Missouri and perhaps Iowa State University forecasts to realized cash prices, but indicate no such relations with other forecasts. In each case, futures exert a causal influence on cash prices, and graphs correspond to the actual 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 error decompositions. The results corroborate prior findings that much of the variation in futures prices is attributable to past innovations in cash and futures prices. In contrast to the prior study, and consistent with our causal analysis, there is evidence that University of Missouri and to a lesser extent Iowa State University forecasts account for notable portions of the error variance in cash prices. Error decompositions also indicate that the USDA outlook slightly more important that the other expert forecasts to futures market. Furthermore, results support the decision to discontinue University of Illinois/Purdue forecasts in 2007, as there is little evidence it provided additional information to cash or futures markets.

Overall, the results suggest that futures and cash markets now rely somewhat more on expert forecasts than would be inferred from Bessler and Brandt's (1992) study. Both their study and this one consider 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. 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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Endnotes

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[1] 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.

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

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

[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).

Table 1. Summary Statistics for Quarterly Data

Variable	*N*	Mean	Standard Deviation	Minimum	Maximum
Missouri – 1974.2-2010.4					
Expert	147	44.36	6.73	27.50	65.00
Futures	147	46.41***	6.90	26.15	63.38
Basis adj. Futures	147	44.58	7.25	22.33	63.41
Cash	147	44.50	7.72	19.49	61.99
Iowa State – 1975.1-2010.4					
Expert	144	45.28	6.82	22.50	60.00
Futures	144	46.57**	6.91	26.43	64.04
Basis adj. Futures	144	45.49	7.40	22.24	61.58
Cash	144	45.71	7.70	19.49	61.98
Purdue/Illinois – 1979.2-2007.3					
Expert	115	46.00	6.73	28.27	65.65
Futures	115	46.65**	6.85	25.29	65.02
Basis adj. Futures	115	46.27	7.24	20.86	64.64
Cash	115	45.76	7.57	19.30	62.05
USDA – 1974.1-2010.3					
Expert	148	45.14	6.81	29.00	61.00
Futures	148	46.06	6.69	26.89	61.55
Basis adj. Futures	148	45.23	6.71	25.47	62.17
Cash	148	45.60	7.33	22.06	61.99

Notes: All statistics are reported as $/cwt. One, two, three asterisks (*, **, ***) indicate the mean is statistically different from that of the corresponding cash series at 10%, 5%, 1% levels, respectively. Sample periods are: Missouri - 1974.2-2010.4; Iowa - 1975.1-2010.4; Illinois/Purdue - 1979.2-2007.4; USDA - 1974.1-2010.4.

Table 2. Augmented Dickey Fuller Tests of Nonstationarity

Variable	N	Structure	Lags	Test Statistic	5% Critical Value
Missouri					
Expert	147	Constant	6	-3.958	-2.887
Futures	147	Constant	7	-3.450	-2.887
Basis adj. Futures	147	Constant	7	-3.900	-2.887
Cash	147	Constant	5	-4.575	-2.887
Iowa State					
Expert	144	Constant	8	-3.432	-2.888
Futures	144	Constant	7	-3.814	-2.888
Basis adj. Futures	144	Constant	7	-3.858	-2.888
Cash	144	Constant	4	-5.834	-2.887
Purdue/Illinois					
Expert	115	Constant & Trend	4	-5.094	-3.449
Futures	115	Constant	4	-5.395	-2.889
Basis adj. Futures	115	Constant	4	-5.150	-2.889
Cash	115	Constant	5	-4.589	-2.889
USDA					
USDAq1	148	Constant	5	-4.200	-2.887
Futures	148	Constant	5	-3.551	-2.887
Basis adj. Futures	148	Constant	5	-3.800	-2.887
Cash	148	Constant	5	-5.022	-2.887

Table 3. VAR Results using Futures Prices Unadjusted for Basis

	Missouri			Iowa State			Purdue/Illinois			USDA		
Variable	Futures	Expert	Cash	Futures	Expert	Cash	Futures	Expert	Cash	Futures	Expert	Cash
$Futures_{t-1}$	0.30***	0.29***	–	0.40***	0.48***	0.33***	0.27**	0.60***	0.28**	0.48***	0.49***	–
	(0.08)	(0.06)		(0.10)	(0.08)	(0.13)	(0.11)	(0.10)	(0.13)	(0.08)	(0.07)	
$Futures_{t-2}$	–	-0.25***	-0.30***	–	-0.21***	–	–	–	-0.21**	–	-0.22***	-0.22**
		(0.05)	(0.09)		(0.06)				(0.10)		(0.06)	(0.09)
$Futures_{t-3}$	–	–	–	–	–	–	–	–	–	–	–	–
$Futures_{t-4}$	0.31***	–	–	0.14**	–	-0.38***	0.17**	–	-0.31***	0.40***	–	–
	(0.07)			(0.06)		(0.11)	(0.08)		(0.08)	(0.07)		
$Expert_{t-1}$	-0.32***	–	–	-0.25***	–	-0.25**	–	–	–	-0.33***	–	–
	(0.10)			(0.09)		(0.13)				(0.08)		
$Expert_{t-2}$	-0.28***	–	–	-0.19***	–	–	–	0.30***	–	-0.24***	–	–
	(0.09)			(0.07)				(0.06)		(0.07)		
$Expert_{t-3}$	–	–	-0.19**	–	–	–	–	–	–	–	–	-0.21***
			(0.09)									(0.08)
$Expert_{t-4}$	-0.18**	–	–	–	–	0.41***	-0.21***	–	–	-0.33***	–	–
	(0.08)					(0.11)	(0.07)			(0.06)		
$Cash_{t-1}$	0.76***	0.67***	0.89***	0.70***	0.47***	0.86***	0.62***	0.34***	0.69***	0.55***	0.42***	0.84***
	(0.08)	(0.06)	(0.08)	(0.08)	(0.07)	(0.10)	(0.10)	(0.09)	(0.11)	(0.06)	(0.05)	(0.08)
$Cash_{t-2}$	-0.20*	-0.20***	-0.25**	-0.35***	-0.21***	-0.47***	-0.37***	-0.36***	-0.28**	-0.17**	–	-0.33***
	(0.10)	(0.07)	(0.11)	(0.10)	(0.08)	(0.11)	(0.09)	(0.08)	(0.12)	(0.07)		(0.10)
$Cash_{t-3}$	0.47***	0.29***	0.43***	0.54***	0.31***	0.46***	0.36***	–	0.43***	0.37***	0.24***	0.43***
	(0.09)	(0.06)	(0.11)	(0.08)	(0.06)	(0.10)	(0.07)		(0.09)	(0.07)	(0.05)	(0.10)
$Cash_{t-4}$	-0.27***	–	–	-0.33***	–	-0.20**	-0.23***	–	–	–	–	–
	(0.07)			(0.06)		(0.10)	(0.07)					
Constant	18.53***	9.00***	19.55***	15.18***	7.04***	11.46***	18.21***	4.85*	19.31***	12.09***	2.61	22.43***
	(3.06)	(2.24)	(3.55)	(2.90)	(2.45)	(3.63)	(3.28)	(2.80)	(3.87)	(3.01)	(2.53)	(3.81)
R^2	0.63	0.75	0.56	0.65	0.71	0.59	0.62	0.68	0.59	0.68	0.72	0.52

Note: One, two, three asterisks (*, **, ***) indicate statistical significance at 10%, 5%, 1% levels, respectively.

Table 4. VAR Results using Futures Prices Adjusted for Basis

	Missouri			Iowa State			Purdue/Illinois			USDA		
Variable	Futures	Expert	Cash	Futures	Expert	Cash	Futures	Expert	Cash	Futures	Expert	Cash
$Futures_{t-1}$	-0.26**	0.14	-0.40***	-0.20*	0.17	-0.32**	-0.17*	–	-0.20	–	–	-0.27***
	(0.10)	(0.09)	(0.12)	(0.11)	(0.10)	(0.13)	(0.10)		(0.13)			(0.10)
$Futures_{t-2}$	–	–	–	–	–	–	–	–	–	–	–	-0.18*
												(0.10)
$Futures_{t-3}$	–	–	–	–	0.24***	–	–	–	–	0.36***	–	–
					(0.05)					(0.07)		
$Futures_{t-4}$	–	–	–	–	–	–	–	–	–	0.37***	0.19***	0.30***
										(0.07)	(0.07)	(0.10)
$Expert_{t-1}$	–	–	–	–	–	–	–	0.49***	–	-0.18**	0.26***	–
								(0.07)		(0.07)	(0.07)	
$Expert_{t-2}$	-0.40***	-0.17*	-0.38***	-0.29***	-0.23***	-0.26***	–	–	–	-0.14**	–	–
	(0.10)	(0.09)	(0.12)	(0.08)	(0.07)	(0.10)				(0.06)		
$Expert_{t-3}$	-0.02	–	-0.14	–	–	–	–	–	–	-0.38***	-0.19**	-0.25**
	(0.06)		(0.09)							(0.08)	(0.08)	(0.10)
$Expert_{t-4}$	–	–	–	–	–	–	–	–	–	–	–	–
$Cash_{t-1}$	1.00***	0.70***	1.06***	0.99***	0.58***	1.00***	0.91***	0.33***	0.88***	0.79***	0.52***	0.94***
	(0.09)	(0.08)	(0.11)	(0.09)	(0.09)	(0.12)	(0.10)	(0.07)	(0.13)	(0.06)	(0.06)	(0.09)
$Cash_{t-2}$	–	-0.19***	–	–	–	–	–	–	–	–	–	-0.21**
		(0.06)										(0.11)
$Cash_{t-3}$	0.32***	0.27***	0.42***	0.22***	–	0.22***	–	–	–	0.05	–	0.47***
	(0.09)	(0.07)	(0.11)	(0.06)		(0.08)				(0.06)		(0.11)
$Cash_{t-4}$	–	–	–	–	–	–	–	–	–	–	0.13**	-0.23**
											(0.06)	(0.10)
Constant	16.14***	11.19***	19.82***	12.84***	10.92***	16.37***	12.34***	8.51***	14.71***	5.47*	3.43	19.42***
	(2.73)	(2.31)	(3.38)	(2.57)	(2.61)	(3.25)	(2.56)	(2.71)	(3.18)	(2.96)	(3.15)	(3.96)
R^2	0.67	0.70	0.57	0.70	0.65	0.55	0.65	0.60	0.52	0.69	0.65	0.54

Note: One, two, three asterisks (*, **, ***) indicate statistical significance at 10%, 5%, 1% levels, respectively.

Table 5. Error Decompositions on Vector Autoregressions using Futures

		Variables' Proportional Contributions to Innovation Standard Error (%)											
		Missouri			Iowa State			Purdue/Illinois			USDA		
Equation	Horizon	Futures	Forecast	Cash	Futures	Forecast	Cash	Futures	Forecast	Cash	Futures	Forecast	Cash
Futures	0												
	1	100%	0%	0%	100%	0%	0%	100%	0%	0%	100%	0%	0%
	2	72%	0%	28%	79%	0%	21%	83%	0%	17%	72%	2%	27%
	3	65%	0%	35%	73%	2%	25%	82%	0%	17%	60%	5%	35%
	4	59%	1%	40%	68%	2%	30%	78%	0%	21%	56%	4%	39%
	5	58%	1%	41%	69%	2%	30%	77%	1%	22%	52%	7%	41%
	6	58%	1%	41%	68%	2%	29%	75%	1%	24%	50%	8%	42%
	7	58%	1%	41%	68%	2%	30%	75%	1%	24%	50%	8%	42%
	8	58%	1%	41%	68%	3%	29%	75%	1%	24%	50%	8%	41%
	9	58%	1%	41%	67%	3%	29%	75%	1%	24%	50%	8%	42%
	10	58%	1%	41%	67%	3%	29%	76%	1%	23%	50%	8%	42%
Expert	0												
	1	51%	49%	0%	56%	44%	0%	52%	48%	0%	28%	72%	0%
	2	53%	23%	25%	67%	21%	11%	69%	25%	6%	43%	41%	17%
	3	44%	19%	36%	62%	18%	20%	72%	21%	7%	32%	29%	39%
	4	41%	19%	41%	59%	17%	24%	73%	20%	7%	28%	25%	47%
	5	37%	18%	45%	57%	15%	29%	71%	19%	10%	25%	23%	52%
	6	36%	18%	46%	57%	14%	29%	71%	18%	11%	24%	22%	54%
	7	36%	18%	47%	57%	14%	29%	70%	18%	11%	24%	21%	55%
	8	36%	18%	47%	57%	14%	29%	70%	18%	11%	24%	21%	54%
	9	35%	18%	47%	56%	15%	29%	70%	18%	12%	25%	21%	54%
	10	35%	18%	46%	56%	15%	29%	70%	18%	12%	25%	21%	54%
Cash	0												
	1	30%	8%	62%	39%	2%	59%	38%	1%	61%	9%	1%	90%
	2	30%	8%	62%	45%	1%	54%	48%	1%	51%	9%	1%	90%
	3	27%	8%	65%	45%	1%	53%	48%	1%	51%	9%	1%	90%
	4	26%	8%	66%	45%	1%	54%	46%	1%	52%	9%	1%	89%
	5	25%	8%	67%	43%	3%	54%	43%	1%	56%	10%	1%	89%
	6	24%	9%	67%	43%	3%	53%	43%	1%	56%	10%	1%	89%
	7	24%	9%	67%	43%	4%	53%	43%	1%	56%	10%	2%	88%
	8	24%	9%	67%	43%	4%	53%	44%	1%	55%	11%	2%	87%
	9	24%	9%	66%	43%	5%	53%	44%	1%	55%	11%	2%	87%
	10	24%	10%	66%	43%	5%	53%	44%	1%	54%	11%	3%	86%

Table 6. Error Decompositions on Vector Autoregressions using Basis Adjusted Futures

		Variables' Proportional Contributions to Innovation Standard Error (%)											
		Missouri			Iowa State			Purdue/Illinois			USDA		
Equation	Horizon	Futures	Forecast	Cash	Futures	Forecast	Cash	Futures	Forecast	Cash	Futures	Forecast	Cash
Futures	0												
	1	100%	0%	0%	100%	0%	0%	100%	0%	0%	100%	0%	0%
	2	62%	3%	35%	67%	1%	32%	73%	0%	27%	58%	0%	42%
	3	51%	2%	47%	56%	1%	43%	66%	0%	33%	45%	0%	55%
	4	46%	2%	51%	52%	1%	47%	64%	0%	35%	42%	3%	54%
	5	44%	2%	54%	50%	1%	49%	64%	0%	36%	41%	4%	55%
	6	42%	2%	56%	49%	1%	50%	63%	0%	36%	39%	4%	57%
	7	42%	2%	56%	49%	1%	50%	63%	0%	37%	39%	4%	57%
	8	42%	2%	56%	49%	1%	50%	63%	0%	37%	39%	4%	57%
	9	42%	2%	56%	49%	1%	50%	63%	0%	37%	39%	4%	57%
	10	42%	2%	56%	49%	1%	50%	63%	0%	37%	39%	4%	57%
Expert	0												
	1	58%	42%	0%	58%	42%	0%	42%	58%	0%	43%	57%	0%
	2	57%	21%	22%	61%	24%	14%	50%	45%	5%	40%	40%	20%
	3	47%	17%	35%	51%	19%	30%	52%	38%	10%	33%	31%	36%
	4	42%	16%	42%	50%	18%	32%	52%	34%	14%	31%	28%	41%
	5	39%	14%	47%	48%	17%	36%	52%	32%	16%	29%	27%	44%
	6	37%	14%	49%	46%	16%	38%	52%	31%	17%	28%	25%	47%
	7	37%	14%	50%	45%	16%	39%	52%	31%	18%	27%	25%	48%
	8	37%	14%	50%	45%	16%	39%	52%	30%	18%	28%	25%	48%
	9	36%	13%	50%	45%	16%	39%	52%	30%	18%	28%	25%	48%
	10	37%	13%	50%	45%	16%	39%	52%	30%	18%	28%	25%	48%
Cash	0												
	1	45%	4%	51%	52%	1%	47%	56%	0%	44%	21%	1%	78%
	2	34%	5%	61%	44%	2%	55%	51%	0%	49%	15%	1%	84%
	3	30%	4%	66%	39%	1%	59%	49%	0%	50%	14%	1%	85%
	4	27%	4%	69%	37%	1%	61%	49%	0%	51%	14%	1%	85%
	5	26%	4%	71%	37%	1%	62%	49%	0%	51%	14%	1%	85%
	6	25%	4%	71%	36%	1%	63%	49%	0%	51%	14%	1%	85%
	7	25%	4%	71%	36%	1%	63%	49%	0%	51%	14%	1%	85%
	8	25%	4%	71%	36%	1%	63%	49%	0%	51%	14%	1%	85%
	9	25%	4%	71%	36%	1%	63%	49%	0%	51%	14%	1%	85%
	10	25%	4%	71%	36%	1%	63%	49%	0%	51%	14%	1%	85%

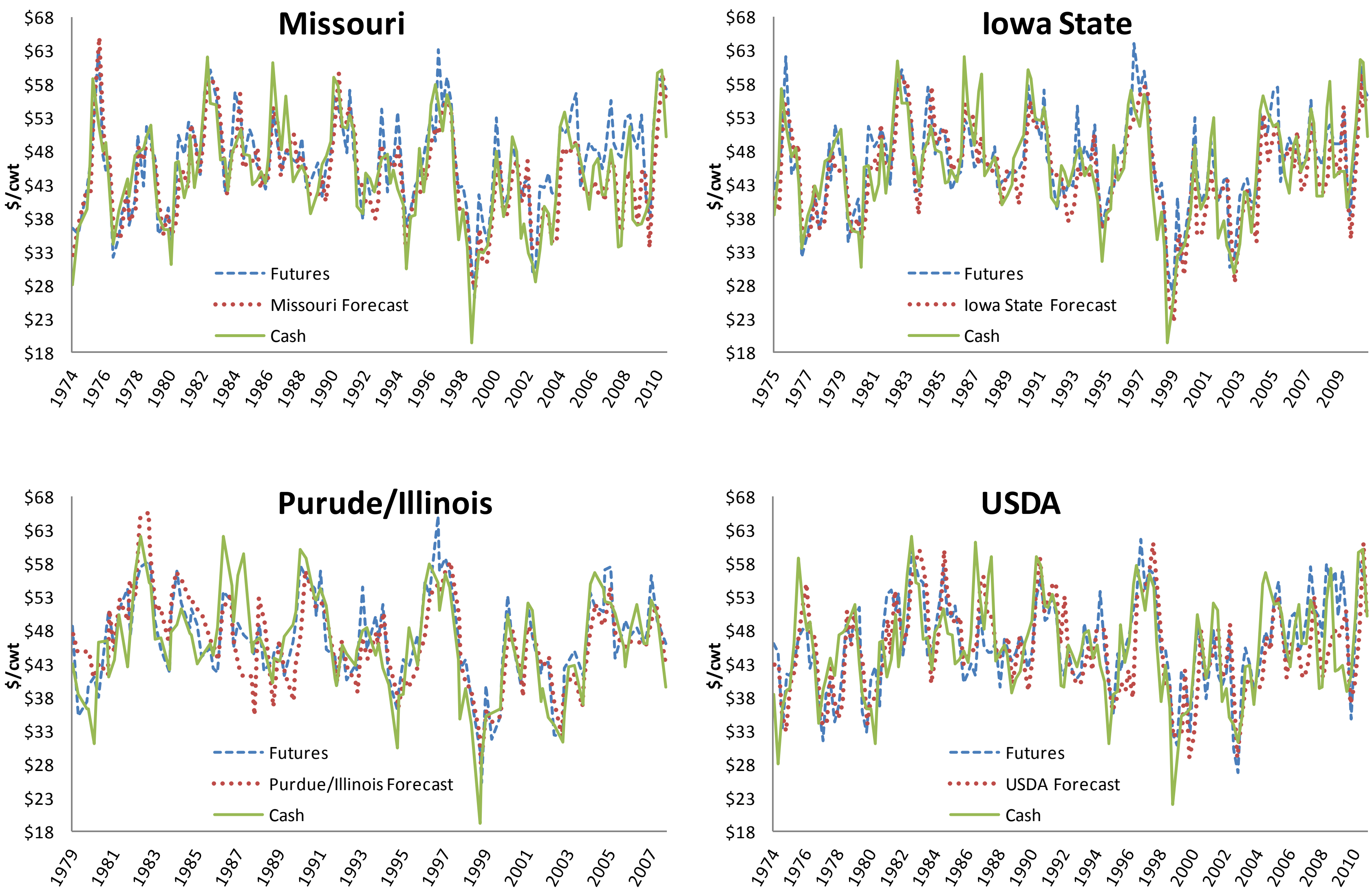

Figure 1. One Quarter Ahead Forecasts, Prior Day Futures, and Realized Cash Hog Prices

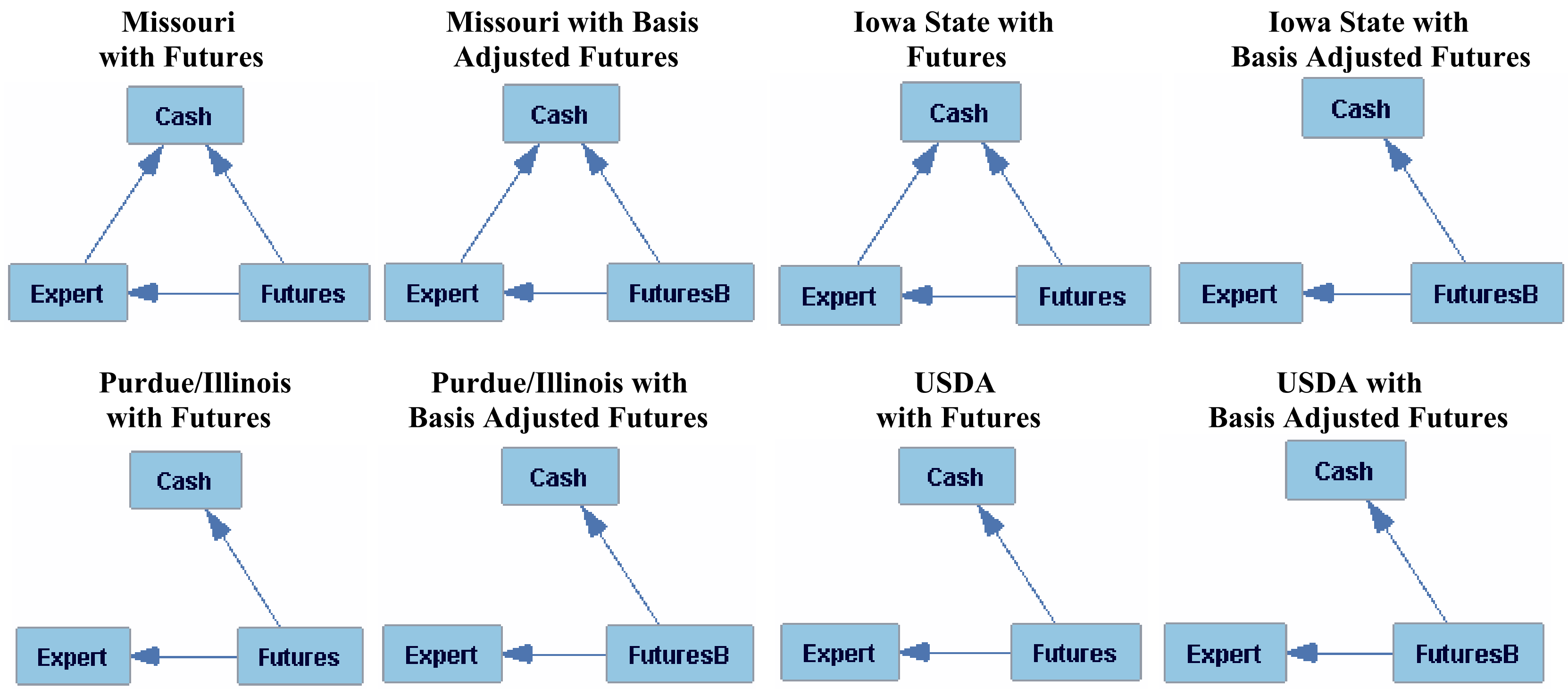

Figure 2. Causal Analysis Results of PC Algorithm Search over Vector Autoregression Innovations Conditional on Prior Knowledge.