Prediction markets: an experimental approach to forecasting cattle on feed

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Abstract

Purpose – The purpose of this paper is to use prediction markets to forecast an agricultural event: United States Department of Agriculture's number of cattle on feed (COF). Prediction markets are increasingly popular forecast tools due to their flexibility and proven accuracy to forecast a diverse array of events.

Design/methodology/approach – During spring 2008, a market was constructed comprised of student traders in which they bought and sold contracts whose value was contingent on the number of COF to be reported on April 18, 2008. During a nine-week period, students were presented three types of contracts to forecast the number of COF. To estimate forecasts a uniform price sealed bid auction mechanism was used.

Findings – The results showed that prediction markets forecasted 11.5 million head on feed, which was about 1.6 percent lower than the actual number of COF (11.684 million). The prediction market also fared slightly worse than analysts' predictions, which on average suggested there would be about 11.795 million head (an over-estimate of about 1 percent).

Originality/value – The contribution of this study was not to provide conclusive evidence on the efficacy of using prediction markets to forecast COF, but rather to present an empirical example that will spark interest among agricultural economists on the promises and pitfalls of a research method that has been relatively underutilized in the agricultural economics literature.

Keywords Animal feed, Experimental design, Forecasting, United States of America

Paper type Case study

1. Introduction

Prediction markets are becoming a widely used tool to forecast outcomes as diverse as presidential election results, movie box office receipts, corporate earnings, and football scores. These markets allow individuals to buy and sell, in an active market, contracts that pay money based on the size or occurrence of a future event. Probably the most well-known prediction markets are the Iowa Electronic Markets, which are primarily used to forecast the outcomes of political elections. For example, people trade contracts that pay $1 if candidate A wins and $0 if candidate B wins. Participants in the market buy and sell the contracts depending on the expected success of each candidate. If the "going price" of the contract is $0.60, this indicates, under certain assumptions, a 60 percent chance that candidate A will win the presidential election.

The rationale of prediction markets rests on the efficient market hypothesis, which posits that in a truly efficient market, the price is the best predictor of the future event. In particular, prediction markets might be viewed as strong efficient in the sense that prices are thought to fully reflect all publicly available information (Fama, 1970). People with private information about the likelihood of observing future events have an incentive to enter the market and profit from their information. Moreover, those participants with

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access to the most unexpected information are those with the greatest incentives to trade in the market (e.g. Kelly, 1956; Shannon, 1948) and thus push the price toward the new expected outcome. This does not mean that all traders are perfectly rational (e.g. they might be loss averse or weight probabilities non-linearly as in prospect theory; Kahneman and Tversky, 1979) or that markets cannot, from time to time, be affected by "irrational exuberance" (Shiller, 1998). However, futures market prices are normally expected to provide the best bet of impending prices at the time the bet is made. Someone with beliefs to the contrary has a strong incentive to enter the market and make bets to the contrary, a fact which would push the price toward the trader's expected outcome. The merits of prediction markets also revolve around Hayek's (1945) insight that market prices reflect more information than is available to any individual trader. That is, markets are an "information aggregator" and market prices convey more information than could be obtained through surveys of individual traders' beliefs[1]. Likewise, Hahn and Tetlock (2006) argue that prediction markets' accuracy is due to the aggregation of disparate pieces of information that occurs when experts trade among each other; something that is often missing with predictions from expert opinion or surveys.

Prediction markets validity is supported by Berg and Rietz (2003) who ground their claim on:

- the dynamic nature of forecasts;
- the aggregation of information across traders through the price formation process;
- empirical evidence that prediction markets' forecasts are unbiased and relatively accurate; and
- the performance of prediction market forecasts compared with alternatives, such as polls, econometric models, and marketing surveys.

Although prediction markets (also referred to as betting markets or ideas markets) have only recently grown in popularity, they have a long history (see Rhode and Strumpf, 2004).

Several previous papers have shown the superior accuracy of prediction markets. For example, Berg *et al.* (2003) compared the results from traditional polls and prediction markets to forecast the winner for presidential elections in 1988, 1992, 1996, and 2000. On average, the poll predicted "wins" correctly 27 percent of the times whereas the accuracy rate for prediction markets was 73 percent (see also Forsythe *et al.*, 1992). Pennock *et al.* (2001) described the use of prediction markets to assess probabilities of concern to the scientific community and policy makers and showed that prices from prediction markets accurately predicted whether particular scientific discoveries occurred in a given time period. Other studies have shown that prediction markets are successful in forecasting outcomes of football games (Servan-Schreiber *et al.*, 2004), firm sales (Chen and Plott, 2002), and sales receipts from opening weekends of Hollywood movies (Wolfers and Zitzewitz, 2004).

1.1 Purpose and justification

There is nothing particularly unique about prediction markets as applied to agriculture. After all, people have been trading commodity futures contracts for a long time. In a sense, futures markets are a kind of prediction market. The term prediction markets, however, is more encompassing in that it refers more broadly to the institutions that have arisen primarily for the purpose of trading upon beliefs about future outcomes (rather than commodities at future dates) for the purpose of prediction (rather than risk management). Moreover, prediction markets can be set up anywhere and on any scale and are not limited to the major exchanges in Chicago or New York. Seen in this light, there is a surprising dearth of applications of prediction markets to agricultural topics despite the wide range of important applications in which they could be employed: BSE, foot and mouth disease, soybean rust, agro-terrorism, etc. Information on the probability of these events would be extremely valuable, as it would allow producers and agribusinesses to prepare for the future and protect themselves against risk. Indeed, improved information on the likelihood of uncertain agricultural events would allow for the emergence of insurance for catastrophic events. At present, it is difficult for insurance markets to develop because probability assessments are highly uncertain.

This paper introduces a unique empirical application of prediction markets to an agricultural topic that has received significant attention in the literature: forecasting the number of cattle on feed (COF). The United States Department of Agriculture (USDA) releases monthly reports indicating the number of cattle in US feedlots. This information is widely anticipated by the livestock industry, market analysts, and futures traders because it provides information on current and future slaughter cattle supplies that affect commercial beef production and prices (Mark and Small, 2007). Given the importance of COF information, a number of companies provide pre-release estimates or forecasts of the USDA COF numbers. The methods used by these companies to derive the forecasts are, however, largely unknown, and the accuracy of such forecasts has been the subject of debate and research. Indeed, a former analyst who helped provide such forecasts on a subscription basis suggested that many times the forecasts were simply derived by making a couple of phone calls to large feedlots or by casual visual inspection of a few lots. Such anecdotes make one wonder whether there might be a more systematic method for forecasting COF.

This paper illustrates how prediction markets can be implemented in regards to an agricultural event and conveys results from our initial attempt to implement a prediction market to forecast the number of COF. Moreover, we show how prediction markets can be used to estimate a statistic usually left to the realm of time series econometrics: the elasticity of demand for fed cattle. The purpose of this paper is not to provide conclusive evidence on the efficacy of using prediction markets to forecast COF, but rather to spark thinking on the promises and pitfalls of a research method that has been relatively underutilized in the agricultural economics literature.

2. Research about COF reports

Several previous studies address questions related to the relationship between forecasts and USDA market reports related to COF, and the relationship between market reports and commodity prices. What follows is a discussion of some of these studies.

Grunewald *et al.* (1993) found that live cattle futures prices were affected by unanticipated information about placements and marketing in COF reports; however, this information was quickly absorbed by prices. Unanticipated information was the difference between USDA COF reports and Knight-Ridder survey data of market analysts' forecast. This result was supported by the findings of Dhuyvetter *et al.* (1997) who found evidence that unanticipated information (i.e. the difference in forecasted and reported numbers) was already reflected in feeder cattle futures prices through live cattle markets.

Colling and Irwin (1990) studied the effect of anticipated and unanticipated information on hog futures markets. Knight-Ridder survey data were used as the anticipated information and the difference between market hog inventories and analysts' expectations was the unanticipated component. They found that survey data had no effect on live hog futures price changes, implying that information was already incorporated into prices before the release of USDA reports. Mann and Dowen (1996) also measured the impact of Knight-Ridder forecasts on hog and pig futures prices and their accuracy with respect to USDA reports. They found that the market did respond to the actual USDA report, but it did not respond to the Knight-Ridder forecasts, suggesting a lack of trader confidence in the Knight-Ridder forecast. On a similar topic, Isengildina *et al.* (2006) found that price volatility went up after the release of COF reports, which means that the reports provide new information to market participants.

Based on the studies reported on both cattle and hog markets, one can conclude that pre-release forecasts and surveys can be, but are not always, good forecasts of initial USDA reports. What about prediction markets? Would they be a better forecasting tool than surveys? In this paper we set up a procedure to forecast COF with prediction markets and provide a case study application of the procedure.

3. Methods

Participants in the prediction market consisted of 23 students enrolled in an upper-level undergraduate course on futures markets in the spring of 2008[2]. Students traded contracts in markets held weekly over a nine-week period. Once a week, beginning on February 13, 2008, participants were asked to buy and/or sell contracts based on their expectations about the number of COF in US feedlots on April 1, 2008 (as reported by the USDA in a report released on April 18, 2008). Prior to the first trading session, market participants were orally instructed (and given an instruction booklet) on how to make money by buying and selling contracts, and how market prices would be determined each week. To motivate traders, the two students with the highest accumulated profits over the semester were given cash prizes, and a portion of the students' grades in the course were determined by their rank-order of profits accumulated over the nine-week trading period. Traders were explicitly encouraged to seek information on COF outside class and were given web links to several sources of information on COF reports.

3.1 The contracts

Each week, three different contracts were traded. In this sub-section, we briefly describe each contract and the reasons why we included the contracts in our experiment. The following sub-sections describe how profits were made and how trading occurred.

The first contract was the simplest and was designed to provide the market's expectation of the number of COF released in the April 18 report. In particular, the first contract, which we refer to as the COF contract, was designed such that the value of the contract was equal to $1 for each 10,000,000 head of COF reported by the USDA-NASS on April 18, 2008. The market operated like a cash-settled futures contract. For example, if the number of COF on April 18 was 11.5 million, a buyer at 11.3 million would be paid $0.02 for each contract in their position, and a seller at 11.3 million would owe $0.02 for each contract sold. Of course, prior to that date traders did not know the actual number of COF on April 18 and thus, they bought and sold contracts based on their expectation of the number that would be released by the USDA.

Wolfers and Zitzewitz (2004) claim that prediction markets can be used to determine causality and they describe how prediction markets can be used as a decision aid by offering a series of contingent contracts that payoff if another event occurs. Because of the previous literature showing the close relationship between COF and live cattle futures prices, we sought to investigate this relationship via the use of prediction markets rather than through the use of time-series data observing how past changes in COF related to changes in live cattle futures prices. In particular, we offered two additional contracts whose values depended on the relationship between the number of COF released and the nearby live cattle futures price. The second contract traded, which we refer to as COF/CME/LO, was worth an amount equal to the June Chicago Mercantile Exchange live cattle futures settlement price (in dollars per pound) if the USDA-NASS reported the number of cattle on April 18 between 10 and 10.5 million head, otherwise the contract was nullified. The third contract, COF/CME/HI, was similar to contract COF/CME/LO with the difference that the number of cattle was in between 11.5 and 12 million head.

Because the supplies of feedlot cattle are fixed in the short run, traders' expectations of live cattle prices under low and high potential supplies provide an estimate of the traders' implied expected slope of the demand curve for cattle. For example, Figure 1 shows two possible supply curves associated with the mid-points of the COF/CME/LO and COF/CME/HI contracts. By observing the prices of the two contracts, the slope of the inverse demand curve can be calculated, i.e. the slope is: $s = (P^{11.75} - P^{10.25})/(11.75$ million $- 10.25$ million), where $P^{10.25}$ and $P^{11.75}$ are the respective observed prices of the COF/CME/LO and COF/CME/HI contracts. Accordingly, the elasticity of demand evaluated at the means can be calculated as: $(1/s) * [0.5 * (P^{10.25} + P^{11.75})/(11$ million$)]$. Even though there is a high probability that these conditional contracts will not pay out, participants still have an incentive to bid their expected values.

3.2 How profits were calculated and how money was made in the market

Based on the outcome of the event, i.e. the USDA report released on April 18, 2008, participants realized profits relating to the number of contracts bought/sold. For a COF contract bought and held until April 18, profits for each contract purchased were: *COF value* − *Purchase price*. If the contract was sold and held until April 18, profits for each contract sold were: *Sales price* − *COF value*. The *COF value* was equivalent to USDA

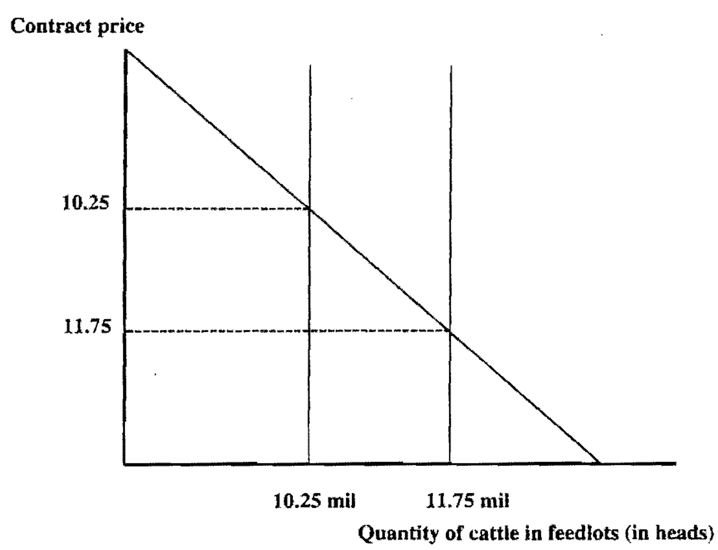

Figure 1.
Effect of high and low cattle supplies on live cattle prices

reported number of COF on April 18 divided by 10,000,000. Students were allowed to buy contracts in one week and sell contracts in a future week or vice versa. If a contract was bought/sold one week and the position was offset by selling/buying in a future week, profits from offsetting positions were equivalent to: *Sales price − Purchase price*. Profits on all contracts not offset by April 18 were determined as previously explained.

To help traders learn how to make money buying and selling COF contracts, traders were encouraged to look at all available information and come up with his/her "best guess" of the number of COF to be reported by the USDA by April 18. We suggested that the number of contracts on which traders offered bids/asks should be positively related to how accurate they believed were their "best guesses." To make money buying contracts, traders were advised to buy contracts that were less than their "best guess" of the number of COF reported on April 18 divided by 10,000,000. Conversely, to make money selling contracts, traders were advised to try to negotiate COF contract prices higher than their "best guess" of the number of COF reported on April 18 divided by 10,000,000.

Traders made profits buying and holding the COF/CME/LO contract only if the USDA reported number of COF on April 18 was between 10 and 10.5 million head. Under this condition, all contracts that were bought and held were worth: *April 18 Chicago Mercantile Exchange Live Cattle futures settlement price for the June 2008 contract in $/lb − Purchase price of COF/CME/LO*. If a contract was sold and the position was not offset, profits were: *Sales price of COF/CME/LO − April 18 Chicago Mercantile Exchange Live Cattle futures settlement price for the June 2008 contract in $/lb* as long as the actual number of COF was between 10 and 10.5 million. Traders could also buy contracts in one week and sell them in a future week or vice versa, and the profits earned/lost from offsetting such positions were simply *Sales price − Purchase price* when the final COF was in the specified range, but would otherwise be zero. As with the COF contract, traders were advised to come up with a "best guess" to help them determine bid and ask prices, where, in this case, the "best guess" was the nearby Chicago Mercantile Exchange live cattle futures price on April 18 if the reported number of COF was between 10 and 10.5 million. Profits made trading the COF/CME/HI contract were computed identical to COF/CME//LO, with the difference that the USDA reported number of COF for April needed to be between 11.5 and 12 million.

3.3 How trade took place in the market

The mechanism used to determine the price of each contract in each week was a sealed-bid uniform price auction. A uniform price auction refers to the fact that, for a particular contract in a given week, all traders faced the exact same price. Each week, trading took place as follows:

- traders were given a decision sheet on which they indicated the number of contracts they wished to buy and/or sell along with the bid (what they were willing to pay) and/or asking (what they were willing to accept) price[3];
- traders completed the decision sheet for each of the three contracts: COF, COF/CME/LO, and COF/CME/HI;
- all bids and asks were entered into a spreadsheet and the price that "cleared the market" was determined; and
- the market prices, number of trades, and information on each individual trader's buy/sells was disseminated back to the traders.

For each contract, the "market clearing price" was the price that maximized the number of trades. This price was determined by plotting all bids for a contract from highest to lowest to construct a "demand curve," and ranking all asks for a contract from lowest to highest to construct a "supply curve." The market price was simply the point at which the constructed supply and demand curves intersected. If a participant's bid was greater than the market-clearing price, he/she purchased the number of units indicated on the decision sheet; if the bid was less than the market clearing price, no purchases were made by that trader. If a trader submitted an ask less than the market clearing price, he/she sold the number of units indicated on the decision sheet. If the ask was greater than the market clearing price, no sales were made for that trader. For each trader and contract, we created an "account," which tracked the number of contracts bought and/or sold, the prices at which the trades occurred, and any profits accrued from offsetting positions. Each trader was given his/her own account statements each week. At the end of the experiment (after April 18), total earnings for each student in the class were calculated by summing the account balances across each of the three traded contracts.

4. Results

Table I presents the primary results of the study, including market price for each contract each week and total number of transactions each week. By April 16, two days before the release of the USDA report, the market price for the COF contract was $1.15005, which indicates that the market expectation of the number of COF was a little over 11.5 million. COF contract prices did not vary much over the nine-week trading period, and in general there was a decline in prices. However, there was a marked increase in the volume of trades that took place over the nine-week trading period. This finding is likely attributable to the traders decreasing their bid-ask spreads as they become more confident due to experience gained each week. We were able to calculate the within-trade bid-ask spread, since each trader submitted bids and asks for each contract each week. The average bid, ask, and spread for each week is presented in Table II. The spreads are calculated as ask price minus bid price. As expected, participants were, on average, rational in asking higher and bidding lower. Spread variability across time is shown in Figure 2. In general, spreads shrunk over time for the three contracts. Early in the experiment, COF spread was 0.12 and on the last day, 0.03.

Table I.
Total number of transaction and market price for COF prediction contracts

Week	COF Total number of transactions	COF Market price ($)	COF/CME/LO Total number of transactions	COF/CME/LO Market price ($)	COF/CME/HI Total number of transactions	COF/CME/HI Market price ($)
Feb. 13	190	1.15500	176	0.94500	110	0.95505
Feb. 20	210	1.15375	165	0.94750	125	0.95000
Feb. 27	275	1.15475	255	0.95000	50	0.95000
Mar. 5	502	1.15462	330	0.95000	147	0.95000
Mar. 12	500	1.15445	450	0.94735	605	0.94625
Mar. 26	270	1.15400	525	0.94200	480	0.94000
Apr. 2	615	1.15325	570	0.93400	690	0.92875
Apr. 9	770	1.15150	700	0.93000	800	0.92000
Apr. 16	570	1.15005	870	0.92525	470	0.91500
Average	434	1.15349	449	0.94123	386	0.93945
SD	205	0.00167	242	0.00921	283	0.01464

Table II. Average bid and ask, spread for the COF prediction market experiment

Week	COF Bid ($)	COF Ask ($)	COF Spread	COF/CME/LO Bid ($)	COF/CME/LO Ask ($)	COF/CME/LO Spread	COF/CME/HI Bid ($)	COF/CME/HI Ask ($)	COF/CME/HI Spread
Feb. 13	1.08	1.2	0.12	0.93	1.05	0.12	0.93	1.06	0.13
Feb. 20	1.13	1.2	0.07	0.93	1.00	0.07	0.93	1.01	0.08
Feb. 27	1.13	1.21	0.08	0.91	0.98	0.07	0.94	0.98	0.04
Mar. 5	1.12	1.18	0.06	0.9	0.97	0.07	0.94	0.97	0.03
Mar. 12	1.13	1.17	0.04	0.93	0.96	0.03	0.93	0.96	0.03
Mar. 26	1.12	1.17	0.05	0.89	0.95	0.06	0.92	0.94	0.02
Apr. 2	1.14	1.18	0.04	0.91	0.93	0.02	0.90	0.93	0.03
Apr. 9	1.14	1.18	0.04	0.92	0.93	0.01	0.91	0.93	0.02
Apr. 16	1.15	1.18	0.03	0.92	0.94	0.02	0.91	0.93	0.02
Average	1.13	1.19	0.06	0.92	0.97	0.05	0.92	0.97	0.04
SD	0.02	0.01	0.03	0.01	0.04	0.04	0.01	0.04	0.04

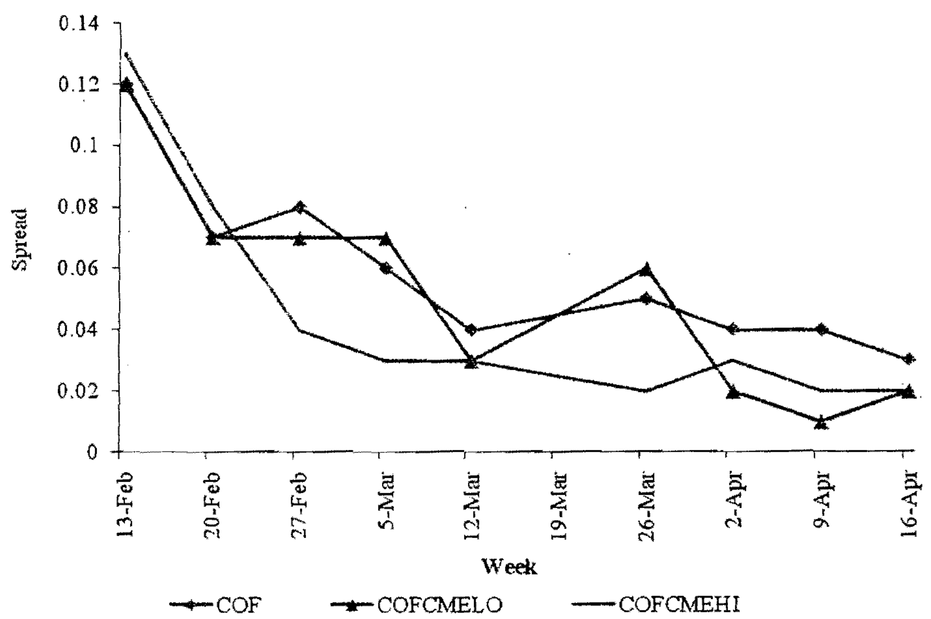

Figure 2. Spreads by contract during the ten-week experiment period

The last columns in Table I show the prices and trade volume for the COF/CME/LO and COF/CME/HI contracts. There was greater variability in prices for these contracts as compared to COF. We would expect the price of COF/CME/LO to exceed that of COF/CME/HI, and while this condition was violated in the initial weeks of trading, the relationship became as expected as experience was gained and as the volume of trades increased.

The obvious question is: how accurate is the prediction market? On April 18, the USDA released the COF report, indicating that 11,684,000 head on feed on April 1. As shown in Figure 3, it is clear that our prediction market ***under***-predicted this outcome by about 183,500 head (11,684,000-11,500,500) or by about 1.57 percent. Is this a high or low level of accuracy? Figure 3 also shows the average of the pre-release forecasts, which was put at 11.795 million on April 16, 2008 (Chicago Mercantile Exchange (CME) Group,

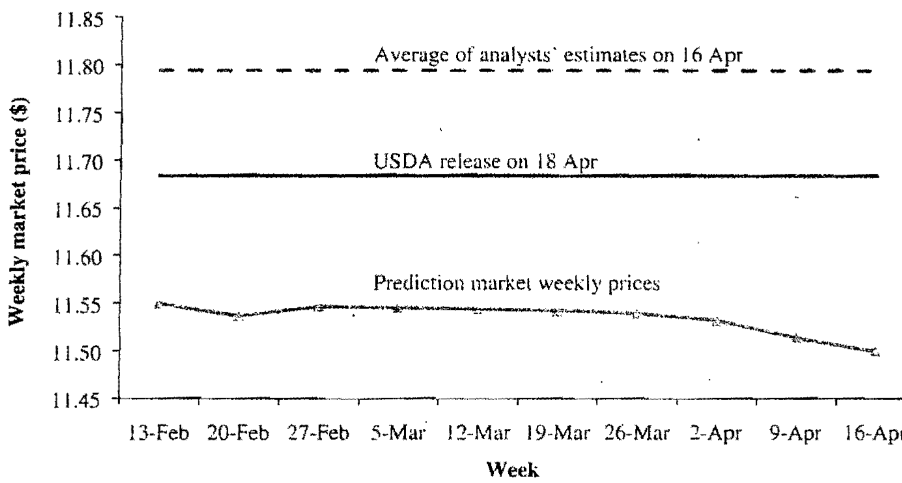

Figure 3.
Predicted and actual number of COF

2008). Thus, the private market analysts *over*-predicted this outcome by about 111,000 head (11,684,000 − 11,795,000) or by about 0.95 percent. More generally, Dhuyvetter *et al.* (1997) showed that the mean absolute deviation (in units of million head) between actual and analyst forecasted number of COF from 1980 to 1995 was 0.114 (with min and max of 0.001 and 0.510). In our particular case of the April 2008 forecast, the prediction market exhibited an absolute deviation (in million head) of 0.1835 and the absolute deviation of the analysts' forecasts was 0.111. Thus, the results seem to suggest that, in this particular one-shot case, the prediction market was less accurate than analysts' predictions, but not markedly so and is within the norms observed by historical standards of analyst accuracy. Interestingly, the prediction market under-predicted actual COF whereas the analysts over-predicted actual COF. In this one case, combining the analyst predictions with the prediction market would have resulted in a very accurate prediction (within 0.3 percent of the actual value with absolute deviation of 0.04).

What about the effect of this particular COF report on cattle prices? Live futures cattle settlement price on April 18, 2008 was $92.825 and one day after, on April 19, it was $92.725 (CME Group, 2008). The variation in live futures prices after the USDA COF report release was a 0.11 percent decrease, suggesting little market reaction for this particular release date. Note that the pre-release estimates implied that analysts expected a higher COF number than was actually reported by the USDA (11.795 million was the pre-release forecast and 11.684 million was the number reported by USDA). Normally, we would expect this outcome to result in a price increase, reflecting a response to now smaller than expected supplies. On this particular date, however, prices slightly fell, perhaps due to other market shocks that were occurring at the same time as the release of the COF report.

Table III reports the implied elasticity of demand for fed cattle based on the market prices in the CME/COF/LO and CME/COF/HI. As can be evidenced, the implied elasticity estimates became much more rational and in line with expectations as trading progressed over time. In the final week of trading, an elasticity of demand of −12.24 was obtained. Results for the first two weeks do not follow the expected relation between quantities supplied and prices. The next two weeks predicted demand was perfectly inelastic and for the next five weeks demand was predicted to be elastic. The average estimate for price demand elasticity was −12.24 (flexibility of −0.08)[4].

This flexibility is considerably higher than that obtained from most time-series econometric estimates. For example, Marsh (2003) estimated a flexibility of −0.69.

5. Discussion and conclusions

Prediction markets are a forecasting tool that is increasing in popularity. To date, however, agricultural economists have yet to utilize prediction markets despite a host of interesting and important topics to which they could be applied. The purpose of this paper was to present a case study of a unique application of prediction markets to a widely studied topic in agricultural economics in an effort to both introduce the research tool and begin a dialog about the merits of prediction markets.

Our results suggest that the prediction market had some success, but that its performance was less than stellar. The prediction market prices forecasted that there would be 11.5 million head on feed, which was about 1.6 percent lower than the actual number of COF (11.684 million). The prediction market also fared slightly worse than private analysts' predictions, which on average suggested there would be about 11.795 million head (an over-estimate of about 1 percent).

There is evidence that many of the traders were confused or misinformed, especially in early trading periods. For the first three trading weeks, prediction market prices suggested an "irrational" expectation that cattle prices would rise if cattle supplies increased. However, by the end of the experiment, this result reversed itself and suggested an own-price elasticity of demand for fed cattle of about −12.24, a figure that is much more elastic than most time-series estimates.

The results from our initial attempt to implement a prediction market suggest that it can be done and that traders appear to gain expertise over time. However, much more research is needed to determine the extent to which prediction markets are more or less accurate than other methods. Moreover, one might question whether we would even expect the prediction markets to be accurate given the particular traders involved in the market: students. While it is not necessary to have people intimately knowledgeable of the market for a market to perform well (e.g. the Iowa Electronic Market accurately forecasted national election outcomes for years using only students and faculty at the University of Iowa), having participants with disparate beliefs and information is needed, as is the motivation to trade when one has increased confidence in their beliefs. Ideally, a prediction market constructed to forecast COF would include traders such as feedlot owners, analysts who forecast the number of COF, academic livestock economists, and the like. Alas, attracting a large enough sample of such individuals to participate in a prediction market to attain market liquidity would be no small challenge.

Week	Price elasticity
Feb. 13	12.89
Feb. 20	51.74
Feb. 27	–
Mar. 5	–
Mar. 12	−117.43
Mar. 26	−64.02
Apr. 2	−24.17
Apr. 9	−12.61
Apr. 16	−12.24

Table III. Estimated price elasticity of demand inferred from prediction market prices

More generally, Wolfers and Zitzewitz (2006) have discussed a variety of challenges with prediction markets including:

- attracting uninformed traders whose motivation to participate in the market is non-economic;
- mechanism design;
- market manipulation by highly informed participants;
- potential miscalibration due to difficulties in distinguishing between small probabilities; and
- separating correlation from causation.

In regard to mechanism design, most of the commercial prediction markets in operation (e.g. see www.intrade.com) use an on-line form of a continuous open outcry auction, where buyers and sellers post bids and asks which can be accepted at any time by any other buyer or seller. Most of the experimental economics research suggests that such continuous auctions are more efficient than the one-shot uniform price auctions that we used in our class-room experiment (Smith, 1991). In our case, we chose the sealed bid uniform price because it provided market liquidity since all traders had to enter bids and asks at a given time each week. Moreover, the time involved in submitting the bids and asks using the uniform price mechanism was minimal and was accomplished in a matter of a few minutes each week. By contrast, a continuous auction requires market participants to take the initiative to log into a central web site, for example, to observe the outstanding bids and asks and to decide whether to transact. With such a mechanism, the trader has to continually re-visit the trading platform to remain engaged in the market.

While our results suggest that prediction markets are not perfect, we are optimistic that the results and discussion presented will spark additional research on the merits of the approach. The potential applications for prediction markets in agricultural economics are virtually limitless. For example, given the findings by Frank *et al.* (2008) that initial USDA market reports are irrational estimates of the final USDA numbers, it might be useful to utilize prediction markets to forecast the final, revised USDA numbers rather than the initial release figures. Alternatively, one could construct a prediction market to forecast the likelihood that an initial estimate will ultimately be revised within a given time frame. Just as we constructed contracts to measure the effect of COF reports on live cattle prices, future research could construct contracts to measure the effects of policies, such as passage of mandatory price reporting or country of origin labeling, or other events, such as a BSE outbreak effect on cattle prices.

Notes

1. Wolfers and Zitzewitz (2006) formally consider the conditions under which prediction markets provide accurate forecasts using an expected utility framework. They argue that having a balanced pool of perfectly informed and uninformed traders, creates the necessary conditions for reasonable equilibrium prices and thus, credible forecasts.
2. A successful prediction market need not have traders that are representative of the population at large (e.g. the Iowa Electronic Markets forecasted election outcomes better than polls even though the market was only initially comprised of students at the University of Iowa); only that the traders have diverse opinions and are motivated to trade. Another important characteristic of panelists is that they be reasonably knowledgeable of the issues at hand; however, research suggests they do not need to be experts. In fact,

experts often forecast worse than non-experts due to overconfidence, e.g. see the review in Surowiecki (2004). In any event, 78 percent of the students participating in this study were male, 9 percent were juniors, 65 percent were seniors, and 26 percent were graduate students. Although 61 percent stated they had a farm background, 61 percent said they had a limited knowledge of the cattle industry and futures markets.

3. Traders could make bids and/or asks on up to 100 contracts for each of the three contract types in each week.
4. If one had a longer time series of prediction market prices for the COF contract, an alternative way to calculate the elasticity of demand would be to regress live cattle futures prices against the COF prices.

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