

ESSAYS ON COMMODITY PRICE VARIABILITY

BY

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DISSERTATION

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## ABSTRACT

This dissertation consists of three papers that investigate different dimensions of commodity price variability which has increased dramatically in recent years.

The first paper analyzes recent volatility spillovers in the United States from crude oil to corn and ethanol markets using futures prices. Spillovers to both corn and ethanol markets are somewhat similar in timing and magnitude, but moderately stronger to the ethanol market. The shares of corn and ethanol price variability directly attributed to volatility in the crude oil market are generally between 10%-20%, but reached nearly 45% during the financial crisis when world demand for oil changed dramatically. Volatility transmission is also found from the corn to the ethanol market, but not the opposite direction. The findings provide insights into the extent of volatility linkages among energy and agricultural markets in a period characterized by strong price variability and significant production of corn-based ethanol.

The second paper investigates short-term price density forecasting procedures in the Lean Hog Futures Market. High price variability in agricultural commodities increases the importance of accurate forecasts. Density forecasts estimate the future probability distribution of a random variable, offering a complete description of risk. In this paper we develop short-term density forecasts of lean hog prices for the 2002-2012 period. For a two-week horizon, we estimate historical densities using GARCH models with different error distributions and generate forward-looking implied distributions, obtaining risk-neutral densities from the information contained in options prices. Real-world densities, which incorporate risk, are obtained by parametric and non parametric calibration of the risk-neutral densities. Then the predictive accuracy of the forecasts is evaluated. Goodness of fit and out-of-sample ac-

curacy comparisons indicate that real-world densities outperform risk-neutral and historical time series generated densities. This supports the notion that a risk premium exists even at a two-week horizon in the hog market and that market participants can use these forecast to develop a better understanding of the final distribution of prices.

In the final paper, we develop and evaluate quarterly out-of-sample individual and composite density forecasts for U.S. hog prices. Individual forecasts are generated from time series models and the implied distribution of USDA, Iowa State University, and University of Missouri outlook forecasts. Composite density forecasts are constructed using linear and logarithmic combinations, and several weighting schemes. Density forecasts are evaluated on predictive accuracy and goodness of fit. Logarithmic combinations using equal and mean square error weights outperform all individual density forecasts and all linear combinations. Comparison of the outlook forecasts to the best logarithmic composite demonstrates the consistent superiority of the composite procedure, and identifies the potential to provide hog producers and market participants with accurate expected price probability distributions that can facilitate decision making.

*To my Grandpa Arturo*

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# Chapter 1

## Introduction

Considerable research has been performed to identify the sources, effects, and implications of the surge in the recent price variability of agricultural commodity markets. Myers, Sexton, and Tomek (2010), Irwin and Sanders (2012), and Serra and Zilberman (2013), identify globalization, monetary policies, cross-market linkages, biofuel policies, speculation, the role of market microstructure, and electronic trading among the possible drivers of commodity price dynamics. However, no consensus exists about whether and to what extent these factors drive price variability. The complex nature of the variability complicates the analysis of its effects and effective management of additional risk on markets, food supply chains, and food security.

This dissertation is composed of three papers that investigate aspects of price variability, information that may be valuable to decision makers in these uncertain times. Evidence suggest a significant link between energy and agricultural markets exist in price levels, exacerbated by increased crude oil price movements and biofuel policies in the United States (Enders and Holt, 2013; Serra et al., 2011). However, relatively less is known about volatility linkages and its transmission.



The first paper studies how much of the price volatility of corn and ethanol can be explained by crude oil price volatility, and how does this relationship evolved in the period 2006-2011. Using weekly futures data, I estimate the conditional volatility of crude oil, corn, and ethanol prices using GARCH models, based on the residuals from a vector error correction model used to explain the relationship between corn and ethanol in levels. Results show that volatility spillovers from crude oil are significant, and particularly high during the financial crisis of 2008.

An important implication of the high variability in commodity prices is the increasing need to develop accurate forecast techniques to guide decision-making. Agricultural producers have traditionally relied on point forecasts, but in the current environment those may not fully characterize the nature of risk. The introduction of risk management instruments as VIX is evidence that information from higher moments of the distribution is important for risk management.

In this context, in the second paper I estimate and evaluate density forecasts, that provide information about the whole price forecast distribution. The focus of the analysis is on the lean hog market for the period 2002-2012, since considerable predictive research already exist in this market. Density forecasts are estimated from historical data using GARCH models, and from forward-looking procedures based on the information content of options prices that yield risk-neutral and risk-adjusted (real-world) densities. Density forecasts are evaluated by goodness of fit using the probability integral transform (PIT), and by out-of-sample predictive accuracy using Kullback-Leibler information criteria which reflect the extent which forecasts attain high-density values at the actual observations. The analysis

is performed using daily data and a two-week forecasting horizon. I find that real-world density predictions outperform forecasts generated using historical data, and non-calibrated risk neutral densities both in terms of goodness of fit and accuracy. Improvements obtained by the calibration from risk-neutral to real-world densities suggest that risk premiums may exist in the lean hog futures markets.

In the third paper, I study density forecasts and their combinations using longer horizons and quarterly cash prices. Although the importance of density forecasts for agricultural commodities has been recognized since the 1960s (Bottum, 1966), until today USDA and leading outlook programs only provide point prices forecasts or interval forecasts at the most. Density forecasts offer information about the uncertainty of predictions and a more precise description of risk to decision makers, which Clements (2004) notes increasingly is an indispensable part of forecasting and decision-making.

In addition, forecast combination has proven valuable for point forecasting, by improving over individual forecasts. In the case of density forecasting, composite procedures are still in development, and to date no studies exist that examine the usefulness of composite density forecast procedures in the agricultural commodity price literature. Therefore, I investigate the usefulness of newly developed density forecast, evaluation, and combination procedures for generating ex-ante distributions of quarterly hog prices using data from 1975 to 2010. Density forecasts with horizons up to three quarters ahead are generated from expert forecasts (USDA, Iowa State University, and the University of Missouri) using the implied distributions of their historical forecast errors. Also, forecasts based on historical data are generated using time series procedures.

Density forecast combination is performed using linear and logarithmic pooling with several weighting schemes. Evaluation and comparison of individual and composite density forecasts follow the same procedures used in paper two (goodness of fit and predictive accuracy). Results for density forecasts match those found in point forecasting literature in which performance of individual density forecasts can be improved by combination. However, performance strongly depends on the combination procedure and weighting scheme used. Logarithmic pooling outperforms linear pooling, and surprisingly the weighting scheme using a simple equal weighted of individual forecasts consistently outperforms more complicated combination procedures. This finding corresponds to the combination puzzle previously detected in point forecasting, that acknowledges the difficulty of identifying composite procedures that consistently. The findings show that a more complete description of price forecast distributions can be obtained with forecast density composite procedures. The procedures and analysis performed can be used to improve USDA and other hog outlook price forecasts.

# Chapter 2

## Volatility Spillovers in the U.S. Crude Oil, Ethanol, and Corn Markets

### 2.1 Introduction

Recently, agricultural commodity prices have exhibited considerable variability. Sumner (2009) argues that the percentage price increases for grains from 2006 through mid-2008 were among the largest in history. Then in the summer of 2008 prices fell sharply but recovered swiftly, and have exhibited unusually large and sustained volatility to the present (Wright, 2011). As seen in figure 2.1, from 1980 to 2005 historical corn volatility measured as the annualized standard deviation of daily percentage price changes was usually below 25%, but since 2006 it has increased, reaching levels above 40%. Prakash (2011) corroborates this volatility for corn as well as for other agricultural commodities using the implied volatility from options.

The current literature offers multiple possible reasons for the strong recent fluctuations in agricultural commodity prices (Baffes, 2011; Wright, 2011; Gilbert and Morgan, 2010; Irwin and Good, 2009). Researchers have identified rapid economic growth in developing

countries, underinvestment in agriculture, low inventory levels, supply shocks in key producing regions, fiscal expansion and lax monetary policy in many countries, the depreciation of the U.S. dollar, high energy prices, and the diversion of food crops into the production of biofuels as contributing to increased volatility. A focal point for understanding the increased price variability is the change in the relationship among energy and agricultural markets influenced by policies to stimulate ethanol production (Hertel and Beckman, 2011; Tyner, 2010; Muhammad and Kebede, 2009).

Energy costs have traditionally influenced agricultural markets, but with the growth in corn-based ethanol production as an energy source (figure 2.2), the relationships among these markets appear to have strengthened. Since ethanol is a substitute for petroleum-based motor fuel and corn is an input in ethanol production, general equilibrium economic models predict that equilibrium petroleum-based energy prices, ethanol, and corn can be viewed as jointly determined (Cui et al., 2011). However, petroleum-based energy markets are much larger than the ethanol and corn markets, suggesting in practice that the direction of causality should run from crude oil to the corn and ethanol markets. Indeed, considerable applied research has explored this hypothesis in domestic and foreign markets (Campiche et al., 2007; Balcombe and Rapsomanikis, 2008). Most studies focused on price level transmission (Serra et al., 2010) and on equilibrium analysis of alternative biofuel policy scenarios (Yano, Blandford, and Surry, 2010; Thompson, Meyer, and Westhoff, 2009).

Less attention has been paid to understanding price volatility (i.e., the conditional variance of price changes, which is viewed as risk), its transmission among these markets, and the degree to which volatility in the energy complex contributed to the recent variability in

agricultural commodity prices.

Volatility spillover occurs when price volatility in one market affects price volatility in others. We investigate volatility spillover from crude oil to corn and ethanol in U.S. markets in order to identify the degree to which systematic variability in oil prices has contributed to variability in corn and ethanol prices.

Zhang et al. (2009) find little evidence of linkages in either price-level or volatility among U.S. oil, ethanol, and corn prices for the period 1989-2007. In contrast, Wu, Guan, and Myers (2011), Du, Yu, and Hayes (2011), and Harri and Darren (2009) find significant volatility linkages between crude oil and corn prices in more recent years. However these researchers do not incorporate ethanol prices despite arguing that the relationship is largely explained by ethanol production. We complement this work by evaluating volatility spillovers to the ethanol market and identifying the direction and strength of the spillovers between corn and ethanol. Additionally, we extend the previous literature by examining these relationships during and after the 2009 financial crisis.

Using a trivariate model (Ng, 2000; Wu, Guan, and Myers, 2011), we find volatility linkages from crude oil market to corn and ethanol markets during 2006-2011, during which corn-based ethanol production accounted for 25-35% of total corn use. The volatility spillovers are particularly strong when the oil market price plummeted during the financial crisis, with higher impact in the ethanol market than in the corn market. Significant spillovers also existed from the corn to ethanol market. The strong linkages among these markets, mixed with high price volatility, create new sources of uncertainty for market participants and policy makers. High volatility results in greater costs for managing risks in productive activities,

complicates price discovery and investment choice, and ultimately may affect the cost of food in domestic and world markets.

## **2.2 Background and Previous**

Studies by Tothova (2011) and Hertel and Beckman (2011) illustrate that crude oil and agricultural commodity prices exhibited relatively low or even negative correlation prior to 2006. However, the combination of high oil prices and ethanol policies has fueled the growth of the ethanol industry, which currently consumes nearly one third of corn produced in the United States. Ethanol production in the United States increased from 3.4 billion gallons in 2004 to 13.8 billion gallons in 2011, while the price of corn doubled. Virtually all ethanol produced is blended into gasoline, contributing 13.19 billion gallons to the 138.50 billion gallons of gasoline consumed in the United States in 2010 (U.S. Energy Information Administration, 2012).

Policy has played a crucial role in stimulating ethanol production growth. Import tariffs and blenders fuel tax credits (per gallon tax credit was \$.51 per gallon before 2009 and \$.45 per gallon after 2009) made added output attractive to refiners. Legislation to improve energy security and to reduce air pollution was key to ethanol market expansion (Muhammad and Kebede, 2009). The Energy Policy Act in 2005 established the Renewable Fuel Standard (RFS) program which mandated that a minimum of 7.5 billion gallons of renewable fuels be incorporated into gasoline supply by 2012. In December 2007, a new RFS was passed under the Energy Independence and Security Act, mandating renewable fuels production of 12 billion gallons by 2012 and 36 billion gallons by 2022.

Ethanol production also has been spurred by the need for an oxygenate to replace Methyl Tertiary Butyl Ether (MTBE) in gasoline blends. MTBE, a petroleum-based oxygenate, was blended with gasoline as a substitute for lead to prevent pre-ignition pinging and to reduce pollution. However, MTBE was banned by many states because of suspected links between cancer and groundwater contamination caused by fuel spills. The elimination of MTBE and its replacement by ethanol were accelerated by the 2005 Energy Policy Act, which made refiners continuing to use MTBE liable for claims (Serra et al., 2011). In the presence of these links among energy and agricultural markets, we expect volatility in crude oil prices to spill over into the corn and ethanol markets, creating volatility there as well.

Zhang et al. (2009) explore ethanol price volatility and its relationship with corn, soybean, gasoline, and oil in the United States by employing a multivariate GARCH framework and using weekly wholesale prices between 1989 and 2007. They split their data in two periods: 1989-1999 as the ethanol pre-boom stage and 2000-2007 as the ethanol boom period. Their results suggest no significant links among oil, ethanol, and corn volatilities in either period. Furthermore, they find no long-run relationships among agricultural and energy price levels.

Du, Yu, and Hayes (2011) investigate the spillover of crude oil prices to agricultural commodity prices using stochastic volatility models and weekly crude oil, corn, and wheat futures prices between November 1998 and January 2009. Consistent with Zhang et al. (2009), they find no evidence of spillover for the earlier portion of their sample (through October 2006). However, between October 2006 and January 2009 the results indicate significant volatility spillover from the crude oil market to the corn market, which they explain by tightened interdependence between these markets induced by ethanol production.



Despite identifying the statistical link between these markets, the extent of the relationship was not clearly determined.

Wu, Guan, and Myers (2011) draw conclusions similar to those of Du, Yu, and Hayes (2011) using weekly data from January 1992 to June 2009. Using a model in which exogenous oil market shocks influence the corn market, they provide a metric to quantify the strength of the volatility spillovers and find evidence of significant spillovers from crude oil prices to U.S. corn spot and futures prices, particularly after the introduction of the Energy Policy Act of 2005. Harri and Darren (2009) also provide insights to the mean and variance dynamics among futures prices of crude oil, corn, and a proxy for exchange rates with daily observations from April 2003 until March 2009. They find significant volatility transmission and evidence of crude oil price variance causing variance of corn prices.

Equilibrium models and simulations have also been used to evaluate the ties among energy and agricultural markets. Many researchers have offered insights on the effects of price variability and the role of biofuel policies such as tax credits and mandates (e.g. Thompson, Meyer, and Westhoff (2009), Yano, Blandford, and Surry (2010), and Hertel and Beckman (2011)). Researchers have identified strong linkages among energy and agricultural markets, but their results do not analyze the relationship of ethanol price volatility to crude oil and corn volatilities under recent policy scenarios and market conditions.

## **2.3 Volatility Spillover Model**

To identify and measure volatility spillovers between crude oil (co), corn (c), and ethanol (th) markets, we use an approach similar to Ng (2000) and Wu, Guan, and Myers (2011) .

Here, an external crude oil shock generates spillovers to the corn and ethanol markets, while the corn and ethanol markets interact. The model is specified as:

$$\Delta co_t = E [\Delta co_t | I_{t-1}] + e_{co,t} \quad (2.1)$$

$$\begin{bmatrix} c_t \\ th_t \end{bmatrix} = \begin{bmatrix} E [c_t | I_{t-1}] \\ E [th_t | I_{t-1}] \end{bmatrix} + \begin{bmatrix} \varepsilon_{c,t} \\ \varepsilon_{th,t} \end{bmatrix} \quad (2.2)$$

$$\begin{bmatrix} \varepsilon_{c,t} \\ \varepsilon_{th,t} \end{bmatrix} = \begin{bmatrix} \varphi_t \\ \omega_t \end{bmatrix} e_{co,t} + \begin{bmatrix} e_{c,t} \\ e_{th,t} \end{bmatrix} \quad (2.3)$$

in equation 2.1 the change of crude oil prices  $\Delta co_t$  ( $\Delta$  is the first difference operator), equals a conditional expected change in crude oil prices formed with information at  $t - 1$ ,  $I_{t-1}$ , plus random shock  $e_{co,t}$ . Equation 2.2 defines corn and ethanol prices at time  $t$  as the sum of the conditional expectations of prices formed with information at  $t - 1$ ,  $I_{t-1}$ , plus random shocks  $\varepsilon_{c,t}$ ,  $\varepsilon_{th,t}$ . Equation 2.3 defines the random shocks of corn and ethanol prices, which correspond to the sum of two terms; the first is the product of the exogenous random shock of crude oil,  $e_{co,t}$ , and the respective spillover coefficient,  $\varphi$  and  $\omega$ , for each market. The second terms are the idiosyncratic errors of corn and ethanol  $\mathbf{e}_t = [e_{c,t}, e_{th,t}]$ , which can be mutually correlated but are uncorrelated to the crude oil innovation. Hence, the overall behavior of price shocks in the corn and ethanol markets,  $\begin{bmatrix} \varepsilon_{c,t} \\ \varepsilon_{th,t} \end{bmatrix}$ , is affected by shocks in the crude oil market and in their own markets, which are not independent of each other but do not affect the crude oil market.<sup>1</sup>

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<sup>1</sup>This reflects the notion that an OPEC announcement can impact corn and ethanol markets, and that weather information for the growing period in South America may affect U.S. corn and ethanol markets, but

To identify the overall effect, we need to specify the structure of the conditional variances for crude oil (i.e.,  $e_{co,t}$ ) and the relationship between the conditional variances in the corn and ethanol markets (i.e.,  $\mathbf{e}_t = [e_{c,t}, e_{th,t}]$ ) over time. We specify these as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{co,t-1}^2 + \lambda_1 d_{t-1} e_{co,t-1}^2 + \alpha_2 \sigma_{t-1}^2 \quad (2.4)$$

$$H_t = C'C + A'e_{t-1}e'_{t-1}A + B'H_{t-1}B \quad (2.5)$$

where  $H_t$  is the BEKK conditional volatility,  $C$  is an upper triangular matrix that corresponds to the constant,  $e_{t-1}e'_{t-1}$  are the squared lagged errors,  $A$  is the matrix of ARCH parameters,  $H_{t-1}$  is the lagged conditional volatility, and  $B$  is the matrix of GARCH parameters.<sup>2</sup> Equation 2.4 models crude oil price volatility as a univariate Asymmetric Generalized Autoregressive Conditional Heteroskedasticity model (GJR-GARCH) introduced to the literature by Glosten, Jagannathan, and Runkle (1993). This model allows asymmetry on the random shock, where  $d_{t-1}$  is a dummy variable that takes a value of 1 if  $e_{co,t-1} \leq 0$  and 0 otherwise. The volatility of the errors  $e_{c,t}$  and  $e_{th,t}$  is specified using the Baba, Engle, Kraft and Kroner (BEKK) specification of a multivariate GARCH which has two desirable characteristics. It is positive definite by construction and it allows the estimation of the volatility spillovers between corn and ethanol. Equation 2.5 defines The BEKK GARCH model.

To identify more clearly how the corn and ethanol volatilities interact and to see how corn and ethanol volatilities are influenced by the volatility in the oil market, first consider the bivariate BEKK GARCH from equation 2.5:

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South American weather is highly unlikely to affect the oil market.

<sup>2</sup>Asymmetry of the GARCH BEKK was not supported using a LM test.

$$\begin{aligned}
\begin{bmatrix} h_{cc,t} & h_{cth,t} \\ h_{thc,t} & h_{thth,t} \end{bmatrix} &= \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} + \\
\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} e_{c,t-1}^2 & e_{c,t-1}e_{th,t-1} \\ e_{th,t-1}e_{c,t-1} & e_{th,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} &+ \\
\begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} h_{cc,t-1}^2 & h_{cth,t-1} \\ h_{thc,t-1} & h_{thth,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} &
\end{aligned}$$

Matrix multiplication leads to:

$$\begin{aligned}
h_{cc,t} &= c_{11}^2 + a_{11}^2 e_{c,t-1}^2 + 2a_{11}a_{21}e_{c,t-1}e_{th,t-1} + a_{21}^2 e_{th,t-1}^2 + b_{11}^2 h_{cc,t-1} + \\
&2b_{11}b_{21}h_{cth,t-1} + b_{21}^2 h_{thth,t-1}
\end{aligned} \tag{2.6}$$

$$\begin{aligned}
h_{thth,t} &= c_{12}^2 + c_{22}^2 + a_{12}^2 e_{c,t-1}^2 + 2a_{12}a_{22}e_{c,t-1}e_{th,t-1} + a_{22}^2 e_{th,t-1}^2 + b_{12}^2 h_{cc,t-1} \\
&+ 2b_{12}b_{22}h_{cth,t-1} + b_{22}^2 h_{thth,t-1}
\end{aligned} \tag{2.7}$$

where  $h_{cc,t}$ , and  $h_{thth,t}$  are conditional idiosyncratic volatilities of corn ( $c$ ) and ethanol ( $th$ ),  $h_{cth,t}$  is the conditional covariance, and  $e_{ij,t}(i, j) = c, th$  are the lagged own squared and cross-market random shocks. Taking the square of equation 2.3 and under the assumption of no correlation between  $e_{co,t}$  and  $e_t$  the conditional variances of ethanol and corn are given by:

$$E(\varepsilon_{c,t}^2 | I_{t-1}) = h_{cc,t} + \varphi^2 \sigma_t^2 \tag{2.8}$$

$$E(\varepsilon_{th,t}^2 | I_{t-1}) = h_{thth,t} + \varphi^2 \sigma_t^2 \tag{2.9}$$

where the significance of  $\varphi^2$  and  $\omega^2$  determine whether volatility spillovers from crude oil markets exist. Volatility spillovers between corn and ethanol are determined by the signs and significance of the terms in equations 2.6 and 2.7.

## 2.4 Data and Preliminary Analysis

Data are the nearby mid-week closing futures (Wednesday) log prices of crude oil West Texas Intermediate (CO) from NYMEX, ethanol (TH) from CBOT, and corn (C) from CBOT for the period July 30, 2006 to November 9, 2011.<sup>3</sup> This corresponds to the period of strong demand for corn-based ethanol production, and sharp and substantial changes in oil prices.

Crude oil, corn, and ethanol prices are available for differing contract months. To develop a conformable and continuous price series, we use the closing prices of the contract months for the commodity with the fewest contracts, which is corn. The corn market has five contracts maturing in December, March, May, July, and September. As the contract comes to maturity, the series is rolled forward to the price of the next closest contract. We do this on the third business day prior to the 25th calendar day of the month preceding the delivery month to avoid price anomalies that can sometimes occur in the delivery month. Since a portion of the analysis requires differenced data which are useful to examine, we define weekly percentage price changes, called returns, as  $R_t = \log P_t - \log P_{t-1}$ . These are computed by using the closing prices of futures contracts.<sup>4</sup>

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<sup>3</sup>Dahlgran (2010) argues despite an open interest that is a small fraction of annual US usage, the ethanol futures contract is reflective of market conditions. In our analysis, we explored the robustness of our findings looking at daily, weekly, and weekly average data to assess the potential effects of limited liquidity in the ethanol market. The results are very similar.

<sup>4</sup>The term “returns” is used in the literature to refer to the percentage change in value of holding an asset

Figure 2.3 shows the prices divided by their own means, which allows us to graph the price series on the same scale. Table 1 presents summary statistics of log prices and returns. The coefficients of variation of ethanol prices and returns are higher than those for crude oil and corn, suggesting that ethanol exhibits higher volatility. The means of the returns are virtually zero, and skewness results suggest that prices and returns are relatively symmetrically distributed. Excess kurtosis indicates that prices are not normally distributed.

Figure 2.4 illustrates the prices and returns dynamics of crude oil, ethanol, and corn. Crude oil displayed a positive trend in prices beginning at the end of 2006 until summer 2008, followed by a steep decrease lasting until spring 2009. The financial crisis that dampened worldwide demand for oil was one of the main causes of the sharp decline. However, crude oil prices rebounded and by fall 2009 were back to 2006 observed levels. Since that point, crude oil prices have exhibited considerable variability. Returns variability for crude oil is high and clustered during the price decline and recovery.

Corn and ethanol prices and their returns exhibit similar dynamics to crude oil, particularly from fall 2007 to the end of 2008. Corn prices fell sharply in fall 2008, similar to crude oil prices, until spring 2009. During 2009 and part of 2010 prices appeared to move within a band, but in summer 2010 they escalated again. By 2011 prices were near the same levels observed prior to the financial crisis. Ethanol prices follow a similar patterns, but exhibit more price variability during 2009 and 2010. Despite the difference in variability, more co-movement between ethanol and corn prices appears to exist starting in fall 2007. Similar to crude oil returns, corn and ethanol returns exhibited more volatility during the steep decline

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for a period of time, and here is synonymous with the weekly percentage price change.

in prices. Table 2.1 shows significant and substantial correlations between prices and returns, in particular a strong correlation between corn and ethanol.

We perform Augmented Dickey Fuller (ADF) and Phillips-Perron unit root tests. Results suggest that the prices are nonstationary, but returns are stationary.<sup>5</sup> Lags for the ADF test were chosen by AIC model selection criterion, and the ACFs and PACFs also were examined to ensure the residuals were white noise.

Table 2.2 shows the results of the Johansen test of cointegration for the three bivariate relationships. The test strongly rejects the null hypothesis of no cointegration between corn and ethanol prices, supporting the presence of a long-run equilibrium relationship between these two markets. We cannot reject the null hypothesis of no cointegration at the 10% level for the other two bivariate relationships: crude oil-ethanol and crude oil-corn.

## 2.5 Estimation

For equation 2.1, the first difference of crude oil log prices, we include three own lags to obtain white noise residuals, which are used to estimate equation 2.4. For equation 2.2, a vector error correction model (VECM) is estimated since there is strong evidence of cointegration between corn and ethanol. Findings from Mallory, Irwin, and Hayes (2012) also support a long-run equilibrium relationship between ethanol and corn. Model selection criterion (AIC) is used to determine lags; the VECM is represented as:

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<sup>5</sup>Test results are available from the authors. Lags for the ADF test were chosen by AIC model selection criterion, and the ACFs and PACFs also were examined to ensure the residuals were white noise.

$$\Delta c_t = \pi_1 ECT_{t-1} + \sum_{i=1}^2 \beta_i \Delta c_{t-i} + \sum_{i=1}^2 \gamma_i \Delta th_{t-i} + \varepsilon_{c,t} \quad (2.10)$$

$$\Delta th_t = \pi_2 ECT_{t-1} + \sum_{i=1}^2 \delta_i \Delta c_{t-i} + \sum_{i=1}^2 \phi_i \Delta th_{t-i} + \varepsilon_{th,t} \quad (2.11)$$

where  $ECT_{t-1}$  denotes the error correction term. Estimating equations 2.10 and 2.11 generates residuals that are the estimates of the corn and ethanol shocks presented in equation (3). These are used to jointly estimate equations 2.3 and 2.5 using a quasi maximum likelihood procedure. While not efficient, this two-stage procedure is asymptotically consistent and is commonly used because it avoids convergence and local maxima problems (Silvennoinen and Terasvirta, 2009).

For equations 2.10, 2.11, and (for consistency) 2.1., we used the continuous price series described earlier. The procedure used to generate the series can create artificial jumps in the data that correspond to the rollover dates, which could potentially affect the results. As identified by Carchano and Pardo (2009), there is no established method to account for the rollover effect when creating a continuous price level series. Here we follow Bessler and Covey (1991) and Franken, Parcell, and Glynn (2011) to assess the potential effects. To test whether the jumps at contract rollover affect our results, we include dummy variables for the rollover dates in the cointegration tests, the corresponding vector error correction model, and in the GJR-GARCH and BEKK estimations. We find the dummy variables to be insignificant in general and to have no effect on the results of the analysis.

Based on the characteristics of the series, we assume the error process for equations



2.4 and 2.5 follow a t-distribution and allow the quasi maximum likelihood procedure to obtain the shape of the distribution that provides the best fit to the series. Diagnostic tests, including portmanteau test, ARCH-LM, normality, and inspection for stationarity (i.e., modulus of the eigenvalues), suggested no misspecification.<sup>6</sup> For equations 2.6 and 2.7 we take the product of the matrix multiplication of equation 2.5 For equations 2.6 and 2.7, we take the product of the matrix multiplication of equation (5) and compute its standard errors using the delta method. The calculations of equations 2.8 and 2.9 follow directly from the estimated results.

## 2.6 Estimation Results

The GJR-GARCH is used to estimate the conditional volatility of crude oil. Results in table 2.3 suggest asymmetry in the ARCH component of the model. Negative innovations generate a bigger impact on volatility than positive shocks; in this case,  $\lambda_1$  is not only larger than  $\alpha_1$ , but  $\lambda_1$  is highly statistically significant, while  $\alpha_1$  is not. The GARCH component indicates that the random shocks have a significant and relatively long-lasting effect. The conditional standard errors of the crude oil market are plotted in figure 2.5. The largest conditional volatility is observed during the financial crisis at the end of 2008 and the recovery period in spring 2009. Table 2.4 presents the results of the vector error correction model and Granger causality tests.

Results indicate unidirectional Granger causality from corn to ethanol prices. Diagnostic tests of the VECM show no evidence of autocorrelation, but there is evidence of ARCH

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<sup>6</sup>Diagnostic tests are available from the authors on request.

effects.

The results in table 2.5 provide the estimates of the price shocks spillovers from crude oil to corn,  $\varphi$ , and crude oil to ethanol,  $\omega$ , with the BEKK coefficients of the idiosyncratic errors of corn and ethanol. Strongly significant spillover coefficients confirm the existence of volatility linkages from the crude oil market, with spillovers to corn being higher than the spillover to ethanol.

## 2.7 Volatility Spillover Ratios

We measure the strength of the volatility transmission from crude oil to corn and ethanol by calculating volatility spillover ratios, which are defined as:

$$\frac{\varphi^2 \sigma_t^2}{h_{cc,t} + \varphi^2 \sigma_t^2} \in [0, 1] \quad (2.12)$$

$$\frac{\omega^2 \sigma_t^2}{h_{th,t} + \omega^2 \sigma_t^2} \in [0, 1] \quad (2.13)$$

Figure 2.5 plots these ratios, which measure the portion of the conditional variability in corn and ethanol prices attributable to crude oil price shocks at different points in time. The spillover effect from the crude oil to corn and ethanol follows the dynamics of the conditional volatility of crude oil. During the period of analysis, volatility spillover ratios from crude oil averaged 14% for corn and 16% for ethanol, displaying a large range between 4% and 44%. However, the histograms (figure 2.6) and summary statistics of the spillover ratios (table 2.6) –in particular their interquartile ranges– suggest that during the period 2006-2011 crude oil shocks have consistently been responsible for 10% to 20% of the conditional volatility of corn and ethanol.

Further, figure 2.5 shows that particularly after the 2009 financial crisis period, volatility spikes in crude oil seem to be closely linked to the peaks in spillover ratios, occasionally reaching more than 20%. Virtually all the spillover ratios higher than 20% took place after the sharp decline of oil prices in 2008. This is more noticeable for ethanol, where its interquartile range shows that spillover ratios higher than 18% took place in 25% of the occurrences. It is clear that ethanol and corn volatilities are strongly influenced by crude oil volatility and tend to move together. Although the spillover ratios to ethanol and corn seem similar in size, ethanol exhibited higher ratios during most of the sample period.

To investigate the volatility spillovers between the corn and ethanol markets, we calculate the parameters of equations 2.6 and 2.7. The top of table 2.8 provides the corn conditional variance,  $h_{cc,t}$ . Most of the volatility in corn is market specific, since the effect of the own lagged squared errors,  $a_{11}^2$ , and the conditional lagged variance,  $b_{11}^2$ , are highly significant. Ethanol does not affect corn volatility since coefficients  $a_{21}^2, 2a_{11}a_{21}, 2b_{11}b_{21}$  are not significant. The bottom of table 2.8 provides the ethanol conditional variance,  $h_{tht,t}$ . Here, own significant GARCH effects exist. The coefficients  $2a_{12}a_{22}$  and  $2b_{12}b_{22}$  show strong spillovers from corn to ethanol volatility.

To further investigate the interactions between corn and ethanol, we provide their conditional correlations obtained from the GARCH BEKK (figure 2.7). Although time varying, the correlations suggest a stronger relationship between corn and ethanol markets, particularly starting in 2008. This is consistent with the observed similarity in spillovers from crude oil to the two markets and the cointegrating relationship estimated; it is evident that these markets have been closely related in recent years.

Finally, to identify the economic magnitude of the increased risk associated with the volatility spillovers for participants in corn and ethanol markets, consider their impact on the price of a corn option (table 2.7). Begin with the price of an at the money call option on a corn futures contract six months from maturity that is trading at \$5.00 per bushel. In the absence of volatility spillover from the oil market and annualized volatility in the corn market of 25%, the Black-Scholes price of the option is \$0.34 per bushel. Here, we estimated that a typical spillover during the period 2006-2011 from oil to corn was approximately 15%. This translates into an annualized corn volatility of 28% with the option price increasing from \$0.34 to \$0.39 per bushel. Therefore, a typical spillover represents an increase on cost of the option of 14% from the baseline, which is equivalent to \$250 per contract. During the height of the volatility, we estimated that spillovers from the oil to the corn market were nearly 45%. In this case the at the money call option price increases from \$0.34 to \$0.47 per bushel, which represents an increase of 38% in the cost of the option. This translates into a \$650 per contract increase in the cost of the option due to volatility spillover from the oil market during the financial crisis.

## **2.8 Conclusions and Remarks**

Using a trivariate model, we identify volatility spillovers from the crude oil futures market to ethanol and corn futures markets during 2006-2011, a period when corn-based ethanol production reached 25-35% of total corn use and the oil market experienced dramatic changes. We find strong and varying volatility transmission from crude oil to the corn and ethanol markets, with moderately more intense effects emerging in the ethanol market. The effect of

crude oil price volatility on corn and ethanol averaged almost 15%, but reached 45% during periods of high variability in the crude oil market. At the maximum, the added volatility as a result of the spillover would have resulted in a 38% cost increase to users of corn options. Spillovers also existed from the corn to ethanol market but there was no evidence of spillovers from ethanol to corn. This transmission is consistent with causality tests performed on the level data, and with the idea that the corn market is able to absorb short-run shocks in demand from the energy sector more readily than the ethanol market because grain can be reallocated from other uses such as exports, feed, food, and stocks. Evidence from the cointegrating relationship, the changes in conditional correlations (particularly after mid-2008), and the systematic nature of the spillovers from the crude oil market indicate that the corn and ethanol markets have been closely connected during the period.

In light of the increased variability, risk management strategies become more important to decision makers. For private decision makers there is evidence that instruments such as the futures market still can offer hedging opportunities (Wu, Guan, and Myers, 2011), but it is clear that the changing nature of the volatilities places a high value on the use of time-vary hedging strategies. Options strategies can also be powerful tools in an environment of high price volatility. For instance, a long straddle position that involves the simultaneous purchase of an at the money call option and a put option can be profitable when prices are rapidly changing. Recently, new risk management instruments such as Volatility Index Futures (VIX) for crude oil and corn also have been introduced at the Chicago Mercantile Exchange. VIX contracts are designed to manage short-term volatility, and their payoffs are determined by changes in volatility. Wang, Fausti, and Qasmi (2012) argue that the Corn

VIX will improve volatility forecasting and enhance market participants' ability to more accurately gauge price risk in the corn market. Over-the-counter variance swaps allow users to trade future realized volatility against current implied volatility. It remains to be seen if the liquidity and performance of these instruments will be sufficient for managing this added market risk.

Developing an understanding of magnitude and timing of market shocks is an important dimension of risk management. Clearly, the effect of crude oil price and biofuel policies on corn and ethanol price volatility is highly dependent on the market context. The main biofuels policy instruments during the period were the blender's tax credit, the Renewable Fuel Standard, and the import tariffs. The subsidy increased demand for ethanol, which in turn increased ethanol and corn prices. The import tariff limited competition with Brazilian ethanol and reduced the market's ability to handle potential unexpected supply disruptions. However, the tariff likely had only a small impact on price volatility during 2006-2011 (Babcock, 2011). In a forward context, the blender tax credit and the import tariffs were eliminated by the end of 2011. Under the mandate, a minimum quantity of ethanol must be consumed, regardless of fuel, corn, and ethanol prices. As processors respond to the changes in the oil market, increases in required ethanol production over time may support the added volatility identified here. However, when the mandate is binding, corn feedstock demand sensitivity to ethanol and energy price shocks will be reduced (Yano, Blandford, and Surry, 2010).

Developing a sense of timing for risk management purposes may be more problematic, since it is difficult to anticipate shocks and their more lasting effects. Government policies

to promote market transparency by improving information and surveillance systems (e.g., IFPRI's Early Warning System) may enable better monitoring of market situations and permit quick response. In addition, since conditional volatility tends to cluster, the information of crude oil volatility combined with volatility spillover ratios to corn and ethanol can be seen as a step towards monitoring and anticipating volatility shocks and their transmission.

## 2.9 Tables and Figures

**Table 2.1:** Summary Statistics and Correlations

				Returns	Returns	Returns
	Crude Oil	Ethanol	Corn	Crude Oil	Ethanol	Corn
Num observations	274	274	274	274	274	274
Minimum	3.54	0.38	0.80	-21.23	-14.74	-16.89
Maximum	4.97	1.08	2.04	25.46	14.16	15.3
1st Quartile	4.18	0.51	1.29	-3.23	-2.43	-2.67
3rd Quartile	4.52	0.83	1.75	3.50	2.70	3.49
Mean	4.35	0.69	1.49	0.07	0.02	0.35
Median	4.36	0.67	1.39	0.46	0.04	0.75
Variance	0.07	0.03	0.08	0.30	0.19	0.26
SD	0.26	0.18	0.28	5.44	4.37	5.12
Skewness	-0.27	0.20	0.33	0.21	-0.18	-0.27
Excess kurtosis	0.18	-1.19	-0.75	3.28	0.98	0.66
Coef. Variation	0.06	0.27	0.19	74.79	232.6	14.65

Correlations			Returns	Returns
	Crude Oil	Ethanol	Crude Oil	Ethanol
Ethanol	0.64*		Ret. Ethanol	0.44*
Corn	0.66*	0.78*	Ret. Corn	0.36*

Notes: Crude oil, Ethanol, and Corn prices are in logs, and the returns are multiplied by 100.

An asterisk (\*) denotes significance at the 1% level.



**Table 2.2:** Johansen Cointegration Tests

a) Corn and Ethanol							
Cointegration Rank	Eigen	Trace Stat	Critical Value		Max Stat	Critical Value	
			95%	99%		95%	99%
None	0.098	32.09*	19.96	24.60	28.09*	15.67	20.20
At most 1	0.015	3.99	9.24	12.97	3.99	9.24	12.97
b) Crude Oil and Corn							
Cointegration Rank	Eigen	Trace Stat	Critical Value		Max Stat	Critical Value	
			95%	99%		95%	99%
None	0.039	16.08	19.96	24.60	10.55	15.67	20.20
At most 1	0.002	5.53	9.24	12.97	5.53	9.24	12.97
c) Crude Oil and Ethanol							
Cointegration Rank	Eigen	Trace Stat	Critical Value		Max Stat	Critical Value	
			95%	99%		95%	99%
None	0.008	8.95	19.96	24.60	6.39	15.67	20.20
At most 1	0.002	2.56	9.24	12.97	2.56	9.24	12.97

Notes: An asterisk (\*) denotes significance at the 1% level. Lag length was selected based on AIC.

**Table 2.3:** GJR-GARCH for Crude Oil

Variable	Coefficient	t-Statistic
$\alpha_0$	0.00	1.77
$\alpha_1$	0.00	0.43
$\lambda_1$	0.14*	2.11
$\alpha_2$	0.88*	15.78

Notes: An asterisk (\*) denotes significance at the 5% level.

**Table 2.4:** Vector Error Correction for Corn and Ethanol Prices

Dependent Variable:		$\Delta c_t$	
Variable	Coefficients	t-Statistic	
$\Delta Corn_{t-1}$	0.09	1.17	
$\Delta Corn_{t-2}$	0.02	0.23	
$\Delta Ethanol_{t-1}$	-0.17	-1.92	
$\Delta Ethanol_{t-1}$	0.15	1.69	
$ECT_{t-1}$	0.01	1.32	
Dependent Variable :		$\Delta th_t$	
Variable	Coefficients	t-Statistic	
$\Delta Corn_{t-1}$	0.17*	2.63	
$\Delta Corn_{t-2}$	0.05	0.73	
$\Delta Ethanol_{t-1}$	-0.11	-1.50	
$\Delta Ethanol_{t-2}$	-0.00	-0.05	
$ECT_{t-1}$	-0.01*	-3.07	
Test for Granger-causality:			
H0: Corn does not Granger-cause Ethanol			
Test statistic	3.67		
p-value	0.01		
H0: Ethanol does not Granger-cause Corn			
Test statistic	2.47		
p-value	0.06		

Notes: An asterisk (\*) denotes significance at the 1% level.

**Table 2.5:** BEKK GARCH

Variable	Coefficients	t-Statistic
$\varphi$	0.36*	6.85
$\omega$	0.30*	7.31
C(c,c)	0.03*	4.75
C(th,c)	0.02*	4.71
C(th,th)	0.00	0.00
A(c,c)	0.45*	4.32
A(c,th)	0.22*	2.34
A(th,c)	-0.12	-1.16
A(th,th)	0.24*	2.63
B(c,c)	0.78*	9.53
B(c,th)	-0.17*	-2.51
B(th,c)	-0.14	-1.18
B(th,th)	0.77*	6.58
$\varphi^2$	0.13*	3.42
$\omega^2$	0.09*	3.65

Notes: An asterisk (\*) denotes significance at the 1% level.

**Table 2.6:** Summary Statistics of Volatility Spillover Ratios

	Estimated Corn Spillover Ratio	Estimated Ethanol Spillover Ratio
Number of observations	271	271
Minimum	0.04	0.05
Maximum	0.43	0.44
1st Quartile	0.10	0.11
3rd Quartile	0.15	0.18
Mean	0.14	0.16
Median	0.12	0.14
SD	0.07	0.07
Skewness	2.01	1.55
Excess kurtosis	4.18	2.42

**Table 2.7:** Economic Magnitude of the Volatility Spillovers in the Corn Market

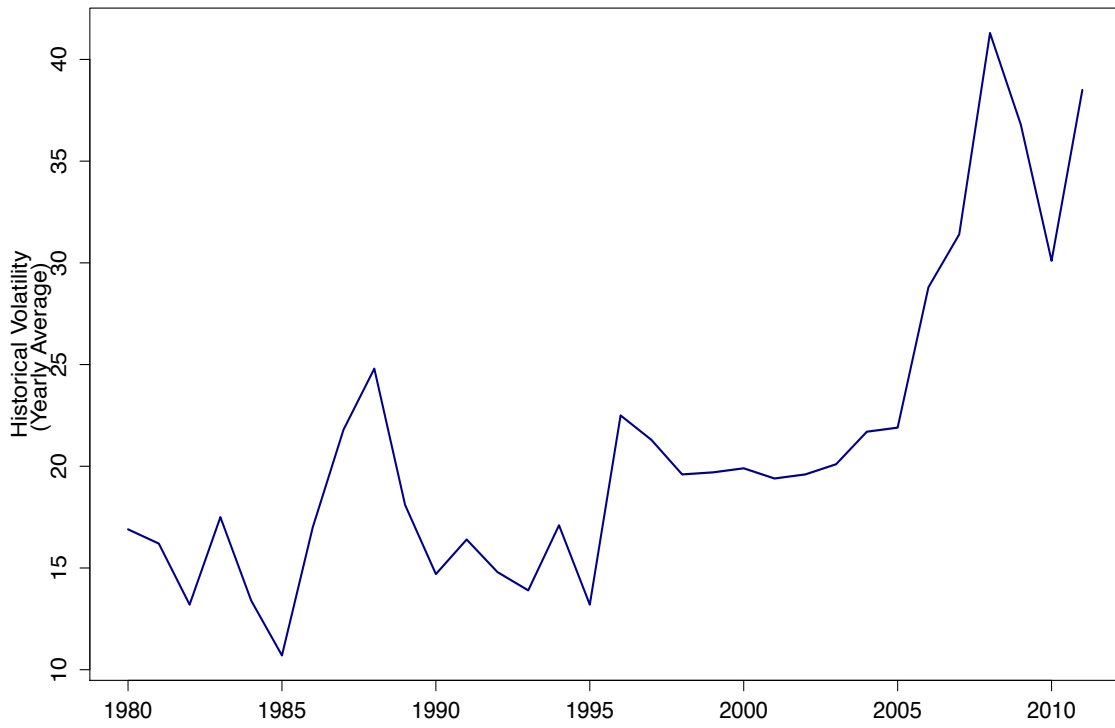
No Spillover from Oil	With 15% Spillover from Oil	With 15% Spillover from Oil
Corn B-S Call Price Volatility	Corn B-S Call Price Volatility	Corn B-S Call Price Volatility
25% \$0.34/bushel \$1,700/contract	28% \$0.39/bushel \$1,950/contract	34% \$0.47/bushel \$2,350/contract

Notes: The risk free interest rate = 5%, the corn futures price = \$5.00, and the strike price = \$5.00 for 6 months to maturity. The annualized corn conditional volatility =  $\sqrt{h_{cc,t} + \varphi^2 \sigma_t^2 \sqrt{52}}$

**Table 2.8:** BEKK Conditional Variances

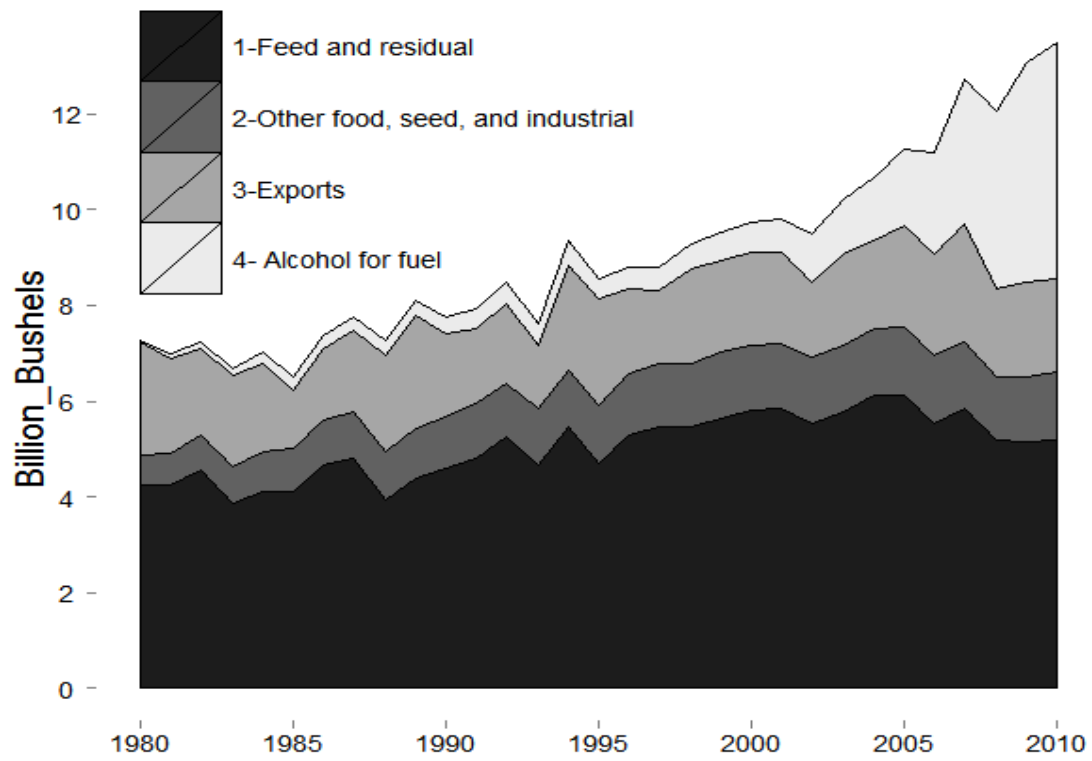
Conditional Variance of Corn								
	$c_{11}^2$	$a_{11}^2$	$2a_{11}a_{21}$	$a_{21}^2$	$b_{11}^2$	$2b_{11}b_{21}$	$b_{21}^2$	
Coefficients	0.00*	0.20*	0.2	0.01	0.62*	-0.22	0.02	
t-Statistics	2.38	2.16	1.58	0.58	4.76	-1.24	0.59	
Conditional Variance of Ethanol								
	$c_{12}^2$	$c_{22}^2$	$a_{12}^2$	$2a_{12}a_{22}$	$a_{22}^2$	$b_{12}^2$	$2b_{12}a_{22}$	$b_{22}^2$
Coefficients	0.00*	0.00*	0.06	0.11*	0.06	0.03	-0.27*	0.60*
t-Statistics	2.37	0	1.17	2.5	1.31	1.25	-2.82	3.29

Notes: An asterisk (\*) denotes significance at the 1% level.

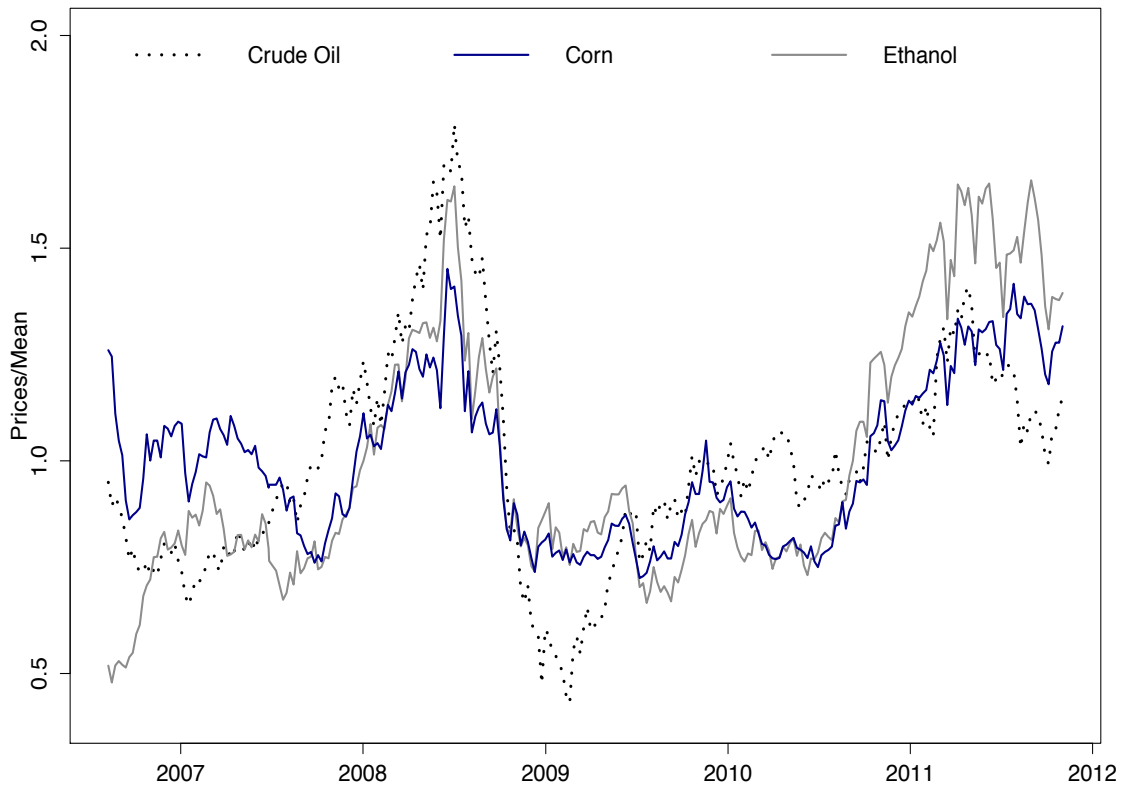


**Figure 2.1:** Annual Corn Volatility, 1980-2011

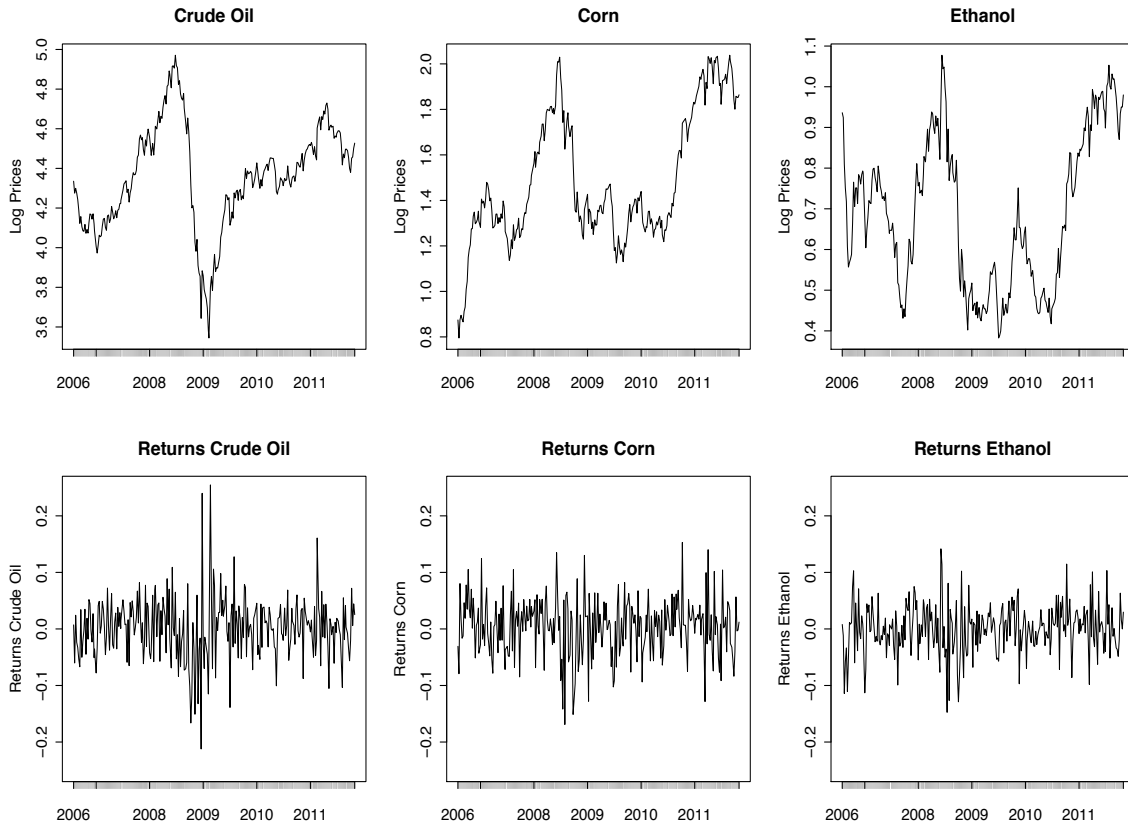




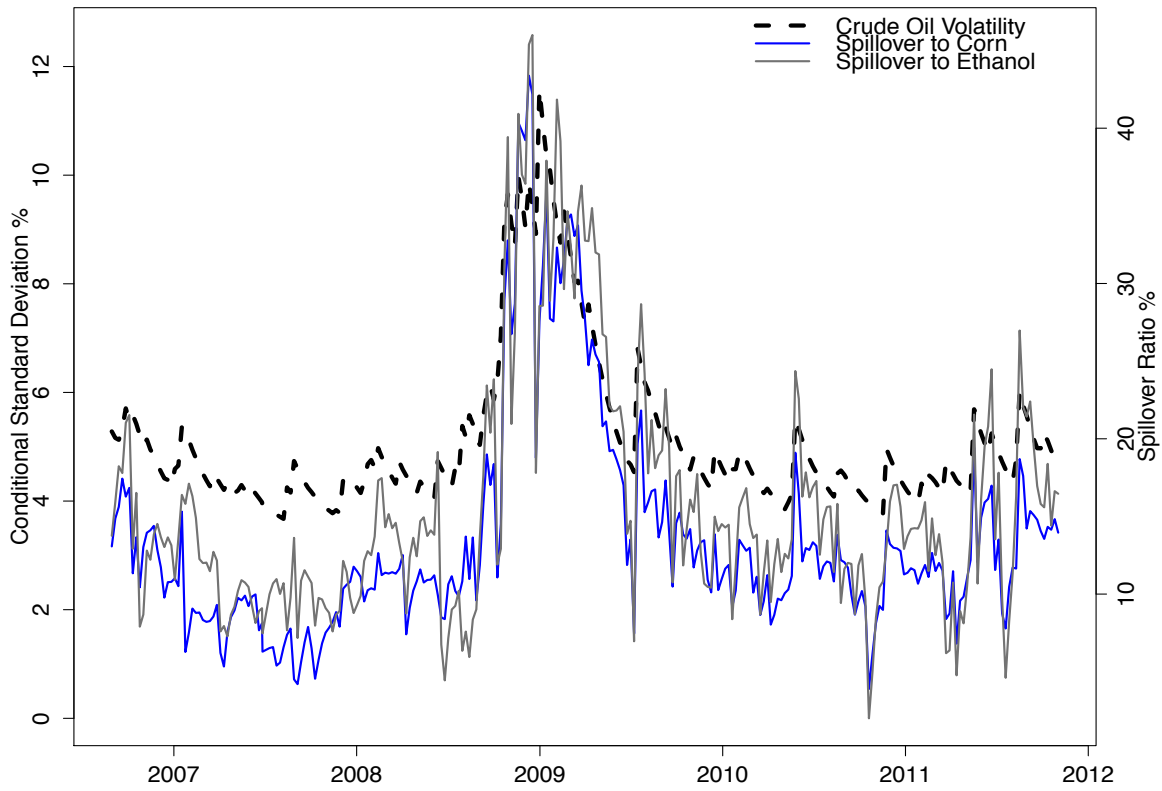
**Figure 2.2:** US Corn Use, 1980-2010



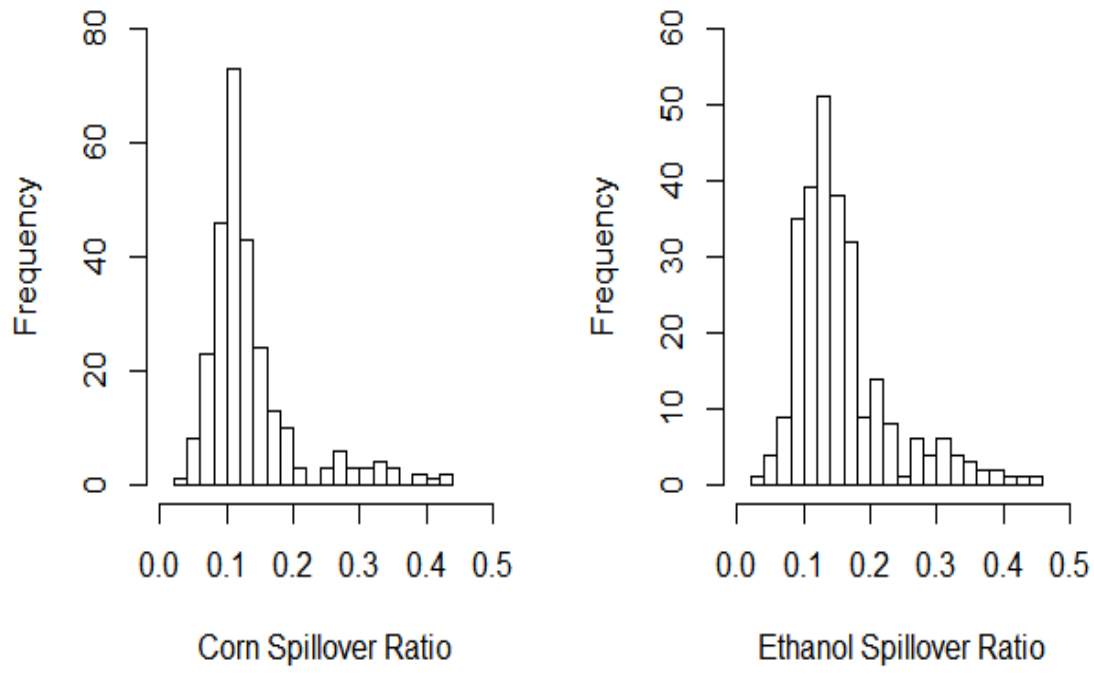
**Figure 2.3:** Prices Divided by Own Mean



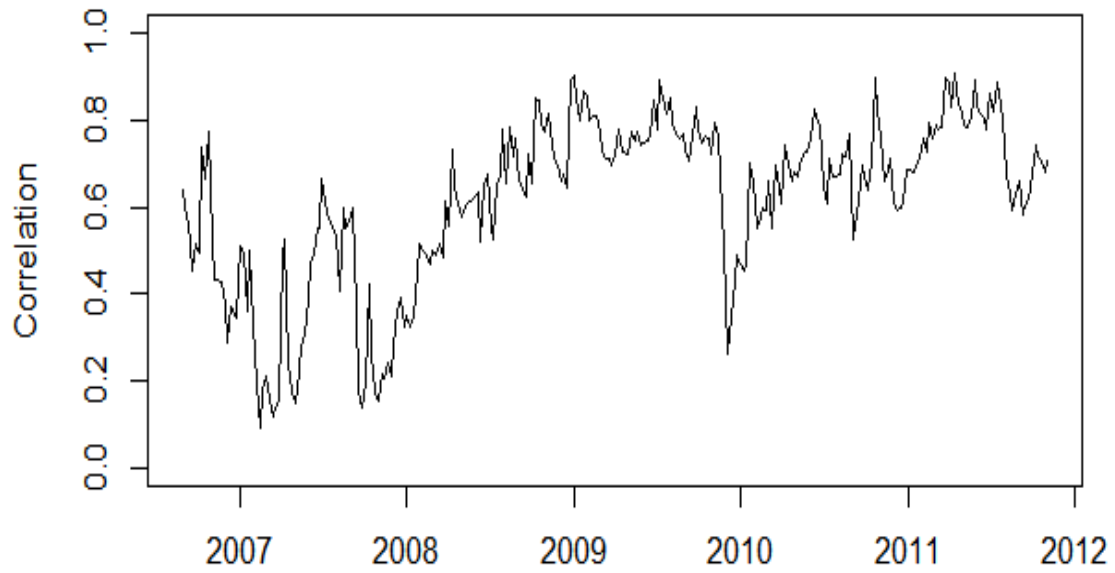
**Figure 2.4:** Log Price and Returns



**Figure 2.5:** Conditional Standard Error of Crude Oil and Corn and Ethanol Spillover Ratios



**Figure 2.6:** Histograms of Ethanol and Corn Spillover Ratios, 2006-2011



**Figure 2.7:** BEKK Correlation between Ethanol and Corn

# Chapter 3

## Short-term Price Density Forecasts in the Lean Hog Futures Market

### 3.1 Introduction

In recent years agricultural commodity markets have experienced heightened price variability. Wang, Fausti, and Qasmi (2012) and Wilson and Dahl (2009) identify that increased commodity price volatility has considerable implications on production, marketing, and risk management practices. In this volatile environment, Isengildina, Irwin, and Good (2004) argue that many individuals rely on forecasts in their decision making and that the value of agricultural forecasts can be substantial. However, traditional forecasting procedures based on a mean-variance framework may not fully characterize the nature of risk in volatile markets. In addition, agricultural prices and returns may exhibit non-Gaussian and non-linearity properties, particularly at higher frequencies (daily, weekly). Further, the preferences of agents in these markets are likely to differ from quadratic functions (Deaton and Laroque, 1992; Myers and Hanson, 1993; Koekebakker and Lien, 2004; Peterson and Tomek, 2005). In this context, estimating density forecasts, the future conditional probability distribution

of prices, offers a thorough description of future uncertainty and provides decision makers with more information than standard point forecasts.(Tay and Wallis, 2000; Timmermann, 2000).

Density forecasting procedures are not new, but it was not until the 1990s that significant interest began to emerge. Applications in macroeconomic forecasting by central banks, the development of Value at Risk measures for financial institutions, and increasing computational power stimulated their use. Pioneering work by Diebold, Gunther, and Tay (1998) promoted the development of density evaluation, which have seen widespread applications in econometrics, asset pricing, and portfolio selection (Amisano and Giacomini, 2007; Gneiting, 2008). For agricultural commodity prices, the importance of density forecasts was identified as early as Bottum (1966) and Timm (1966), who recommended the development of probabilistic outlook forecasts similar in form to those used in weather forecasting. Several papers have provided estimation procedures (i.e. (Sherrick, Garcia, and Tirupattur, 1996; Silva and Kahl, 1993)), yet the use of density forecasts for agricultural commodity prices has been limited.

The purpose of the paper is to estimate forecast densities for lean hog futures prices, and to assess their predictive power using recently developed evaluation measures. To generate density forecasts we employ two general procedures: one is based on historical data using GARCH models, and the second is a forward-looking procedure based on the information content of options prices which provides risk-neutral and risk-adjusted densities. To evaluate the out-of-sample forecast performance, we use the probability integral transforms (*PIT*) adopted by Diebold, Gunther, and Tay (1998), and the Berkowitz test introduced by



Berkowitz (2001). The models are compared using the out-of-sample log likelihood based on the Kullback-Leibler information criteria as suggested by Bao, Lee, and Saltoglu (2007). The analysis is performed with a two-week forecasting horizon using daily settlement futures prices and options prices for lean hogs from December 1996 to February 2012. The short-term nature of the forecast horizon reflects the observation that most market activity occurs in the nearby contract as hedgers and participants offset their market positions. The starting date of analysis corresponds to the switch in futures and options contracts from live to lean hog contracts, and from physical delivery to cash settlement.

We focus on the hog market because considerable predictive research already exists which may allow us to compare our findings to prior studies. For instance, the reliability of hog futures prices to accurately reflect subsequent cash prices has been a traditional area of market research. More recently researchers have begun to investigate the degree to which the implied volatilities from the hog options reflect subsequent realized volatility. While the recent evidence is mixed, the empirical findings using monthly and bimonthly observations (e.g., two and four months) suggest that futures prices provide long-run unbiased forecasts, but that short-run inefficiencies in forecasting may exist (McKenzie and Holt, 2002; Carter and Mohapatra, 2008; Frank and Garcia, 2009). In terms of the options market, Szakmary et al. (2003) and Egelkraut and Garcia (2006) identify biases in implied forward volatility forecasts of subsequent realized volatility. Historical volatilities also add information to the market generated implied volatilities in predicting realized volatility, implying options prices do not contain all available information or may not account adequately for risk. Similarly, McKenzie, Thomsen, and Phelan (2007) show that long hog straddle positions executed on

Hogs and Pigs Report days are profitable if transaction costs are under certain levels.

In contrast, Urcola and Irwin (2010) analyze market efficiency of lean hog options contract looking at several trading strategies such as options straddles and strangles. They find that returns on options are often small, and even large returns are not statistically significant. They conclude that returns are not sufficiently large enough to allow for consistent speculative profits for off-floor traders. Hence while the bulk of the evidence suggests that short-term biases in market prices and their volatilities may exist, developing strategies to take advantage of them may indeed prove challenging. Regardless, hog price density forecasts can play an important role in understanding spreads and assist traders in managing their daily risk. Packers and retailers interested on dynamic pricing and optimal inventories may be able to take advantage of information to develop pricing strategies or protect themselves from added volatility, skewness, and kurtosis. Accurate density estimates also can help exchanges to determine appropriate margins and daily price limits and permit a clearer understanding of the existence and magnitude of volatility and tail risk premiums. Higher price volatility can reduce the effectiveness of traditional risk managerial tools which may not be able to address the added variance and tail risk directly. As a consequence, instruments such as volatility index options and futures, which are used to trade and hedge short-term market volatility, are being implemented in agricultural markets. For instance, the CME introduced VIX (volatility index) contracts for corn and soybeans in 2011. Wang, Fausti, and Qasmi (2012) contend that these instruments will enhance market participants' ability to accurately gauge price risk and manage volatility risk. Effective pricing of these instruments requires knowledge of higher moments of the price distributions, suggesting that

density price forecasts may provide important inputs into the analysis, management, and pricing of these new tools. To date no research has investigated the ability to generate accurate forecast densities in the hog market using either historical information or market generated forecasts.

The findings are informative for forecasting and understanding the hog market. We find that historical time series based model with normal and student-t underlying distribution have a poor goodness of fit. But GARCH-GED, and the forward looking techniques are well calibrated. While no significant difference in terms of predictive accuracy (sharpness) between the best density forecast based on time series models (GARCH-GED) and the risk-neutral density (RND) exist, the risk-adjusted (real-world) densities are superior to both historical and risk-neutral densities in sharpness and goodness of fit. Improvements obtained by the calibration from risk-neutral to real-world densities suggest that risk premiums exist in the lean hog futures markets. A finding consistent with Szakmary et al. (2003), Egelkraut and Garcia (2006) and McKenzie, Thomsen, and Phelan (2007).

## **3.2 Density Forecast Estimation**

Following Taylor (2005), Liu et al. (2007), and Høg and Tsiaras (2011) densities are derived using two approaches, historical and implied. We obtain historical densities by estimating GARCH models and allowing the distributions of the standard errors to be characterized by alternate functional forms. Implied densities rely on extracting the information contained in the prices of option contracts, which should reflect aggregated risk-neutral market expectations on the underlying asset when the option contracts expire.

## 3.3 Historical Densities

### 3.3.1 Estimation

GARCH models of daily returns of lean hog futures prices are simulated in order to provide historical densities. For the in-sample specification of the mean and variance dynamics, we use the GJR-GARCH specification proposed by Glosten, Jagannathan, and Runkle (1993), which permits asymmetric volatility response to news and has been shown in various studies to reflect market reaction (e.g., Wu, Guan, and Myers (2011)). The model is:

$$r_t = \mu_0 + \sum_{i=1}^m \delta_i r_{t-i} + \varepsilon_t \quad (3.1)$$

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 I(\varepsilon_{t-1} < 0) + \beta h_{t-1} \quad (3.2)$$

$$\varepsilon_t = \sqrt{h_t} \eta_t, \eta_t \sim i.i.d \ D(0, 1) \quad (3.3)$$

In equation 3.1,  $r_t = \log(P_t) - \log(P_{t-1})$  corresponds to the logarithmic return of lean hog price  $P_t$ , which is equal to the sum of  $m$  lagged returns and the error term  $\varepsilon_t$ . In equation 3.2 the conditional variance of price returns  $h_t$  corresponds to past innovations  $\varepsilon_{t-1}^2$  plus the lagged conditional variance  $h_{t-1}$ . An asymmetric response emerges through an indicator function ( $I(\varepsilon_{t-1} < 0)$ ) that takes a value of 1 if ( $\varepsilon_{t-1} < 0$ ) and 0 otherwise. Equation 3.3 describes the error term as the product of the conditional standard deviation  $\sqrt{h_t}$  and a random error  $\eta_t$ , where  $D(0,1)$  is a zero mean unit variance probability distribution.

To provide flexibility, in addition to the standard normal (N), we consider other error distributions, including: a standardized t (T), a generalized error distribution (GED), a normal inverse Gaussian (NIG), and a generalized hyperbolic (GH). The last distributions allow for

skewness and kurtosis and permit a comprehensive representation of the density forecasts. For model selection, we use AIC and BIC criteria and misspecification tests on the standardized residuals from the estimated models, including autocorrelation and homoscedasticity. Tests generally pointed to the use a AR(5)-GJR-GARCH(1,1).<sup>1</sup> Although the GARCH component varied modestly in a few estimations, we maintain the GJR-GARCH(1,1) for model consistency following Høg and Tsiaras (2011). In support Bao, Lee, and Saltoglu (2007) find that the accuracy of density forecasts depends more on the choice of the distribution than on lags of the conditional variance.

### 3.3.2 Simulation

The AR(5)-GJR-GARCH-based forecast densities are constructed using a procedure suggested by Taylor (2005). First, for a particular date  $t$ , we use the five most recent years of daily logarithmic returns to estimate the parameters of the model by maximum likelihood. By drawing a random number from distribution  $D$  and multiplying it by  $\sqrt{h_t}$  a set of new residuals  $\varepsilon_t$  are generated. These are used to update the conditional variance and then calculate simulated returns. This is repeated from time  $t$  until the forecast horizon  $t + n$ . In this paper  $n$  corresponds to ten business days that results in a density prediction of the final price of the futures/options contract two weeks before expiration. The simulated returns are compounded and are multiplied by the price at time  $t$  to generate the forecast,  $P_{t+n} = P_t \exp(r_{t+1} + r_{t+2} + \dots + r_{t+n})$ . To create the density forecast we repeat this process

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<sup>1</sup>The models are estimated in R using the package rugarch. Misspecification tests are available from the authors.

100,000 times.<sup>2</sup> To produce a smooth distribution we apply a Gaussian kernel density with bandwidth equal to  $0.9N^{-\frac{1}{5}}\sigma$ , where  $\sigma$  is the standard deviation of the forecast value and  $N$  the number of simulations.<sup>3</sup>

### 3.4 Risk-neutral Densities from Options

An option contract gives the holder the right to make a transaction on an underlying asset at a later date for a specific price (strike price). The owner of a call option has the right but not the obligation to buy the underlying asset, while the owner of a put option has the right but not the obligation to sell. Option prices contain useful information about aggregate market expectations that can be used to extract the implied distribution of future commodity prices. The price of a European call option is equal to the present value of its final payoffs, which allows us to write:

$$\begin{aligned}
 c(X) &= e^{-r_f T} E^Q[(S_T - X)] \\
 &= e^{-r_f T} \int_0^\infty \max(x - X, 0) f_Q(x) dx \\
 &= e^{-r_f T} \int_X^\infty \max(x - X) f_Q(x) dx
 \end{aligned} \tag{3.4}$$

where  $X$  is the strike price,  $c(X)$  is the price of the call option,  $S_T$  is the price of the underlying contract,  $r_f$  is the free risk rate,  $T$  is the time to maturity,  $f_Q$  is the risk-neutral probability distribution, and  $E^Q$  is an expectation. This holds for a complete set of exercise prices  $X \geq 0$ , and  $\int_0^\infty f_Q(x) dx = 1$ . Breeden and Litzenberger (1978) show that the existence

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<sup>2</sup>Bootstrapping techniques have also been used, examples include Rosenberg (2002) and Pascual, Romo, and Ruiz (2006).

<sup>3</sup>The results differ only negligibly after applying the Gaussian kernel density.

and uniqueness of a risk-neutral density  $f_Q$  can be inferred from European call prices  $c(X)$  from contracts with continuous strike prices and lack of arbitrage opportunities. The risk-neutral density (RND) is given by:

$$f(x) = e^{r_f T} \frac{\partial^2 C}{\partial X^2} \quad (3.5)$$

The estimation task is to find a risk-neutral density  $f_Q(x)$  that provides a reasonable approximation to observed market prices.

Several methods have been proposed to recover risk-neutral densities from option prices (See Jackwerth (2000) and Taylor (2005)). For instance Shimko (1993) estimates interpolations for the volatility smile, Melick and Thomas (1997) use log normal mixtures, and Aït-Sahalia and Lo (1998) follow non-parametric estimations. Examples in the agricultural economics literature include Fackler and King (1990), Sherrick, Garcia, and Tirupattur (1996), and Egelkraut, Garcia, and Sherrick (2007). We follow a similar approach but using the Generalized Beta distribution of the second kind (GB2) as the implied density as in Liu et al. (2007) and Høg and Tsiaras (2011).<sup>4</sup> In addition to its flexibility, Taylor (2005) advocates the use of the GB2 because its desirable characteristics including: the tails are fat relative to lognormal distributions, estimates are not sensitive to the discreteness in options prices, closed-form expressions for the probability density and cumulative distribution functions, and solutions and calibrations are relatively easy to obtain.

The GB2 density has four parameters  $\theta = (a, b, p, q)$ , allowing for the estimation of the

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<sup>4</sup>Sherrick, Garcia, and Tirupattur (1996) use the Burr-3 distribution which is a special case of the GB2.

mean, variance, skewness, kurtosis. Its probability distribution function is defined as:

$$f_{GB2}(x|a, b, p, q) = \frac{a}{b^a B(p, q)} \frac{x^{ap-1}}{[1 + (x/b)^{p+q}]}, x > 0 \quad (3.6)$$

with  $B(p, q) = \Gamma(p)\Gamma(q)/\Gamma(p+q)$  where  $\Gamma$  is the gamma function. The density is risk-neutral when the underlying futures price  $F$  is

$$F = E^Q[S_T] = bB(p + \frac{1}{a}, q - \frac{1}{a})/B(p, q) \quad (3.7)$$

To obtain the risk-neutral density, we find the parameter vector  $\theta$  that minimizes the sum of the squared differences between the observed market and theoretical option prices (Ji and Brorsen, 2009):

$$\min h(\theta) = \sum_{i=1}^n (C_{market}(x_i) - C(X_i|\theta))^2 + (P_{market}(x_i) - P(X_i|\theta))^2 \quad (3.8)$$

where  $C_{market}(x_i)$  and  $P_{market}(x_i)$  are the market call and put prices at the strikes  $X_i$ , and  $C(X_i|\theta)$  and  $P(X_i|\theta)$  are the theoretical prices at the strikes  $X_i$ . The theoretical prices are developed by replacing  $f_q$  by  $f_{GB2}(x|a, b, p, q)$  in equation 3.4 and by applying the constraint in equation 3.7. the European call option price is given by

$$c = (X|\theta) = e^{-r_f T} \int_x^\infty (x - X) f_{GB2}(x|\theta) dx \quad (3.9)$$

$$F e^{-r_f T} [1 - F_{GB2}(x|a, b, p + \frac{1}{a}, q - \frac{1}{a})] - X e^{-r_f T} [1 - F_{GB2}(x|\theta)]$$

where  $F_{GB2}$  is the cumulative distribution function of GB2 density. The functional form in equation (3.9) is used in the minimization problem, and the put is calculated using the



put-call parity condition.

### 3.5 From Risk-Neutral to Real-World Densities

A fundamental idea in pricing theory is that the value of an asset is equal to its expected discounted cash flows. Risk-neutral densities assume that risk is irrelevant for pricing future cash flows, but if an investor is risk-averse and rational then risk-neutral implied densities from option contracts are likely to provide inaccurate forecasts.

In fact, the difference between the risk-neutral-density and the objective forecast can be used to infer the degree of risk aversion of the representative agent (Bliss and Panigirtzoglou, 2004). A possible approach to adjust densities so that they incorporate risk is to assume a particular utility function and a degree of a risk aversion for the agent, as implemented for equity markets in Bakshi, Kapadia, and Madan (2003), and Liu et al. (2007). However, Høg and Tsiaras (2011) demonstrate that such simple transformations are usually problematic since the estimated stochastic discount factors generally do not match agents' expected risk aversion behavior.

In the case of agricultural commodity futures the situation seems even more complex than in equities because it has been difficult to establish if a risk premium exists. For instance, Frank and Garcia (2009) found no evidence of time varying risk premium on corn, soybean meal, and lean hogs at two- and four-month horizons. Egelkraut and Garcia (2006) looked at different forecasting horizons for volatility finding evidence that the lean hog markets may demand a risk premium for bearing volatility risk when volatility becomes less predictable. How volatility risk affects risk premium is also a puzzling question. Han (2011) argues that

risk premiums are positively related to volatility and negatively related to volatility risk, and it is the volatility risk premium that distorts the positive relation between the market risk premium and market systematic risk.

An alternative approach that avoids some of the previous difficulties involves the use of statistical methods. Real-world densities are obtained via statistical calibration of the risk-neutral densities that are viewed as misspecified. The procedure searches for a function that calibrates the risk-neutral density to the observed data without making assumptions about the utility functions purporting to represent investor's risk preferences (de Vincent-Humphreys and Noss, 2012). Fackler and King (1990) describe the calibration process as one that improves a set of densities judged against the assumption that the random variables defined by their cumulative distribution functions (cdf) are uniformly distributed.

The process described by Fackler and King (1990) follows the idea of a probability integral transform defined by Rosenblatt (1952). Let  $f(y)$  and  $F(y)$  denote the probability and cumulative distribution function of a random variable  $y$  and  $X$  corresponds to the actual realization of the random variable. The probability integral transform (*PIT*) is given by:

$$PIT = \int_{-\infty}^X f(y)dy \equiv F(X) \quad (3.10)$$

Rosenblatt (1952) shows that if  $X$  is a continuous random variable then PIT is a uniform random variable in the interval  $[0,1]$ . Therefore if the actual observed data  $X$  has been generated from function  $f(y)$  its PIT is distributed  $U(0,1)$ . We follow this strategy, using the approach of Fackler and King (1990) and Shackleton, Taylor, and Yu (2010) performing parametric and non-parametric density calibration.

We first obtain risk-neutral densities using the GB2 density, and link risk-neutral and real-world densities through a calibration function. Let  $f_Q(v)$  and  $F_Q(v)$  be the risk-neutral density and the risk-neutral cumulative distribution function of the underlying asset  $v$  at time  $T$ ,  $v_T$ . Denote  $G(u)$  as the real-world cumulative distribution of random variable  $U = F_Q(v_t)$ , and  $g(u)$  its first derivative. Then the real-world cumulative distribution function  $F_p(v)$  and probability density function  $f_p(v)$  of  $v_t$  are:

$$F_p(v) = G(F_Q(v)) \quad (3.11)$$

$$f_p(v) = \frac{dF_p(v)}{dv} = \frac{dG(F_Q(v))}{dv} = \frac{dG}{dF_Q} \frac{dF_Q}{dv} = g(F_Q(v))f_Q(v) \quad (3.12)$$

In effect, the real-world density is generated through point-wise multiplication of the calibration function and the option-implied risk-neutral density. Here, to estimate the real-world densities we use the risk-neutral densities obtained from the solution of equation 3.8,  $\theta_{GB2}$ , and use two calibration functions, a parametric function based on the Beta distribution, and a non parametric function based on a kernel density from the empirical distribution.

For parametric calibration we follow Fackler and King (1990) who also used the Beta distribution. As identified by de Vincent-Humphreys and Noss (2012) and Taylor (2005) this distribution has a number of advantages. It nests the uniform distribution and it allows for the risk-neutral and real-world measures to be identical without imposing transformation. The beta distribution also is parsimonious as it only depends on two parameters, but still it has a flexible shape that allows with simple transformation shifts in mean, variance, and skewness. Further, the parameters can be easily estimated by applying maximum likelihood.

If  $G(\cdot)$  is the cumulative distribution function of the Beta distribution defined as:

$$G(u|\alpha, \beta) = \frac{1}{B(\alpha, \beta)} \int_0^u s^{\alpha-1}(1-s)^{\beta-1} ds \quad (3.13)$$

$$\text{where } B(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha + \beta)}$$

then the calibration density  $g(\cdot)$  is its derivative

$$g(u|\alpha, \beta) = \frac{u^{\alpha-1}(1-u)^{\beta-1}}{B(\alpha, \beta)} \quad (3.14)$$

The parameters of the Beta density  $\alpha$  and  $\beta$  are estimated by maximizing the following log-likelihood function:

$$\log(L(v_1, v_2, \dots, v_t)) = \sum_{t=1}^n \log(f_p(v_t|\theta_{GB2}, \alpha, \beta)) \quad (3.15)$$

This selects the parameter values  $\alpha$  and  $\beta$  that produce the beta distribution that is most likely to have produced the actual data. Therefore, estimating the real-world densities from the set of historical risk-neutral densities and price out-turns amounts to estimating the parameters  $\alpha$  and  $\beta$  of the beta distribution (de Vincent-Humphreys and Noss, 2012).

Fackler and King (1990) acknowledge that a disadvantage of a parametric approach is that the form chosen may not represent the calibration function well in some cases. Therefore, as an alternative we also employ non-parametric calibration. The non-parametric calibration allows multimodal shapes in the density, a stylized fact that is common in practice. Following Shackleton, Taylor, and Yu (2010), we construct the real-world density using the past realizations of  $u_t = F_{Q,t}(v_t)$  then the series is transformed into a new series  $z_t = \Phi^{-1}(u_t)$ , where  $\Phi(\cdot)$  is the cdf of the standard normal. A normal kernel density  $h(z)$  is obtained with

empirical distribution  $H(z)$ . The empirical calibration of  $u_t$  is then  $G(u) = H(\Phi^{-1}(u_t))$ , therefore the real-world cdf and pdf of the forecast is:

$$F_p(v) = G(F_Q(v)) \text{ and } f_p(v) = \frac{f_q(v)h(z)}{\Phi(z)} \quad (3.16)$$

### 3.6 Evaluation of the Density Forecasting Performance

Density forecasts can be assessed using two criteria: goodness of fit that evaluates whether the density forecast correctly specifies the actual realization of the underlying random variable, and sharpness that refers to how accurate are the density forecasts. To measure goodness of fit performance Diebold, Gunther, and Tay (1998) popularized the probability integral transform (PIT) developed by Rosenblatt (1952). Plugging into equation 3.11, the probability and cumulative density forecast function  $f(y_t)$  and  $F(y_t)$  of a random variable  $y_t$  at time  $t$ , and representing  $Y_t + n$  as the actual realization of the random variable at the forecast horizon yields:

$$PIT_t = \int_{-\infty}^{Y_{t+n}} f(y_t)dy \equiv F(Y_{t+n}) \quad (3.17)$$

In this case, the  $PIT$  is the value that the predictive cdf attains at the observation  $Y_{t+n}$ . Although the true random variable distribution is often unobservable, Diebold, Gunther, and Tay (1998) and subsequent literature exploits the fact that when the forecast density equals the true density, then the  $PIT$  follows a uniform variable in the  $[0, 1]$  interval ( $U(0, 1)$ ) and is independent and identically distributed (iid). Hence, evaluation of whether the conditional forecast density matches the true conditional density can be performed by a test of the joint hypothesis of independence and uniformity of the sequence of  $PIT$ s.

Berkowitz (2001) suggests transforming the *PIT* distribution from Uniform to Normal. As explained by Mitchell and Wallis (2011) several advantages can be obtained by this transformation. For instance there are more tests available for normality than uniformity; it is easier to test autocorrelation, and the normal likelihood can be used to construct likelihood ratio tests. Suppose  $\phi^{-1}$  denote the inverse of the standard normal distribution, Berkowitz (2001) shows that for any sequence of *PIT* that is iid  $U(0, 1)$ , it follows that  $z_t = \phi^{-1}(PIT_t)$  is an iid  $N(0, 1)$ . Under the Berkowitz transformation, independence and normality are tested jointly by using a likelihood ratio test on the following model:

$$z_t - \mu = \rho(z_{t-1} - \mu) + \varepsilon_t, \quad \varepsilon_t \sim i.i.d N(0, \sigma^2) \quad (3.18)$$

The null hypothesis is that  $z_t$  follows an uncorrelated Gaussian process with zero mean unit variance against an AR(1) with unspecified mean and variance. Therefore, the likelihood ratio can be set as  $LR_3 = -2(L(0, 1, 0) - L(\hat{\mu}, \hat{\sigma}^2, \hat{\rho}))$ , that follows a  $\chi^2$  distribution with three degrees of freedom.

### 3.7 Out-of-Sample Forecast Comparisons

The preceding methods offer measures of the reliability of density forecasts relative to the data generating process; however, in practice we are also interested in comparing competing forecasting methods. We implement that comparison by assigning scoring rules, which are defined by Gneiting and Raftery (2007) as functions of predictive distributions and realized outcomes used to evaluate predictive densities. In this paper as a scoring rule we use the out-of-sample log likelihood values (OLL), in similar fashion as Bao, Lee, and Saltoglu (2007),

Shackleton, Taylor, and Yu (2010) and Mitchell and Wallis (2011).

Bjørnland et al. (2011) link logarithmic scores to the Kullback-Leibler information criterion (*KLIC*). The *KLIC* of the  $i$ th model is given by:

$$KLIC_i = E \left( \log \left( \frac{h(y_t)}{f_i(y_t)} \right) \right) \quad (3.19)$$

where this expectation is taken with respect to the true unknown density  $h(y_t)$ . For a continuous distribution the expectation can be expressed as:

$$KLIC_i = \int_{-\infty}^{\infty} \log \left( \frac{h(y_t)}{f_i(y_t)} \right) h(y_t) dy \quad (3.20)$$

$$\int_{-\infty}^{\infty} \log(h(y_t)) h(y_t) dy - \int_{-\infty}^{\infty} \log(f_i(y_t)) h(y_t) dy \quad (3.21)$$

The *KLIC* represents the expected divergence of the model density relative to the true unobservable density across the domain of the true density. Therefore, the *KLIC* would attain a lower bound of zero only if  $h(y_t) = f_i(y_t)$ .

Furthermore, although the expected value of  $h(y_t)$  is unknown, it is considered as a fixed constant, therefore, the *KLIC* is minimized by maximizing  $\int_{-\infty}^{\infty} \log(f_i(y_t)) h(y_t) dy$  (Bao, Lee, and Saltoglu, 2007; Bjørnland et al., 2011) Assuming ergodicity this expression can be expressed by:

$$OLL_i = \sum_{t=0}^{n-1} \log(f_t(y_t)) \quad (3.22)$$

The out-of-sample log-likelihood statistic ( $OLL_i$ ) for model  $i$ , can be used to rank predictive accuracy of alternative procedures. The best forecast method yields the highest value which corresponds to the procedure that produces the closest to the true but unknown density.

To assess whether the predictive accuracy of alternate procedures differs significantly, we test the out-of-sample log likelihood differences using a technique described by Mitchell and Hall (2005). In this technique we regress the differences in the OLL between competing forecasts  $i$  and  $j$  on a constant and use HAC standard errors to determine its significance.

$$OLL_i - OLL_j = c \tag{3.23}$$

where  $c$  is the constant. If the difference between forecasts is positive and significantly different than zero, then density forecast  $i$  is considered a superior to density forecast  $j$ . The HAC covariance matrix is estimated using Newey and West (1994) non-parametric bandwidth selection procedure (Zeileis, 2004).

### 3.8 Data

Data consist of daily settlement prices of lean hog futures and options traded at the Chicago Mercantile Exchange (CME) obtained from the Commodity Research Bureau (CRB). The futures data start January 31, 1996 and end February 14, 2012; the options data start January 16, 2002 and end February 14, 2012. To estimate the GARCH models, logarithmic returns calculated as  $r_t = [\ln(P_t) - \ln(P_{t-1})]$ , are obtained using the nearby contract, except when there are ten days or less to delivery, in which case the returns are calculated using the next closest delivery contract. Returns are always calculated using the same delivery contract. We proxy the short-run interest rate ( $r_f$ ) with the 3-month Treasury Bill rate that is obtained from the Federal Reserve Bank.

The options in the data are American-style written on futures contracts of lean hogs. The



underlying futures contract expires on the tenth business day of the expiration month, the same day as the option contract. There are eight contracts in a calendar year for lean hog options and futures, with expirations in February, April, May, June, July, August, October, and December. The lean hog future contract uses cash settlement to the CME Lean Hog Index,<sup>5</sup> that is a two-day weighted average of lean hog values collected by USDA from the Western Cornbelt, Eastern Cornbelt, and MidSouth regions, this ensures convergence between futures and cash prices.

We collect option prices ten business days before expiration, which usually corresponds to fifteen calendar days. Although trading activity in many markets declines rapidly during the expiration month, it remains similar to the next nearby contract in the hog option market. This may be the result of a market with low liquidity. Regardless, at expiration and nearby contracts, sufficient trading activity exists for a range of strike prices to extract the implied distribution.

The final option price data consist of 81 sets. To construct real-world densities from risk-neutral ones, previous data are required to estimate the calibration function. We start using the first 2 years of data (16 observations) for the initial calibration, after which calibration is performed recursively by adding observations to the calibration set. As a result, there are 65 real-world densities. Since the dataset corresponds to call prices of American options and our estimation requires European options, the Barone-Adesi and Whaley (1987) approximation is used. We filtered the options data eliminating strikes with no volume trade, and not complying with the put-call parity conditions.

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<sup>5</sup>Settlement procedures can be found at [http:// www.cmegroup.com/rulebook/CME/II/150/152/152.pdf](http://www.cmegroup.com/rulebook/CME/II/150/152/152.pdf).

## 3.9 Results

Table 3.1 presents summary statistics of daily prices and returns of lean hogs from December 1996 to February 2012. Lean hog prices moved in a range of \$86 from \$21.10 to \$107.45. However the prices observed between the 25th and 75th percentile only move within \$22.12 range. Similarly for returns, while the overall range moves between -7.6 and 6.3 percent, the interquartile range only moved within the range of -0.83 to 0.83 percent. Mean and median for returns are close to zero as frequently observed in commodity prices. The price distribution for the whole period is slightly negatively skewed and shows excess kurtosis.

Figure 3.1 shows the price and returns during the period. Prices exhibit an overall positive trend, however strong swings can be observed in several periods. Since 2006 lean hog prices seem to follow the pattern common to other agricultural commodities. A strong price increase until 2008, a sharp decrease in late 2008 and beginning of 2009 during the financial crisis, followed by a swift recovery that lasted at least until the end of 2011 (Abbott, 2013).

### 3.9.1 Densities

Eighty-one density forecasts are generated for the contracts expiring from January 2002 until February 2012, and calibration of risk-neutral densities leads to generating sixty five real-world densities starting in January 2004. We generate eighty-one graphs for each density forecast.<sup>6</sup> Figure 3.2 illustrates a density forecast generated in August, 2011. By analyzing those figures, several patterns emerged across the period. Even though the GJR-GARCH

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<sup>6</sup>Figures of density forecasts are available from the authors.

density forecasts do vary with time, the normal and the standardize t-distribution exhibit very similar patterns. In a few occasions all the distributions generate nearly the same shape, however the GARCH estimations that allow higher moments often exhibit a more leptokurtic distribution and also are slightly skewed to the right. In the case of the risk-neutral distributions the variation is more pronounced.

Although the risk-neutral density and the GARCH-GJR densities often produce similar looking distributions, the risk-neutral density are usually more leptokurtic and exhibit mass concentrated in the right tail, perhaps reflecting a market sentiment of increasing prices. The real-world density calibrated parametrically show patterns that do not seem to deviate from the risk-neutral density, but the non-parametric calibrated densities exhibit less leptokurtosis than the risk-neutral densities.

### 3.9.2 PIT Histograms and Berkowitz Test

Histograms of *PIT* values are used as preliminary assessment of uniformity. If the *PIT* values are spread evenly in the  $[0, 1]$  interval, then the bins in *PIT* histogram would be uniform. We present the *PIT* histograms of the GARCH models and the risk-neutral density in Figure 3.3 that corresponds to eighty-one observations from January 2002 to February 2012. In figure 4 we include the real-world densities; recall calibration requires a training period, therefore real-world densities are from January 2004 to February 2012 corresponding to sixty-five observations. The densities for the GARCH models and risk-neutral density are also presented for that period. The histograms are divided in 10 bins, corresponding to deciles. Although somewhat uniform, the PIT diagrams exhibit under-dispersion. Since

observations are clustered in the first and the last bins the variance or kurtosis of the target densities are underestimated (Høg and Tsiaras, 2011).

To evaluate the uniformity and independence of the *PITs* we use the Berkowitz test. We evaluate the same two periods used to construct the PIT histograms in Figures 3.3 and 3.4. Results of the test presented in Table 3.2 indicate that for the sixty-five observations the real-world parametric, real-world non-parametric, risk-neutral density, GARCH-GED, and GARCH-NIG are satisfactory forecasts since their tests fail to reject the null hypothesis at the 10% level. Real-world densities outperform the risk-neutral, and forward-looking estimated densities exhibit a better goodness of fit than the historical models. For the eighty-one observations, the GARCH-NIG becomes significant at 10%, and the GARCH-GH although not significant at 5% it is significant at 10%. The GARCH-T and in particular the GARCH-N are close to the critical value at the 5% level, rejecting the null hypothesis in both periods, indicating their density forecast performance is inferior.

### 3.9.3 Out-of-Sample Log-Likelihood

Table 3.3 presents the results of the out-of-sample log-likelihood. According to the Kullback-Leibler information criterion the densities that are closer to the true density have the highest out-of-sample log likelihood (OLL). Following this criterion the results for the 81 observations starting in January 2002 show that the real-world densities are the preferred methods.

In Table 3.4 we test whether the differences in OLL between competing forecast are significant, a test of difference on predictive accuracy (sharpness). We compare the sharpness of

GJR-GARCH-GED, the time series based forecast that exhibits the highest OLL, against alternative GARCH models and the risk-neutral density (RND) for the eighty-one observations starting in 2002. The outcome of the test of predictive accuracy shows no significant difference in terms of sharpness between forecasting models. On the other hand, for the sample starting in 2004 that includes RWD-P and RWD-NP we find significant differences between the calibrated densities relative to the risk-neutral density and the best GARCH model (GRJ-GARCH-GED) at the 10% level. No significant differences in predictive accuracy are found between the parametric and the non-parametric calibration. Similarly to the findings for the 81 observations, there is no difference in sharpness between risk-neutral density and GJR-GARCH-GED for the 65 observations. GJR-GARCH-GED does not dominate alternative GARCH models nor the risk-neutral density with the exception of GJR-GARCH-N that exhibits a significant difference at the 10% level.

### **3.10 Conclusions**

In an environment of high commodity price variability decision-makers require information beyond the one offered by traditional point forecasts. Density forecasting is a prediction tool that incorporates ex-ante the uncertainty of the forecast, and provides information about higher moments of the distribution. In this paper we estimate and evaluate density forecasts of lean hog futures prices using two approaches. The first method generates forecasts based on historical data, using an AR(5)-GJR-GARCH(1,1) model and alternate error distributions. The second method is a forward-looking approach that obtains an implied risk-neutral density from options prices assuming a generalized beta distribution (GB2). Assuming the

risk-neutral densities fail to adequately account for risk, they are adjusted parametrically and non-parametrically into real-world densities.

Overall, the findings suggest the risk-neutral and real-world density functions generally provide the most accurate representations of the price distributions in terms of goodness of fit. With respect to sharpness (predictive accuracy) real-world densities exhibit the best out-of-sample performance. Among the historical GARCH models, only the GED error structure seems to reflect the price distributions reasonably well. Interestingly, adjusting the risk-neutral densities improves the forecasts, indicating that the risk-neutral density do not completely reflect the underlying densities. This is consistent with results found in other markets, for instance, Shackleton, Taylor, and Yu (2010) for equities, and Høg and Tsiaras (2011) for crude oil, show that real-world densities outperform risk-neutral density and historical densities at short-term horizons (one month or less). Our findings support the notion that real-world densities are superior to historical and risk-neutral density forecast for two weeks horizons.

Improvements to goodness of fit and accuracy of the forecasts obtained by the calibration from risk-neutral to real-world densities imply that risk premiums may exist in the lean hog futures markets, a finding consistent with Szakmary et al. (2003), Egelkraut and Garcia (2006), and McKenzie, Thomsen, and Phelan (2007) for volatility risk. Markets appear to value not only risk premiums in the mean levels, but also in volatility, and in the tails. New instruments such as Volatility Index (VIX) and Skew Index, developed in the equities derivative markets, acknowledge these dimensions of risk and the need to price, trade, and hedge them. Agricultural markets have already started to adopt such instruments and density fore-

casting is a tool that should guide decision making on these markets. Traditional options markets can also benefit from more accurate forecasts that incorporate higher moments by developing a better understanding of the final distribution of prices.

## 3.11 Tables and Figures

**Table 3.1:** Descriptive Statistics

	Prices	Returns
Num observations	3806	3806
Mean	63.90	-0.04
Median	62.80	0.00
Variance	179.69	2.26
SD	13.40	1.50
Minimum	21.10	-7.63
Maximum	107.45	6.31
1st Quartile	54.83	-0.83
3rd Quartile	72.95	0.83
Skewness	0.20	-0.23
Excess kurtosis	1.05	1.68
Coef. of Variation	0.21	37.40

Notes: Returns are multiplied by 100



**Table 3.2:** Berkowitz Test

Density Forecasting Method	$LR_3$		$LR_3$	
	81 obs.	p-value	65 obs.	p-value
GARCH-Normal	7.8454	0.0493*	7.9121	0.0478*
GARCH-Standardized T	7.7475	0.0515*	7.5110	0.0572*
GARCH-General Error Distribution (GED)	6.1092	0.1064	6.0109	0.1111
GARCH-Normal Inverse Gaussian (NIG)	6.5920	0.0861*	6.1084	0.1064
GARCH-Generalized Hyperbolic (GH)	6.8206	0.0778*	6.6192	0.0851*
Risk Neutral Density (RND)	4.6765	0.1970	4.8400	0.1838
Real World Density-Parametric (RWD-P)			3.7712	0.2872
Real World Density-Non Parametric (RWD-NP)			3.4711	0.3245

\* Significant at 10%

Notes: 81 observations start in January 2002, 65 observations start in January 2004, both series end in February 2012.

All GARCH models are GJR-GARCH(1,1)

**Table 3.3:** Out-of-Sample Log-Likelihood

Density Forecasting Method	81 obs	65 obs
GARCH-Normal	-220.35	-177.35
GARCH-Standardized T	-220.14	-177.43
GARCH-General Error Distribution (GED)	-215.36	-172.89
GARCH-Normal Inverse Gaussian (NIG)	-217.86	-174.49
GARCH-Generalized Hyperbolic (GH)	-218.35	-176.18
Risk Neutral Density (RND)	-216.21	-173.11
Real World Density-Parametric (RWD-P)		-169.46
Real World Density-Non Parametric (RWD-NP)		-167.42

Notes: 81 observations start in January 2002, 65 observations start in January 2004, both series end in February 2012.

All GARCH models are of the form GJR-GARCH(1,1)

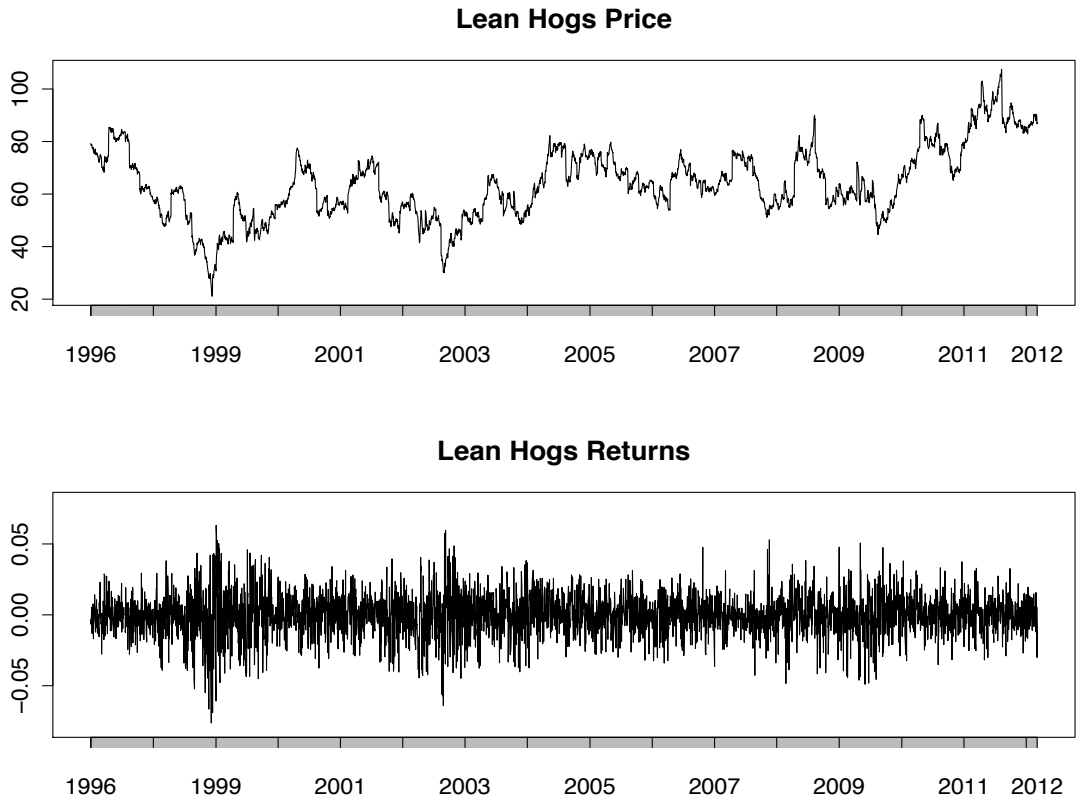
**Table 3.4:** Test of Equal Predictive Accuracy

81 Observations			
	Difference	SE	P-value
GED vs Normal	4.99	3.32	0.137
GED vs Std T	4.78	3.11	0.128
GED vs NIG	2.5	3.44	0.469
GED vs GH	2.99	2.97	0.317
GED vs RND	0.85	2.22	0.703
65 Observations			
	Difference	SE	P-value
RWD-NP vs RWD-P	2.04	2.16	0.348
RWD-NP vs RND	5.69	2.97	0.059*
RWD-P vs RND	3.65	2.03	0.077*
RWD-NP vs GED	5.47	3.12	0.084*
GED vs RND	0.22	1.03	0.831
GED vs Normal	4.46	2.64	0.095*
GED vs Std T	4.54	2.74	0.102
GED vs NIG	1.6	2.23	0.475
GED vs GH	3.29	2.33	0.163

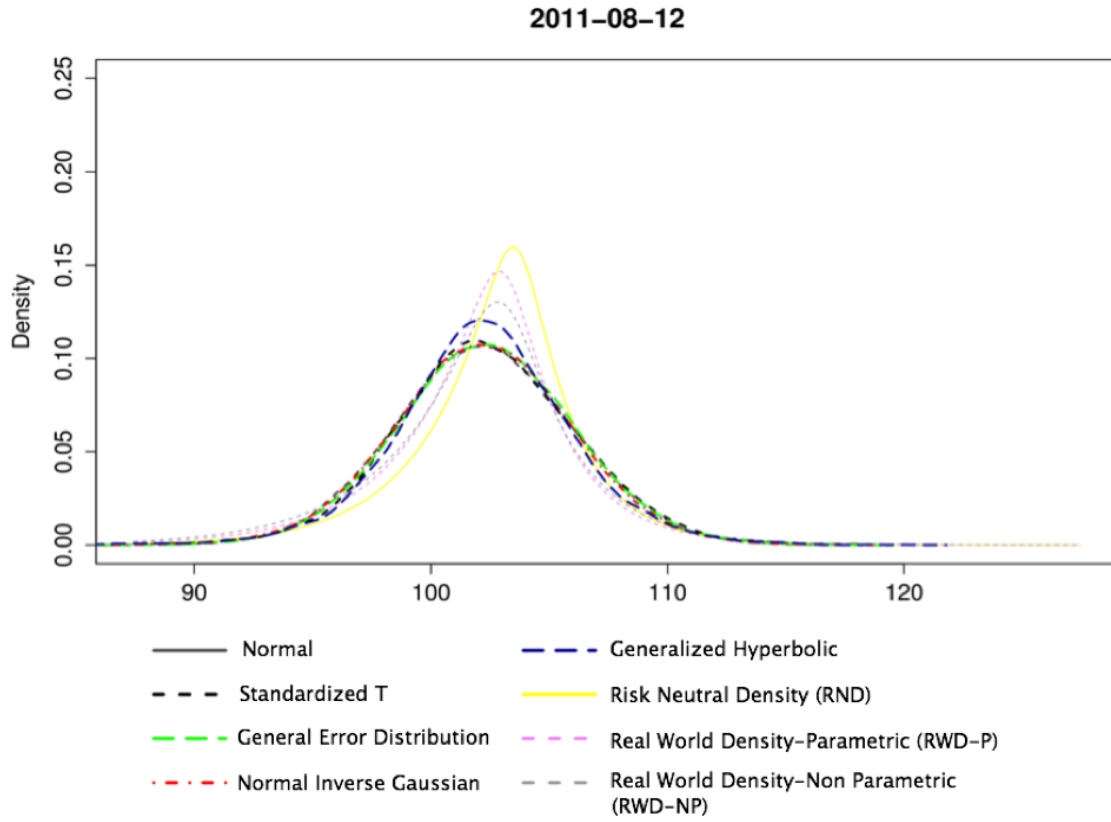
\* Significant at 10%

Notes: 81 observations start in January 2002,  
65 observations start in January 2004, both series  
end in February 2012.

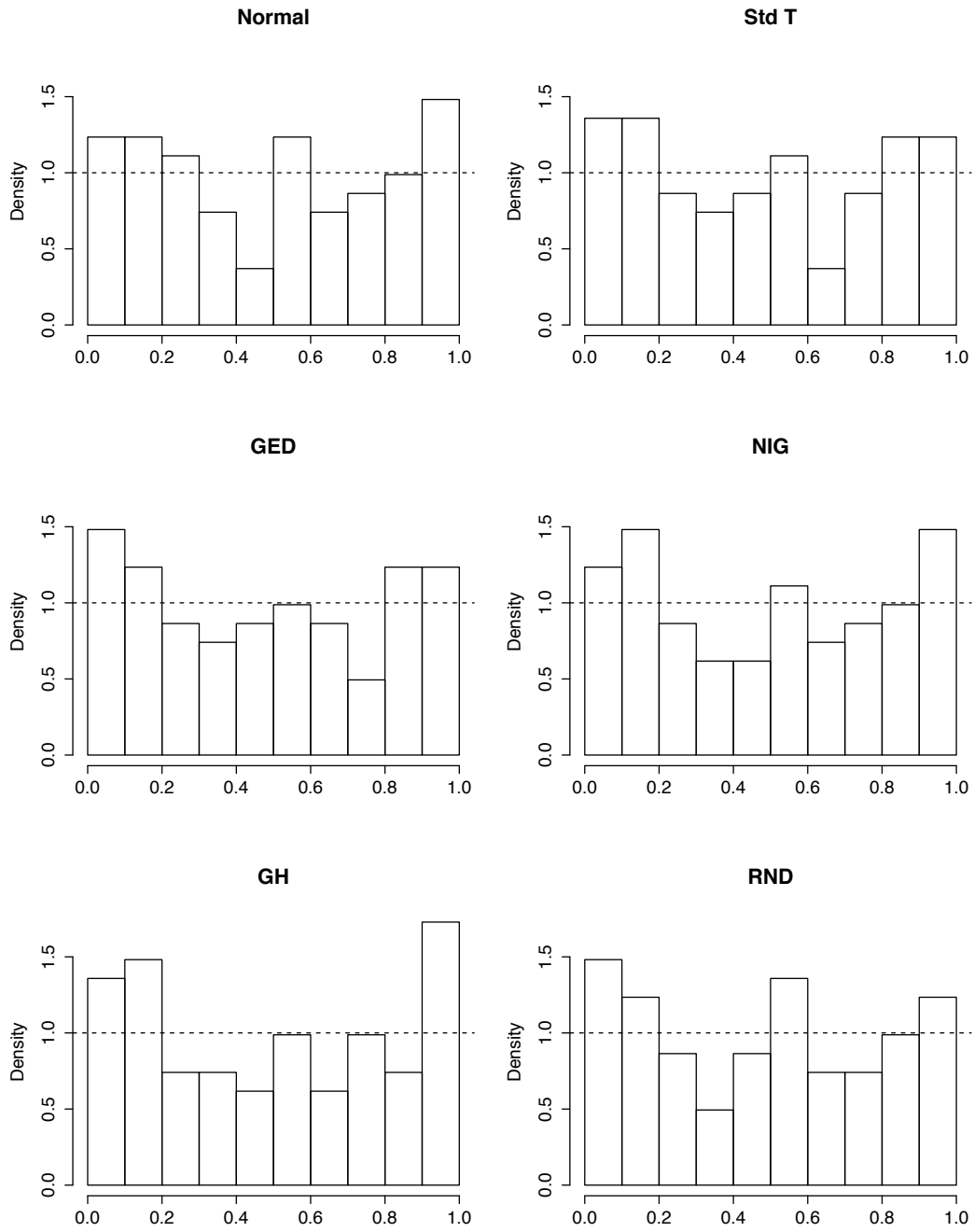
All GARCH models are of the form GJR-GARCH



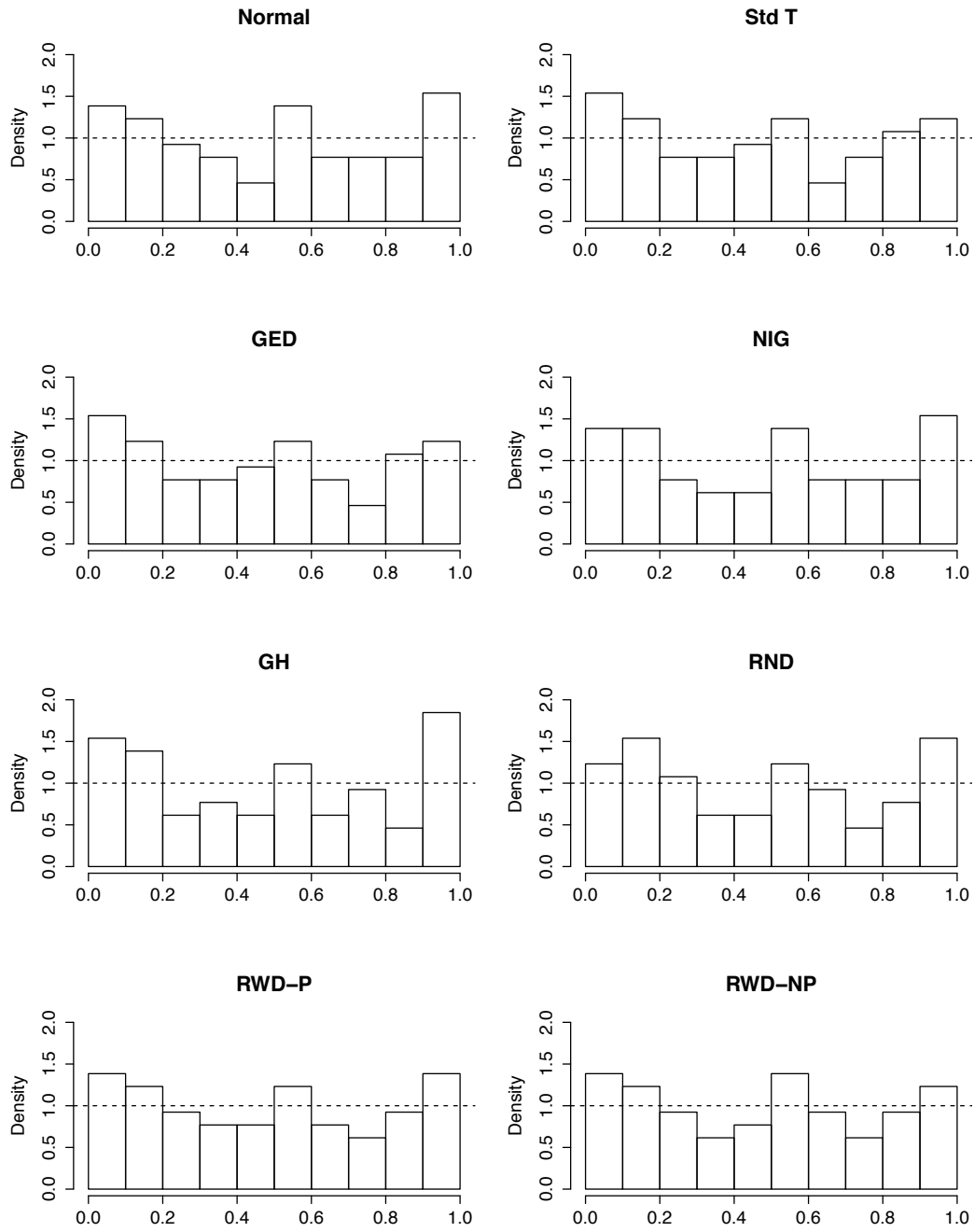
**Figure 3.1:** Lean Hog Price and Returns



**Figure 3.2:** Fifteen Day Ahead Density Forecasts for GJR-GARCH Models, Risk-Neutral Density, and Real-World Density on August 12, 2011



**Figure 3.3:** Probability Integral Transforms (PIT) Histograms January 2002 to February 2012 (81 observations)



**Figure 3.4:** Probability Integral Transforms (PIT) Histograms January 2004 to February 2012 (65 observations)

# Chapter 4

## Price Density Forecasts in the U.S. Hog Market: Composite Procedures

### 4.1 Introduction

In a variety of settings agricultural economists have been involved in developing better price forecasts to assist decision makers (Leuthold et al., 1970; Brandt and Bessler, 1981; Bessler and Kling, 1986; Zapata and Garcia, 1990; Wang and Bessler, 2004; Colino et al., 2012). Often, research has provided innovative techniques for generating and combining point forecasts, and considerable evidence exists that composite forecasts dominate the best individual forecasts. While these studies have been informative, they focused on point forecasts and often used an out-of-sample root mean squared error (RMSE) measure to assess the degree of risk in prices. Point forecasts only deliver the mean of the probability distribution of prices, and the RMSE measure is calculated ex-post so it fails to produce an ex-ante measure of forecast uncertainty.

An attractive alternative is direct density forecasts and density composite methods. Density forecasts offer information about the uncertainty of predictions and a more precise



description of risk to decision makers, which Clements (2004) notes increasingly is an indispensable part of forecasting and decision-making. In addition, combining density forecasts limits the risk of choosing a model that performs badly (Corradi and Swanson, 2006; Hall and Mitchell, 2007; Geweke and Amisano, 2010). Furthermore, the search for effective methods for density forecasts and their combination is empirically motivated by the need to develop forecast methods that are robust to unknown instabilities, and the need to reduce idiosyncratic biases (Aastveit et al., 2012).

The importance of density forecasts for agricultural commodity prices was recognized as early as the mid-1960s by Bottum (1966) and Timm (1966), but their subsequent development and use have been scarce. Research has mainly focused on estimation procedures (Fackler and King, 1990; Sherrick, Garcia, and Tirupattur, 1996; Egelkraut, Garcia, and Sherrick, 2007) with less attention on forecast evaluations and comparisons. To date, no studies exist that examine the usefulness of composite density forecast procedures in the agricultural commodity price literature.

Recently, Colino et al. (2012) investigated predictive accuracy of quarterly point forecasts of hog prices from outlook programs, futures prices, and a variety of time series models with the goal of providing more precise information to decision makers. Forecasts from outlook programs traditionally have been an important source of information for hog industry producers, meat packers, and retailers. Colino et al. (2012) confirm the difficulty of generating accurate individual forecasts and find composite procedures improve on the predictive performance of individual forecasts. However, given the increasing desire to assess uncertainty, density forecasts and their composites may provide a valuable source of information.

In this article we investigate the usefulness of newly developed density forecast, evaluation, and combination procedures for generating ex-ante distributions of quarterly hog prices from 1975 to 2010. To generate our density forecasts we use the AR(5), exponential smoothing, and Vector Autoregression (VAR) time-series models from Colino et al. (2012) and the same data, which allows for convenient comparison of our forecast densities with their point forecasts. We also generate individual forecasts based on an implied distribution of expert forecasts from three outlook programs: USDA, Iowa State University, and the University of Missouri. Since each outlook program forecasts price for a different geographic market on a different date, we estimate, develop composite densities, and evaluate forecasts for each outlook separately. To correspond to actual program forecast horizons, forecasts for Iowa and Missouri are developed for up to three quarters ahead, while those for USDA are developed for only up to two quarters ahead. We base the implied distributions of outlook hog price forecasts on the distribution of their historical forecast errors, following a procedure suggested by Isengildina-Massa et al. (2011).

To combine density forecasts we use linear and logarithmic pooling with several weighting schemes. To evaluate and compare individual and composite density forecasts we use sharpness and calibration (Mitchell and Wallis, 2011). Sharpness refers to the precision of a forecast and is measured by a forecast's log score, which reflects the extent to which forecasts attain high-density values at the actual observations. To further evaluate predictive accuracy, we examine differences in log scores between forecasts using a Diebold and Mariano-type test and by calculating cumulative differences in log scores over time. Calibration refers to whether a forecast density resembles the true price distribution. It is measured

using the probability integral transform (PIT), and evaluated using Berkowitz's test on the normalized PIT.

Similar to findings from the literature on point forecasting, out-of- sample performance of individual density forecasts can be improved by combination. However, performance strongly depends on the distribution and weighting scheme used. Findings show that logarithmic pooling outperforms linear pooling in both sharpness and calibration. The logarithmic equal weighted composite consistently outperforms recursive and other combination procedures, and is virtually indistinguishable from the logarithmic mean square error composite. The strong performance of the equal weighted composite corresponds to the well-known combination puzzle previously detected in point forecasting, that acknowledges the difficulty of identifying composite procedures that consistently outperform a simple equal weight model (Smith and Wallis, 2009). The findings show that a more complete description of price forecast distributions can be obtained with forecast density composite procedures. The procedures and analysis performed can be used to improve USDA and other hog outlook price forecasts and the information provided to decision makers in this market.

## Data

Quarterly data from the first quarter of 1975 to the fourth quarter of 2010 are used to estimate, evaluate, and combine hog price density forecasts for three outlook programs. Interval forecasts of hog prices are available from USDA for one and two quarters ahead ( $h=1$  and  $h=2$ ). We infer their point forecasts to be the mid-point of the price interval forecast. Since no distribution over the interval is offered, we follow Isengildina-Massa et al.

(2011) in obtaining the implied distributions of the USDA interval forecast by estimating the distribution of forecast errors. To estimate the univariate time series models we use observed prices reported by USDA. Observed and forecast hog prices are collected from USDA Livestock, Dairy, and Poultry Outlook. Following Colino et al. (2012), we also use a Vector Autoregression (VAR) forecasting model. Data to estimate the VAR mode include observed hog price, pork production, sows farrowing, and beef prices obtained from USDA, and a quarterly average corn price assembled from Barchart.

Iowa State University experts generate forecasts up to three quarters ahead ( $h=1$ ,  $h=2$ , and  $h=3$ ) of live hog cash prices in Iowa. The observed Iowa prices are used in univariate time series models, and in a corresponding Iowa VAR model that includes the other non-hog price variables used in the USDA VAR.<sup>1</sup> Forecast and observed prices are collected from various issues of Iowa Farm Outlook.

University of Missouri experts generate forecasts up to three quarters ahead, reflecting the live hog cash price in Missouri. Corresponding univariate and VAR models using the Missouri price were used to generate forecasts. Forecast and observed prices are collected from the University of Missouri Farm Marketing. Figure 4.1 shows the forecasts and corresponding hog prices for each outlook program; figure 4.2 provides the other variables included in the VAR models. Data sources are summarized in table 4.1. <sup>2</sup>

For analysis we divide the data into three periods. The first period corresponds to the data used for initial estimation of the models. In the second period, we develop the weights

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<sup>1</sup>The Iowa live hog cash price is the Iowa-Minnesota plant quarterly average delivered \$ / carcass cwt. price adjusted by 74%

<sup>2</sup>Data and code to replicate results are available from the authors

that are used to generate the composite forecast. Finally, in the third period we perform out-of- sample evaluation of individual and composite forecasts.

## **4.2 Individual Forecasting Models and Initial Estimation**

We use a set of forecasts generated from time series models and outlook programs that have been used previously in the literature (Bessler and Kling, 1986; Zapata and Garcia, 1990; Colino, Irwin, and Garcia, 2011; Colino et al., 2012). These models represent reasonable procedures that have been applied frequently to forecast hog prices. Since our primary focus is not on finding the best possible specification for each individual model, but rather to investigate the additional information that density forecasts and their composites offer, they should provide a structure for analysis. The individual models include univariate time series such as ARIMA, exponential smoothing, and No change, and multivariate time series such as Vector autoregression (VAR). We also consider experts' forecasts from three outlook programs USDA, Iowa State University, and University of Missouri.

### **AR, VAR, and No-Change Forecast Models**

We start by estimating individual time series based forecasting models, and implied distributions of forecasts from outlook programs. After testing for stationarity, identifying the lag structure, and examining residuals, we choose an autoregression of order 5 (AR(5)) and an unrestricted vector autoregression of order 5 (VAR(5)). The VAR(5) specification is consistent with previous hog price forecasting literature, and is the result of a thorough process of examining potential variables, and preliminary estimations of reduced form VARs (Colino

et al., 2012). Another forecasting procedure is No change or naive, this forecast takes the value of the current observation, and the variance of the forecast error is developed by using the last 40 observations. Density forecasts from the AR(5), VAR(5), and No change are generated from forecast errors of the models under the assumption of normality, which could not be rejected when testing the residuals.<sup>3</sup>

### **Exponential Smoothing Model**

The U.S. hog industry has undergone structural change during the last two decades. Figure 4.2, shows a positive trend in pork production, while sow farrowing has remained relatively constant. Significant production expansion is a result of new breeding technologies and capital concentration, particularly in the 1990s. To account for potential structural changes and also the influence of seasonality, we include an exponential smoothing model to allow added flexibility.

Exponential smoothing techniques are a class of forecasting methods with the property that forecasts are weighted combinations of past observations, with weights decreasing exponentially Hyndman and Khandakar (2008). The exponential smoothing method decomposes the systematic (non-random) part of a series into three elements, trend, seasonality, and level. Several functional forms may arise depending on whether the interaction of the three elements is additive or multiplicative, and also if trend, and/or level are included. We may have models that include both trend and seasonality, and others that only include one element. In our forecast estimation using exponential smoothing, the optimal values of the

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<sup>3</sup>Test of residuals failed to identify ARCH effects or autocorrelation.

smoothing parameters are calculated for each period with density forecasts developed from forecast errors under the assumption of normality.

For initial estimation of the time series based forecasts we start by using the sample from 1975.I-1984.IV which generates the forecast for 1985.I. Initial estimation of the next forecast is done recursively by adding the last observation to the sample, for instance, to generate the forecast for 1985.II with one horizon ahead ( $h=1$ ) we use the sample of 1975.I-1985.I.

### **Expert Forecasts**

As mentioned, experts' forecasts were obtained from the outlook programs. Since outlook programs do not provide density forecasts (only intervals at most), implied density forecasts are developed using the distributions of the expert's forecast errors (Isengildina-Massa et al., 2011). Define *percentage price forecast errors* =  $[(forecast - observed)/observed] \cdot 100$ . Using this measure, we generate and examine histograms, density functions, and cumulative distribution functions of the errors. We also use Cullen Frey graphs that allow us to accurately identify the degree of skewness and kurtosis in the distributions (Cullen and Frey, 1999). Initial densities resemble a normal distribution <sup>4</sup> and the distributions of forecast errors show little skewness with kurtosis close to three (figure 4.3 and 4.4). Among the other competing distributions such as logistic, uniform, exponential, gamma, and beta, the normal is the closest distribution to the expert's forecast errors. <sup>5</sup>

Using the normal density for the forecast errors distribution, we fit the data using maximum likelihood estimation. We follow the same sample and recursive procedures for initial

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<sup>4</sup>Figures are available from the authors

<sup>5</sup>As a robustness check 5000 bootstraps are included for the skewness-kurtosis location of the sample distribution.

estimation used for the time series models, and evaluate goodness of fit using Anderson-Darling statistics. This statistic never rejects normality, confirming the use of a parametric fit of the forecast errors with a normal distribution. After initial estimation of the individual forecasts we proceed to forecast combination, using different combination functional forms and weights choice methods.

### 4.3 Density Forecast Combination: Linear and Logarithmic Opinion Pools

Research in economics on forecasting and combining densities is emerging (Elliott and Timmermann, 2008). Kascha and Ravazzolo (2010) contend that “our knowledge of when and why predictive density combinations work is still very limited,” recognizing the need to increase our understanding of the circumstances when procedures are most effective. Timmermann (2006) identifies a number of viable alternatives to formulate density composites, however no consensus exists as to the most effective method.

Combining density forecasts imposes new requirements beyond those for combining point forecasts. In the case of point forecast evaluation and combination, the performance criteria are often based on root mean square error (RMSE), defined as the square root of the sum of squares of forecast errors:

$$RMSE = \sqrt{\frac{1}{n} \sum (p_t - y_t)^2}, \quad (4.1)$$

where  $p_t$  is the point forecast that corresponds to the mean of the density forecast, and  $y_t$  is the observed price. Combining density forecasts is less straightforward. In particular, a



combined density may have different characteristics than the individual densities used to construct it. For instance, a linear combination of normal distributions with different means and variances will be a mixture normal (Hall and Mitchell, 2007), and for many distributions analytical solutions of the combinations are not feasible requiring use of simulation techniques (Bjørnland et al., 2011). Hence, the combination must result in a distribution, implying it must be convex and probabilities should always sum to one.

Several approaches to combine probability distributions have been considered in the literature including linear and logarithmic pools with equal weights (Wallis, 2005), combination of weights based on the Kullback-Leibler information criterion (KLIC) (Amisano and Giacomini, 2007; Hall and Mitchell, 2007; Jore, Mitchell, and Vahey, 2010), Bayesian framework (Geweke and Amisano, 2010; Eklund and Karlsson, 2007), and recalibration of linear combinations (Ranjan and Gneiting, 2010; Gneiting and Ranjan, 2013). Here, we employ the most widely used composite procedures, linear and logarithmic pooling with the alternate weighting schemes. These pooling procedures are rather straightforward and have been shown to work well with quarterly data that demonstrate limited deviations from normality and no ARCH effects (Kascha and Ravazzolo, 2010) which is consistent with the structure of the data and models we use.<sup>6</sup> The first approach is the convex linear combination (“linear pool”):

$$\bar{F}_c = \sum_{i=1}^N \omega_{t+h,i} F_{t+h,i}, \quad (4.2)$$

where the pool  $\bar{F}_c$  is made up of N competitive forecast densities  $F_{t+h,i}$ ,  $\omega$  its weight with  $0 \leq \omega_{t+h,i} \leq 1$  and  $i$  represents forecast models. The second approach is the logarithmic

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<sup>6</sup>The hog price series is stationary.

opinion pool with densities expressed by:

$$\bar{f}^l = \frac{\prod_{i=1}^N \omega_{t+h,i} f_{t+h}^i}{\int \prod_{i=1}^N \omega_{t+h,i} f_{t+h}^i}, \quad (4.3)$$

where  $\omega_{t+h,i}$  are weights chosen such that the integral in the denominator is finite.

The logarithmic combination offers several advantages for the distributions observed here. It retains the symmetry of the individual forecasts for the case of normal densities (Winkler, 1968). For instance, consider a set of normal densities with means and variances  $\mu_i, \sigma_i, i = 1 \dots N$ , and denote transformed weights by  $\alpha_i = \frac{\omega_i}{\sigma_i^2}$ . The logarithmic pool is a normal density,  $N(\mu_c, \sigma_c^2)$ , with mean and variance given by  $\mu_c = \sum_{i=1}^N \alpha_i \mu_i / \sum_{i=1}^N \alpha_i$ , and  $\sigma_c^2 = (\sum_{i=1}^N \alpha_i)^{-1}$ . Hora (2004) also shows that application of linearly combined forecasts can produce suboptimal density forecasts, as a linear pool tends to be over dispersed and gives prediction intervals that are too wide on average. In contrast, logarithmic pools are less dispersed than linear combinations and also are unimodal (Genest and Zidek, 1986).

## 4.4 Choice of weights

To aggregate predictive densities, weights of each forecast method need to be identified. Having estimated the models through 1984.IV, we use forecasts for 1985.I-1993.IV to obtain composite weights. These weights are then used to generate out-of-sample composite forecasts beginning on 1994.I, the start of the evaluation period. Subsequent composite forecasts are generated by recursively adding the last observation to the estimation window through 2010.IV.

We develop the weights using four procedures: Recursive log score weights (RLSW),

mean square error weights (MSEW), equal weights (EW), and all weight on the best model (Select). RLSW allocates weights by maximizing the log score when the forecast is generated. Log score is the logarithm of the probability density function of the forecast evaluated at the realized value. It serves as a measure of forecast performance, and more weight is given to models with higher log scores.

### Recursive Log Score Weights

The recursive log score weights (RLSW) for forecast h-steps ahead as defined in Amisano and Giacomini (2007), Hall and Mitchell (2007), and Jore, Mitchell, and Vahey (2010) is:

$$\omega_{t+h,i} = \frac{\exp \sum_{\tau=t_s}^h \ln(f_i(y_{t+h}))}{\sum_{k=1}^N \exp(\sum_{\tau=t_s}^h \ln(f_k(y_{t+h}))}, \quad (4.4)$$

where  $y_{t+h}$  is the actual observation,  $\tau = t_s$  is the beginning of a training period used to initialize the weights,  $i$  corresponds to the individual forecast model,  $k$  includes all individual models from 1 to the total number of models  $N$ . RLSW are based on the log score of the out-of-sample performance of density forecast models, the weight for each model is the ratio of its log score performance over the sum of the log score performance of all models. Since the weights are updated recursively through time, Jore, Mitchell, and Vahey (2010) recommend it's use in the presence of structural changes or uncertain instabilities. However, Kascha and Ravazzolo (2010) find that it does not perform well relative to other more direct weighting schemes. They attribute the poor relative performance to the small sample size in the training period and to model uncertainty, i.e., when large differences in forecast ability among models exist.

## Mean Square Error Weights

The second procedure to develop weights is based on mean squared error weights (MSEW) and is often used in point forecasting. It is calculated as:

$$\omega_{t+h,i} = \frac{1/MSE_{t+h,i}}{\sum_{k=1}^N 1/(MSE_{t+h,k})}, \quad (4.5)$$

where  $MSE_{t+h,i} = \frac{1}{(t-h)} \sum_{\tau=t_s}^h (y_{t+h} - \mu_{t+h,i})^2$ , where  $y_{t+h}$  is the actual observation and  $\mu_{t+h,i}$  is the mean forecast of model  $i$ . The weights in this procedure also change in the evaluation period to allow for a model's improving forecast performance.

## Equal Weights

The third procedure, equal weights (EW), gives the same weight to all models (Wallis, 2005). In point forecasting, numerous studies find that simple equal weighted combinations outperform more sophisticated adaptive and weighting methods (Bjørnland et al., 2011; Colino et al., 2012). However, it is not clear if such a result can be generalized to density combinations. Jore, Mitchell, and Vahey (2010) find recursive log score weights give more accurate forecasts than other weight schemes when analyzing U.S. macroeconomic data. They contend that RLSW takes into account shifting variance and structural breaks. Kascha and Ravazzolo (2010) also find the same result for US inflation, but for other countries considered (UK, New Zealand, and Norway) RLSW weights yields worse forecasts than alternative schemes. Bjørnland et al. (2011) examined Norwegian GDP and inflation using a suite of models, and find that logarithmic RSLW outperformed forecasts from other schemes. Results from the literature appear to be mixed, and evidence suggests that a solution for

an optimal forecast combination procedure is uncertain. Different combining rules may be suitable in different situations, as a result there is not a single all-purpose optimal combining procedure (Winkler, 1986).

### **Best Selection**

The final procedure identified as (SELECT) chooses the individual model at each period with the best average log score up to the time the forecast is generated, giving all the weight to that model.

## **4.5 Evaluation of Density Forecasts**

Accurate density forecasts should generate estimates that give a high density value at the actual observation and produce probability estimates that are correct. The first criterion is called sharpness, while the second is called calibration Mitchell and Wallis (2011). Evaluating density forecasts is complicated because the true density is not observed, even after realization of the forecasted variable. Nevertheless, several approaches have been developed to assess these two dimensions of accuracy.

### **Sharpness**

To assess predictive density sharpness, we use log scoring rules (Gneiting and Raftery, 2007; Bjørnland et al., 2011). The log score is the logarithm of the probability density function of the forecast evaluated at the realized value. Scoring rules serve as a way to compare forecasts by measuring the distance between the true distance and a (possibly misspecified) model. This is based on the link between logarithmic scores and the Kullback-Leibler information

criterion. KLIC measures the expected divergence of a model's density from the true density and is defined as:

$$\begin{aligned}
 KLIC_i & \int h(y_t) \ln \frac{h(y_t)}{f_i(y_t)} dy \\
 & = E(\log(h(y_t))) - E(\log(f_i(y_t))),
 \end{aligned}
 \tag{4.6}$$

where  $h(y_t)$  is the true density and  $f_i(y_t)$  is the predictive density of model  $i$ . KLIC is non-negative and attains its lower bound only when  $h(y_t)$  equals  $f_i(y_t)$ . Although  $h(y_t)$  is unobserved, notice that a comparison between competing models  $KLIC_i$  and  $KLIC_j$  only requires evaluation of  $E(\log(f_i(y_t)))$ , since the expected true density  $E(\log(h(y_t)))$  can be treated as a constant across the models and cancels out. This implies that minimizing KLIC involves maximizing the  $E(\log(f_i(y_t)))$ . This term, known as the average logarithmic score or log score, can be estimated by:

$$E(\log(f_i(y_t))) = \frac{1}{n} \sum_{t=0}^{n-1} \log(f_i(y_t)).
 \tag{4.7}$$

The log score rewards models that on average allocate higher probability to events that actually occur. For example, in figure 4.5 consider density forecast functions  $f_1(y)$  and  $f_2(y)$  evaluate ex-post in time  $t$  at the realized price  $y_t$ . Density  $f_1(y)$  is preferred to  $f_2(y)$  since it assigns a higher probability to the realized price. Note this also applies to the monotonic transformation comprising the log scores  $\log(f_1(y_t))$  and  $\log(f_2(y_t))$ .<sup>7</sup> In our empirical analysis we calculate log scores to compare density forecasts for the out-of-sample observations, and set the weights of one of the combinations schemes following Bjørnland

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<sup>7</sup>Since the density function is a value between zero and one, the codomain of the log score is  $(-\infty, 0)$  where less negative values (closer to zero) are preferred to more negative values.

et al. (2011) and Kascha and Ravazzolo (2010).

To further assess the predictive accuracy of alternative forecasts, we test the significance of differences in log scores between forecasts, and calculate a cumulative log score measure that identifies how differences in log scores change over time. For the test of predictive accuracy we also regress the differences in the log scores of competing forecasts on a constant and use heteroskedasticity and autocorrelation consistent estimators (HAC) robust standard errors to determine its significance:

$$\log(f_1(y_t)) - \log(f_2(y_t)) = c, \quad (4.8)$$

where  $c$  is the constant (Mitchell and Hall, 2005; McDonald and Thorsrud, 2011). If the difference is positive and significantly different than zero, then  $f_1(y_t)$  is considered a superior density forecast than  $f_2(y_t)$ . The HAC covariance matrix is estimated using Newey and West (1994) non parametric bandwidth selection procedure (Zeileis, 2004). Examination of how forecasting methods perform over time can also be informative for decision makers. We compare forecast behavior of competing methods over time by calculating the cumulative difference of the log scores (ClnS):

$$ClnS = \sum_{\tau=t_s}^t \ln(f_1(y_{t+h})) - \ln(f_2(y_{t+h})), \quad (4.9)$$

where  $f_1$  and  $f_2$  correspond to the competing forecasts. ClnS increases over time when  $f_1$  is more accurate than  $f_2$ .

## Calibration

To assess calibration, Diebold, Gunther, and Tay (1998) propose the use of the probability integral transform (PIT) as a measure of goodness of fit across all forms of probabilistic forecasts. PIT is defined as:

$$PIT_t = \int_{-\infty}^{Y_{t+n}} f(y_t) dy \equiv F(Y_{t+n}), \quad (4.10)$$

where  $f(y_t)$  and  $F(Y_t)$  are the probability and cumulative density functions of variable  $y_t$ , and  $Y_{t+n}$  is the realized value at the forecast horizon  $n$ . As shown in Rosenblatt (1952), given the true data generating process, cumulative densities at the realizations will be uniform. Similarly, if a density forecast is correctly specified, the probability integral transform of the series of realizations is uniformly distributed, and in the case of one-step-ahead forecasts, it is also independently and identically distributed (iid). Therefore, uniformity and iid characteristics of PIT series serve as a test of correct specification of the distribution, independent of any loss function, and overcomes the problem of not observing the true distribution directly.

Despite these attractive attributes, tests of uniformity tend to have low power. As an alternative Berkowitz (2001) proposed a transformation of the series from uniform to normally distributed, arguing that tests for normal distribution have more power. We evaluate individual and combined densities' goodness of fit (calibration) by means of the Berkowitz test where the original PIT series is transformed. Let  $\phi^{-1}$  be the inverse of the standard normal distribution. If a sequence of  $PIT_t$  is iid and  $U(0,1)$ , then  $z_t = \phi^{-1}(PIT_t)$  is iid and  $N(0,1)$ . By using a likelihood ratio, independence and normality can be jointly tested.

Using sharpness and calibration as forecast evaluation criteria is a departure from proce-



dures performed in point forecasting. Point forecasts are generally evaluated by root mean square error (RMSE). While a strong correlation exists between log scores and RMSE, the relationship is not one to one (Kascha and Ravazzolo, 2010). Forecast evaluation criteria that focus on features of the probability distribution are especially relevant when prices are highly variable. This is particularly true if a decision maker's loss function is not quadratic and depends on higher moments of a possible outcome (Bjørnland et al., 2011). McDonald and Thorsrud (2011) argue that the recent financial crisis has highlighted the importance of having not only good point forecasts, but also a good assessment of the whole range of possible outcomes.

## 4.6 Results

We perform out-of-sample forecast evaluation of individual and composite forecasts for the period 1994.I-2010.IV. Tables 4.2, 4.4, and 4.6 provide sharpness results for USDA, Iowa State University, and University of Missouri related forecasts. Along with the average log score ( $\ln S$ ), root mean square error (RMSE) is presented for comparison because it is a traditional measure of point forecast performance.

Tables 4.3, 4.5, and 4.7 present selected pair-wise tests of competing models in which individual and composite models are compared against the best composite model to determine if the differences are statistically significant. Since in tables 4.2, 4.4, and 4.6 the logarithmic pooling with equal weights model is usually the best overall forecast in terms of sharpness (highest log score) across all horizons, most pairwise comparisons are made relative to this model. Table 4.8 provides the calibration (goodness of fit) of individual and

combined density forecast measured using the Berkowitz test on the normalized probability integral transform (PIT).

## **Sharpness**

### **USDA**

Table 4.2 provides the results for the individual and composite forecasts of USDA prices. Results show the exponential smoothing (Exp Smoothing) procedure has the best performance at  $h=1$  and  $h=2$ , with the highest (less negative) log score (lnS). Exponential smoothing gives more weight to recent observations, incorporating instabilities, and cyclical components in a more flexible way. The USDA's implied forecast performed poorest at both horizons.

Although a close relationship between average log score lnS and RMSE exists, the correspondence is not one-to-one. For instance, VAR(5) exhibits the lowest RMSE among individual models across different horizons, however its out-of-sample density forecast performance ranks comparatively low in terms of log scores. Also note that exponential smoothing is the best forecast in terms of sharpness in both  $h=1$ , and  $h=2$ , but it ranks second in terms of RMSE at  $h=1$ , and is only third at  $h=2$ . Heterogeneous results at different horizons, and differences in ranking between point and density forecast criteria provide further motivation to consider density composites since they can provide insurance against selecting an ineffective procedure.

Results of the density combinations show that pooling either linearly or logarithmically improves sharpness over the individual models. The composites based on equal (EW) and mean square error (MSEW) weights always outperform individual forecasts. Logarithmic pooling based on MSE weights (Log MSEW) provides the best combination at the first

horizon ( $h=1$ ) followed closely by the equally weighted logarithmic composite (Log EW). At  $h=2$ , Log EW becomes the best combination.

Based on the apparent superior performance of the log equal weighted composite (Log EW), we test whether Log EW differs statistically from selected competing forecasts. Specifically, we test for equal predictive accuracy between Log EW and the best individual forecast (Exp Smoothing), the best linear pooling forecast (Lin MSEW), the USDA implied forecast, and the other logarithmic pooling forecasts that based on alternate weighting schemes. We also compare the best linear pooling model (Lin MSEW) to the best individual forecast model to further assess the effect of pooling. Results in table 4.3 indicate that Log EW composite dominates the best individual model (Exp Smoothing), the best linear composite (Lin MSEW), but does not differ statistically from the logarithmic mean square weighted composite (Log MSEW) at either horizon.

Several related points emerge from these findings. First, while average log scores for the linear equally weight (Lin EW) and mean square error (Lin MSEW) are superior to the individual forecasts, the best linear composite, Lin MSEW, does not differ statistically from the best individual forecast (Exp Smoothing). When compared to the statistical performance of the Log EW this suggests that the functional form of the combination influences accuracy, and also supports the notion that it is difficult to improve on equally weighted forecasts. Second, the USDA forecast does not perform well relative to Log EW, indicating that its density forecasts can be substantially improved using composite methods. Finally, RLSW weights provided substantially worse forecasts than alternative combination schemes, and in cases even worse than some individual models. The test of equal predictive accuracy finds

significant differences between Log RLSW and the best weighting procedure (Log EW).

Figure 4.6 provides the cumulative differences of log scores at one- and two-quarter horizons ( $h=1$  and  $h=2$ ). Comparisons are made between the best density combination and the best individual model (Log EW vs Exp Smoothing), the best logarithmic and the best linear pool (Log EW vs Lin MSEW), and the best density combination and the USDA (Log EW vs USDA). Cumulative difference in log scores between the best logarithmic and the best linear pool show only a modest increase from 1994 to 2010 at both  $h=1$  and  $h=2$ . The difference between the best logarithmic pool and the exponential smoothing although significant (table 4.3) is small for  $h=1$ , but becomes increasingly larger at  $h=2$ . This is consistent with the effectiveness of the exponential smoothing model at capturing shorter-term characteristics, and its decline in accuracy relative to the Log EW at the longer horizon. USDA forecasts are consistently outperformed by the best combination at both  $h=1$  and  $h=2$ . In light of the previous findings, this is not surprising.

### **Iowa State University**

Table 4.4 provides the results for Iowa State and related forecasts. For the individual models, they show that the exponential smoothing procedure performs best at  $h=1$  and  $h=2$ . However, at  $h=3$ , the AR(5) model exhibits the highest lnS. In terms of RMSE, the Iowa forecast and the VAR model show superior performance compared to the other individual models.

Results for the density combinations present a pattern similar to the USDA combinations. Linear or logarithmic pooling improve sharpness over the individual forecasts, com-

posite models based on equal and MSE weights always outperform the individual forecasts. Logarithmic pooling based on EW weights (Log EW) provide the best combination at  $h=2$  and  $h=3$ , and is virtually the same as Log MSEW at  $h=1$ . Combinations also show improvement over individual forecasts when evaluated by RMSE. However when using RMSE, it is not clear which functional form is superior. The linear pooling with MSE weights shows the smallest RMSE at  $h=1$  and  $h=3$ , but at  $h=2$  the logarithmic pooling with MSE weights is the smallest.

In table 4.5, we present the test results of differences of predictive accuracy. Tests of predictive accuracy are made between the best overall model (Log EW) and the best individual model (Exp Smoothing), the best linear pool (Lin MSEW), the Iowa State implied forecast, and the other logarithmic pools based on different weighting schemes. Test results resemble the findings encountered in the USDA forecasts. The Log EW composite dominates the best individual model, the Iowa outlook forecast, and the best linear composite (Lin MSEW). Again, the Log EW and the Log MSEW are virtually identical at all horizons, the best linear composite (Lin MSEW) is not statistically superior to the best individual forecast, and the RLSW weights regardless of the functional form of the composite exhibit poor forecasts relative to other composites and to some individual forecasts.

Figure 4.7 presents the cumulative differences of log scores between the best density combination and the best individual model (Log EW vs Exp smoothing), the best logarithmic pool and the best linear pool (Log EW vs Lin MSEW), and the best density combination and the Iowa (Log EW vs Iowa) for the three horizons ( $h=1$ ,  $h=2$ ,  $h=3$ ). At  $h=1$  both the exponential smoothing and the linear composite based on mean square error (Lin MSEW)

are outperformed modestly by Log EW with the difference being fairly stable. At  $h=2$  and  $h=3$ , Exp Smoothing becomes progressively worse relative to the Log EW, while the decrease in performance of Lin MSEW is slightly less pronounced. The Log EW is clearly superior to the Iowa outlook program (Iowa) at all three horizons, with the difference being more accentuated at distant horizons.

## **Missouri**

The individual and composite forecast results and predictive accuracy tests for the Missouri are presented in tables 4.6 and 4.7. The findings are similar to results for Iowa State. Using log scores as a criterion, combinations with equal and MSE weights outperform individual forecasts. In terms of predictive accuracy tests, the logarithmic pooling with equal weights (Log EW) is superior to the best individual model, the Missouri program, and in comparisons with composite models except the Log MSEW whose predictive accuracy is almost identical. The composite forecasts based on recursive log score weights (RLSW) do not perform well relative to forecasts from other composite procedures and the best individual models. Plots of the cumulative differences between Log EW and Missouri forecast increase steadily over time at all horizons, and are rather similar across the three horizons (figure 4.8). Again, similar to Iowa, the cumulative differences between Log EW and the best individual forecast (Exp Smoothing), and the best linear composite (Lin MSEW) are less pronounced over time, but increase at the most distant horizon. These findings add support the conclusion that Log EW outperforms other forecast methods during the evaluation period.

A difference that does emerge in the Missouri findings involves a discrepancy that arises

between the RMSE and log score criteria. Using the RMSE criterion the Missouri program outperforms all composite forecasts at  $h=1$ . At  $h=2$  the best overall forecast in terms of RMSE criterion is the log pool with MSE weights, and at  $h=3$  it is the linear pool with MSE weights. When using log scores as a criterion, the forecast results are more consistent across horizons with the findings for USDA and Iowa, supporting the benefits of these combinations and in general the equally weighted logarithmic approach.

### **Calibration**

Table 4.8 provides the calibration (goodness of fit) of individual and combined density forecast at  $h = 1$  using the Berkowitz test on the normalized probability integral transform (PIT). Recall that a density forecast is calibrated (correctly specified) if the joint null hypothesis of normality and no autocorrelation of the normalized PITs is not rejected. Results indicate that Exponential smoothing, No Change, and the implied forecast from outlook programs are calibrated (Berkowitz test fails to reject the null at 5% level), AR(5) is calibrated for the USDA and Missouri prices but is not well calibrated for the Iowa prices. The VAR(5) model is not calibrated since it strongly rejects the null of the Berkowitz tests for all three forecast prices. Notice while the VAR(5) is the best individual model in terms of RMSE (table 4.2), it is actually the worst model in terms calibration and ranks relatively low in sharpness.

Results in table 4.8 show that all logarithmic pooling combinations are calibrated, with the exception of Log MSEW for Missouri at the 10% level of significance. In contrast, the linear pooling combinations are not calibrated. The results demonstrate a clear dominance of logarithmic over linear pooling in terms of calibration, which corresponds with the small

but significant difference in sharpness and predictive accuracy at  $h=1$ . Also, recall that the linear pooled forecasts do not improve over the best individual density forecasts as established by the test of equal predictive accuracy. On balance, equally weighted logarithmic combinations (Log EW) and logarithmic pooling with MSE (Log MSEW) are superior to individual densities, linear combinations, and to combinations derived from recursive weights.

## 4.7 Summary and Conclusions

In this article we investigate the density forecasting performance of different individual and composite procedures using hog prices, different time series models, and forecasts provided by the USDA, Iowa State University, and University of Missouri. In theory, composite forecasts can provide information from additional sources and protect against bad forecasts when using a particular model. These advantages can lead to superior density forecast accuracy.

The evaluation of the density and composite forecasts was based on sharpness and calibration. In terms of sharpness, we find that the performance of the individual forecasts varied substantially although exponential smoothing appeared to be the best individual model across different horizons. Consistent with the emerging density forecast literature, density forecast combinations improved the sharpness over individual forecasts, but the form of the combination and the weighting procedures influenced the performance. Linear composites improved over individual forecasts, but the test of equal predictive accuracy indicated that the difference was not always statistically significant. In contrast, logarithmic composites based on equal MSE weights were always better than the individual forecasts and the linear composites in terms of sharpness. The best logarithmic composite (Log EW) also was



statistically more accurate than the other forecasts investigated except for logarithmic with MSE weights forecasts which were nearly identical. Somewhat unexpectedly, the sharpness performance of the linear and logarithmic recursive log score weight forecasts (RSLW) was quite poor. Previous research has also identified that recursive log score weighting scheme has performed poorly in other situations. The exact reason for the poor performance is uncertain, but may point to the complexity of the weighting scheme. Regardless, this finding clearly identifies the need for careful empirical assessment of alternate weighting schemes as different combining rules appear to be more suitable in different situations.

The relationship between log scores and RMSE criteria for selecting the most accurate forecasts although close in some cases is not one to one. We found differences in the ranking of the performance of individual forecasts, and also it is not clear which pooling functional form, either linear or logarithmic, offers the best RMSE performance. However, irrespective of the functional form, we find that composite forecasts improve over the best individual forecasts with the exception of Missouri forecasts at the first horizon where the Missouri outlook forecast exhibited the lowest RMSE.

Most of the individual forecast models were well calibrated, except for the VAR(5) which exhibited the best individual point forecasts based on RMSE. Interestingly, the poor VAR(5) performance also emerged in sharpness comparisons and point to the importance of using log score measures when evaluating densities and their relative accuracy. All logarithmic pooled forecasts are well calibrated, while the linear pooled forecasts generally reject the null hypothesis. The only linear pooled forecast that fails to reject the null hypothesis of calibration is the linear RLSW composite that performs poorly in terms of sharpness. The

relatively poor performance of the linear composites is consistent with research which has shown that linear combinations can provide prediction intervals that too wide. Logarithmic composites in contrast tend to be less dispersed and unimodal which facilitates calibration.

Similar to Colino et al. (2012) we find that the use of composite forecasting methods can improve over the outlook forecasts. Here, in terms of sharpness, logarithmic composite density forecasts with equal weights and MSE weights are superior, and the best logarithmic pooling forecast is statistically more accurate. Detailed comparison of the relative performance of the USDA, Iowa, and Missouri forecasts and the best logarithmic forecast over time demonstrates the consistent superiority that increases in magnitude through time particularly at more distant horizons. The clear superiority of these logarithmic density forecasts identifies the potential to provide hog producers and market participants with more accurate expected price probability distributions, which can facilitate decision making. Importantly, the logarithmic equal weighted forecasts show consistently the best performance. This finding is in line with the combination puzzle, that states the difficulty of improving over a simple equal weighted combination, this was also found by Colino et al. (2012) for the point forecast procedures. Furthermore, since equal weights is the easiest combination to generate, this reduce the complexity and costs of developing these density forecasts and provide a more readily available alternative.

## 4.8 Tables and Figures

**Table 4.1:** Sources of Quarterly Data, 1975.I - 2010.IV

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<b>Observed USDA Hog Price:</b> Livestock, Dairy, and Poultry Outlook, Barrows & gilts, n. base, i.e. \$/cwt <a href="http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1350">http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1350</a> and Red Meat Yearbook before 2005
<b>Observed Iowa Hog Price:</b> Quarterly average from monthly hog prices of Iowa-Southern Minnesota plant delivered (\$/carcass cwt) Adjusted live price for 74% dress from 49-52% lean <a href="http://www.extension.iastate.edu/agdm/livestock/pdf/b2-10.pdf">http://www.extension.iastate.edu/agdm/livestock/pdf/b2-10.pdf</a>
<b>Observed Missouri Hog Price:</b> Barrows & Gilts, price/cwt, 51-52% Lean Live <a href="http://agebb.missouri.edu/mkt/bull8c.htm">http://agebb.missouri.edu/mkt/bull8c.htm</a>
<b>Sows Farrowings:</b> Number of Sows from USDA NASS hogs and pigs <a href="http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1086">http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1086</a>
<b>Commercial Pork Production:</b> NASS Livestock slaughter <a href="http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1096">http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1096</a>
<b>Beef price:</b> Livestock, Dairy, and Poultry Outlook, Choice steers, 5-area Direct, \$/cwt <a href="http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1350">http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1350</a> and Red Meat Yearbook before 2005
<b>Corn prices:</b> Quarterly average of daily prices, \$/bushel AgMAS, <a href="http://www.barchart.com">http://www.barchart.com</a>
<b>USDA Hog Price Forecast:</b> Livestock, Dairy, and Poultry Outlook, Barrows & gilts, n. base, i.e. \$/cwt Midpoint of the interval forecast <a href="http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1350">http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1350</a>
<b>Iowa Hog Price Forecast:</b> Quarterly hog price forecasts are collected from various issues of Iowa Farm Outlook
<b>Missouri Hog Price Forecast:</b> Barrows & Gilts, price/cwt, 51-52% Lean Live <a href="http://agebb.missouri.edu/mkt/bull8c.htm">http://agebb.missouri.edu/mkt/bull8c.htm</a>

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**Table 4.2:** Average Log Score and RMSE for Individual and Combined USDA Forecasts, 1994.I - 2010.IV

Individual Model	h=1		h=2	
	lnS	RMSE	lnS	RMSE
AR(5)	-3.1084	5.2208	-3.4565	7.0539
Exp Smoothing	-3.0239	4.9617	-3.4105	7.2099
No Change	-3.2979	6.3042	-3.6565	9.0628
VAR(5)	-3.1403	4.6601	-3.4563	6.0508
USDA	-3.6276	6.5739	-3.8515	8.1550
Combinations				
Select	-3.2807	5.2626	-3.5672	6.9216
Linear Pooling				
Lin RLSW	-3.1223	4.9429	-3.4772	6.6941
Lin MSEW	-3.0225	4.6335	-3.3252	6.1841
Lin EW	-3.0668	4.7816	-3.3694	6.4490
Logarithmic Pooling				
Log RLSW	-3.1380	4.9023	-3.5053	6.6111
Log MSEW	-2.9320	4.4868	-3.2149	5.9335
Log EW	-2.9360	4.5114	-3.2093	5.9769

**Table 4.3:** Test of Equal Predictive Accuracy, USDA Forecasts

Log Score Comparison	h=1		h=2	
	Diff.	P-value	Diff.	P-value
Log EW vs Exp Smoothing	0.0880	0.0270**	0.2012	0.0001**
Log EW vs USDA	0.6916	0.0000**	0.6422	0.0000**
Log EW vs Lin MSEW	0.0866	0.0000**	0.1159	0.0000**
Log EW vs Log RLSW	0.2020	0.0004**	0.2960	0.0054**
Log EW vs Log MSEW	-0.0040	0.7485	0.0056	0.8185
Lin MSEW vs Exp Smoothing	-0.0429	0.2446	0.0411	0.3963

\*\* Significant at 5%, \* Significant at 10%

**Table 4.4:** Average Log Score and RMSE for Individual and Combined Iowa State Forecasts, 1994.I - 2010.4

Individual Model	h=1		h=2		h=3	
	lnS	RMSE	lnS	RMSE	lnS	RMSE
AR(5)	-3.1910	5.5862	-3.5662	7.6974	-3.6906	8.3645
Exp Smoothing	-3.0598	5.1365	-3.4435	7.4149	-3.7029	9.4044
No Change	-3.3434	6.5562	-3.7071	9.4363	-3.7442	9.9777
VAR(5)	-3.2090	4.8994	-3.5166	6.3292	-3.8809	8.2448
Iowa	-3.3403	4.8661	-3.7563	6.9176	-3.8871	8.0871
Combinations						
Select	-3.1735	5.3032	-3.5683	6.5386	-3.8386	8.4633
Linear Pooling						
LIN RLSW	-3.1297	5.1473	-3.5273	6.4857	-3.7704	8.4289
LIN MSEW	-3.0473	4.6090	-3.3852	6.3403	-3.5802	7.6908
LIN EW	-3.0553	4.6823	-3.4098	6.5409	-3.5853	7.7991
Logarithmic Pooling						
LOG RLSW	-3.1318	5.1365	-3.5270	6.4324	-3.8087	8.4373
LOG MSEW	-2.9767	4.6970	-3.2700	6.2578	-3.5009	7.7580
LOG EW	-2.9799	4.7250	-3.2698	6.3291	-3.4767	7.7252

**Table 4.5:** Tests of Equal Predictive Accuracy, Iowa State Forecasts

Log Score Comparison	h=1		h=2		h=3	
	Diff.	P-value	Diff.	P-value	Diff.	P-value
Log EW vs Exp Smoothing	0.0799	0.0829*	0.1737	0.0053**	0.2262	0.0020**
Log EW vs Iowa	0.3604	0.0000**	0.4865	0.0000**	0.4104	0.0001**
Log EW vs Lin MSEW	0.0674	0.0495*	0.1154	0.0003**	0.1035	0.0411**
Log EW vs Log RLSW	0.1519	0.0043**	0.2572	0.0717*	0.3319	0.0376**
Log EW vs Log MSEW	-0.0032	0.5891	0.0002	0.9915	0.0242	0.3437
Lin MSEW vs Exp Smoothing	0.0045	0.9106	0.0336	0.5431	0.1176	0.0682*

\*\* Significant at 5%, \* Significant at 10%

**Table 4.6:** Average Log Score and RMSE for Individual and Combined Missouri Forecasts, 1994.I - 2010.IV

Individual Model	h=1		h=2		h=3	
	lnS	RMSE	lnS	RMSE	lnS	RMSE
AR(5)	-3.1355	5.3340	-3.5669	7.5827	-3.7255	8.3591
Exp Smoothing	-3.0300	4.9904	-3.4472	7.4250	-3.6777	9.2294
No Change	-3.2979	6.2885	-3.6757	9.1722	-3.6888	9.5815
VAR(5)	-3.1531	4.7155	-3.5475	6.4037	-3.9305	8.3434
Missouri	-3.2975	4.2738	-3.7639	6.7088	-3.8622	7.8775
Combinations						
Select	-3.1562	5.4229	-3.5475	6.4037	-3.7409	8.4609
Linear Pooling						
LIN RLSW	-3.1137	5.1830	-3.5556	6.4347	-3.7475	8.3770
LIN MSEW	-3.0383	4.3409	-3.3867	6.2613	-3.5867	7.5595
LIN EW	-3.0337	4.4438	-3.4058	6.4235	-3.5799	7.6057
Logarithmic Pooling						
LOG RLSW	-3.1046	5.1702	-3.5519	6.4216	-3.7295	8.3314
LOG MSEW	-2.9292	4.4671	-3.2667	6.2498	-3.4915	7.7245
LOG EW	-2.9336	4.4944	-3.2604	6.2804	-3.4656	7.6519

**Table 4.7:** Tests of Equal Predictive Accuracy, Missouri Forecasts

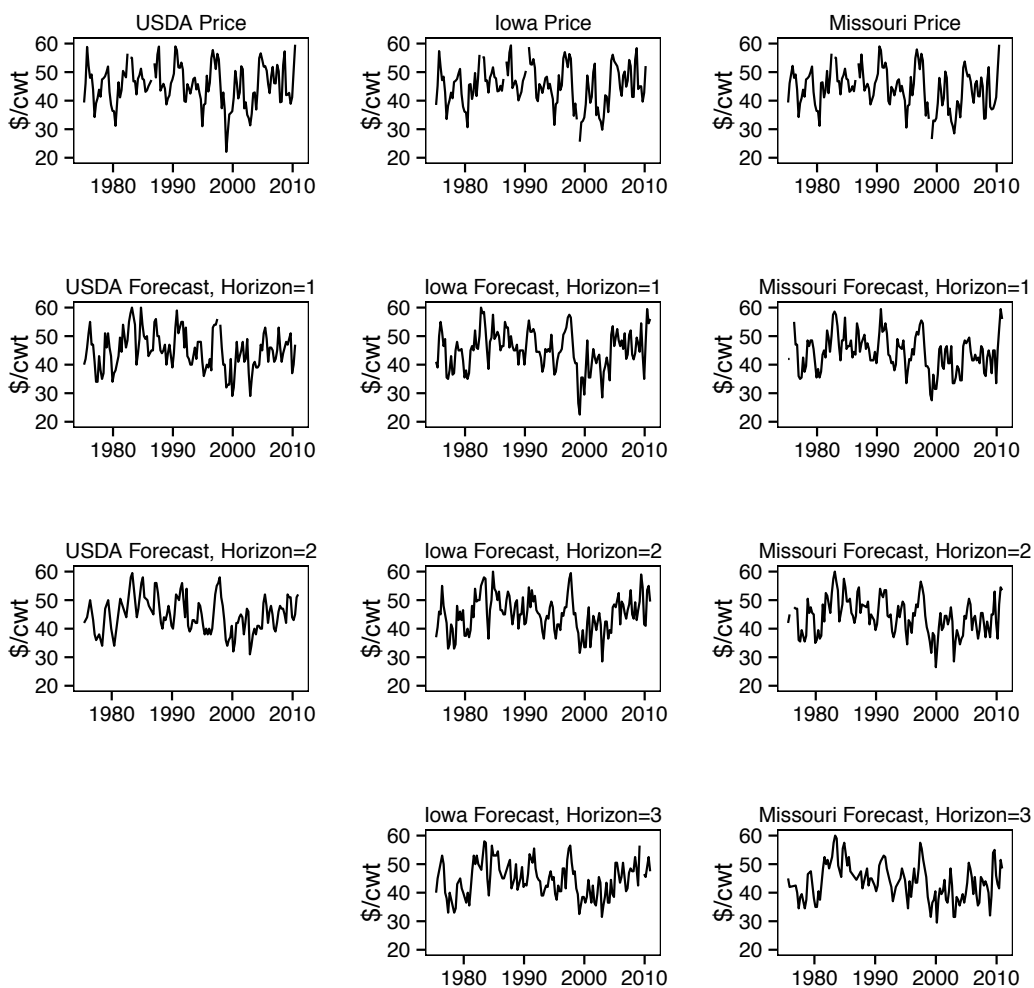
Log Score Comparison	h=1		h=2		h=3	
	Diff.	P-value	Diff.	P-value	Diff.	P-value
Log EW vs Exp Smoothing	0.0964	0.0275**	0.1868	0.0022**	0.2121	0.0048**
Log EW vs Missouri	0.3639	0.0000**	0.5035	0.0000**	0.3966	0.0001**
Log EW vs Lin MSEW	0.1047	0.0000**	0.1262	0.0001**	0.1212	0.0227**
Log EW vs Log RLSW	0.1711	0.0019**	0.2915	0.0213**	0.2639	0.0407**
Log EW vs Log MSEW	-0.0044	0.4433	0.0063	0.7482	0.0259	0.1719
Lin MSEW vs Exp Smoothing	-0.0038	0.9263	0.0414	0.4771	0.0978	0.1687

\*\* Significant at 5%, \* Significant at 10%

**Table 4.8:** Berkowitz Test for Calibration at h=1

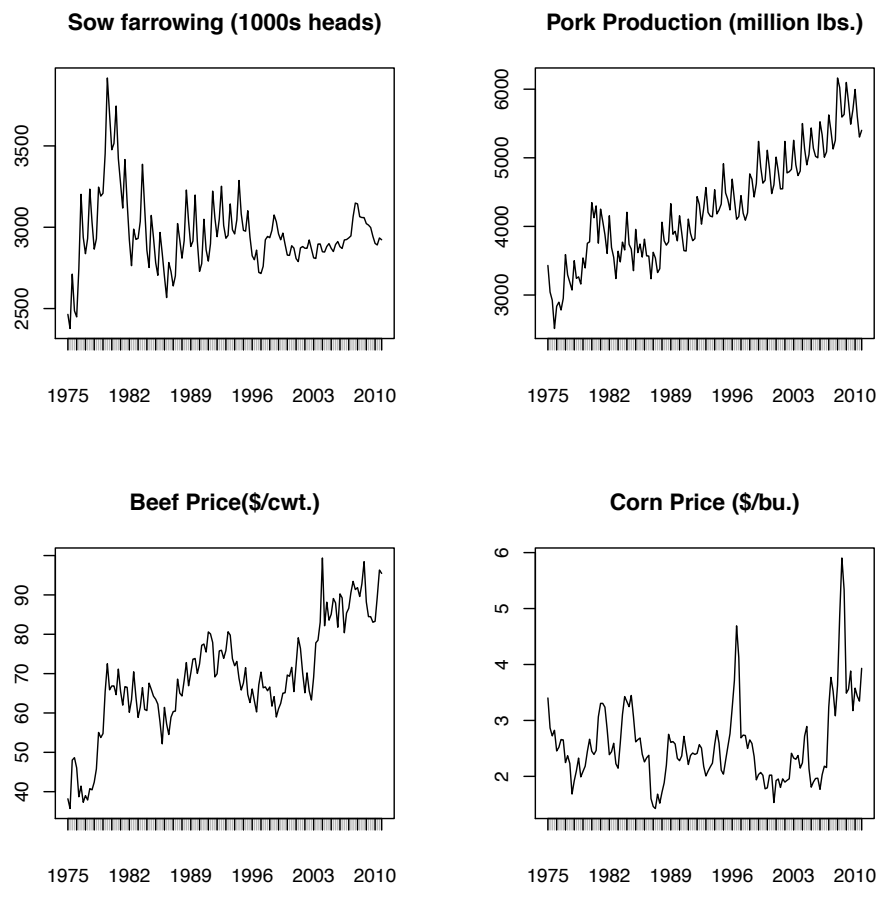
	USDA		Iowa		Missouri	
Individual Model	LRatio	P-value	LRatio	P-value	LRatio	P-value
AR5	6.2187	0.1014	6.4466	0.0918*	5.7594	0.1239
Exp. Smoothing	4.1360	0.2471	3.3831	0.3362	5.2462	0.1546
No Change	2.1301	0.5458	1.6392	0.6505	1.1729	0.7595
VAR5	28.5000	0.0000**	24.3607	0.0000**	21.7938	0.0001**
Outlook Program	4.1281	0.2480	4.4828	0.2138	3.2342	0.3569
Combinations						
Select	4.4443	0.2173	4.3227	0.2287	3.9821	0.2634
Linear Pooling						
Lin RLSW	7.2534	0.0642*	7.1537	0.0672*	6.7425	0.0806*
Lin MSEW	9.9236	0.0192**	9.6729	0.0216**	7.5597	0.0560*
Lin EW	8.4223	0.0380**	8.6707	0.0340**	7.1733	0.0666*
Logarithmic Pooling						
Log RLSW	4.7221	0.1933	4.5211	0.2104	4.8915	0.1799
Log MSEW	5.4944	0.1390	5.4727	0.1403	6.3715	0.0949*
Log EW	4.7923	0.1877	4.9985	0.1719	4.9878	0.1727

\*\* Significant at 5%, \* Significant at 10%

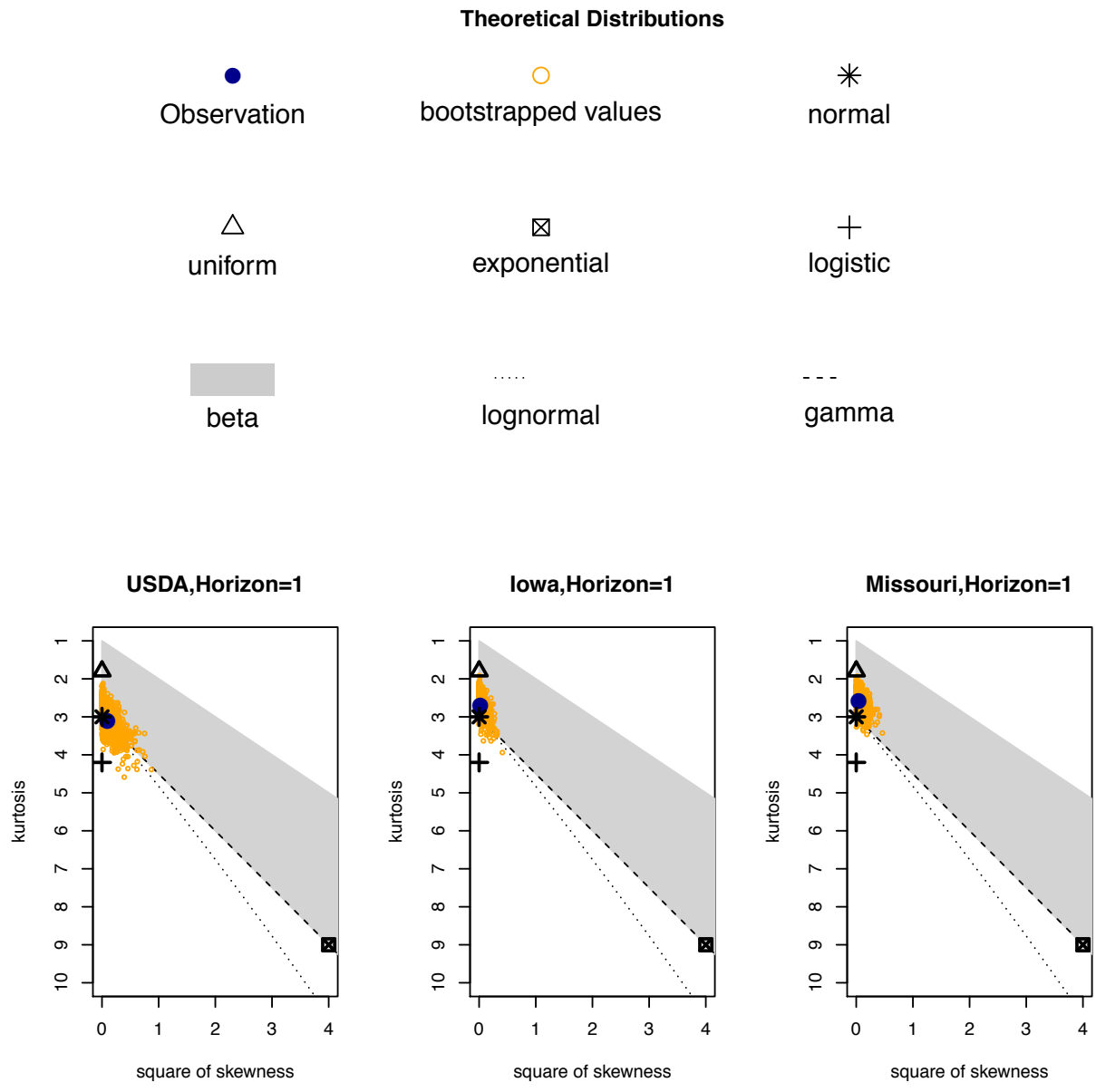


**Figure 4.1:** Quarterly U.S. hog prices and USDA, Iowa State University, and University of Missouri forecasts. 1975.I - 2010.IV.

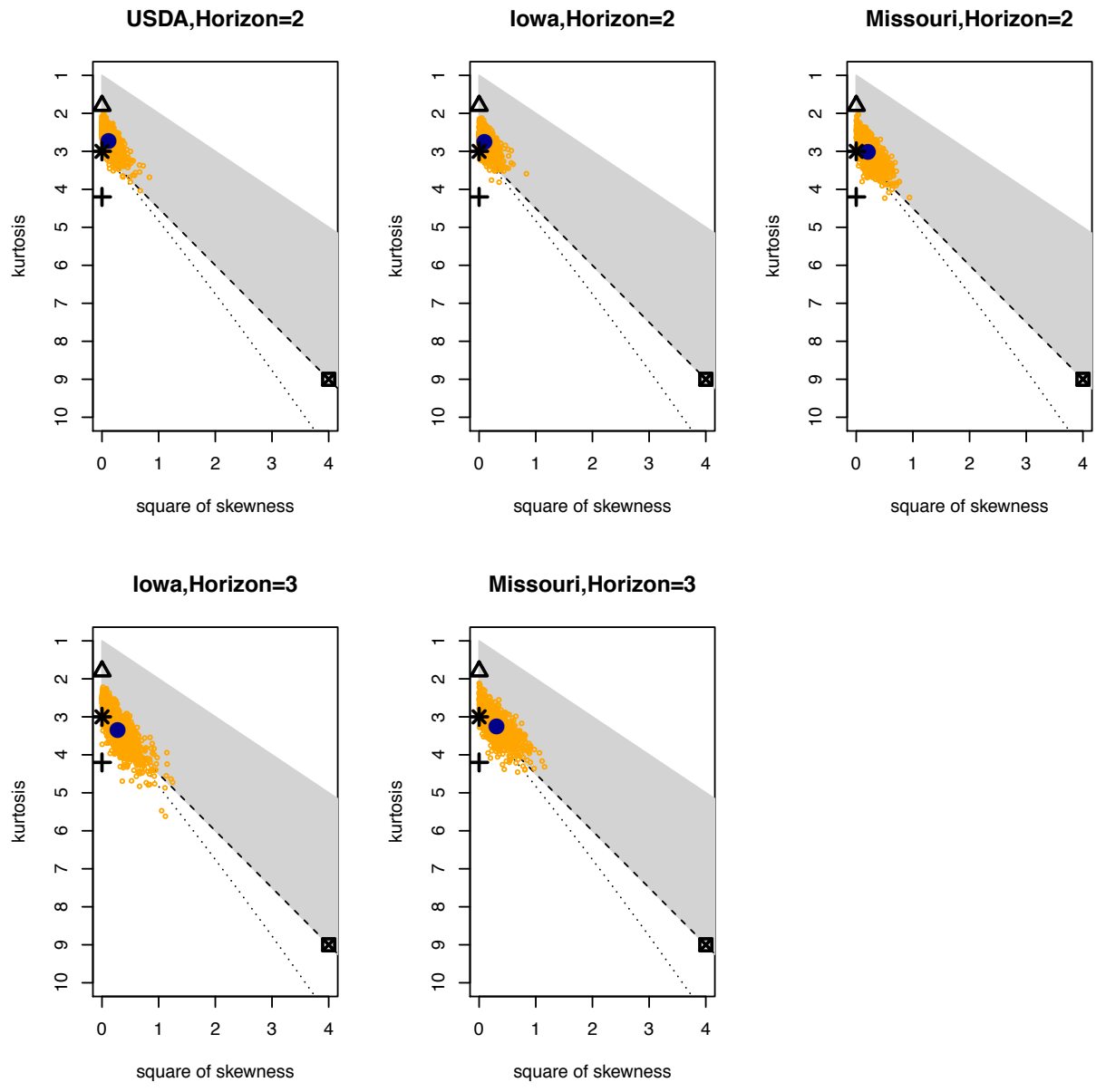




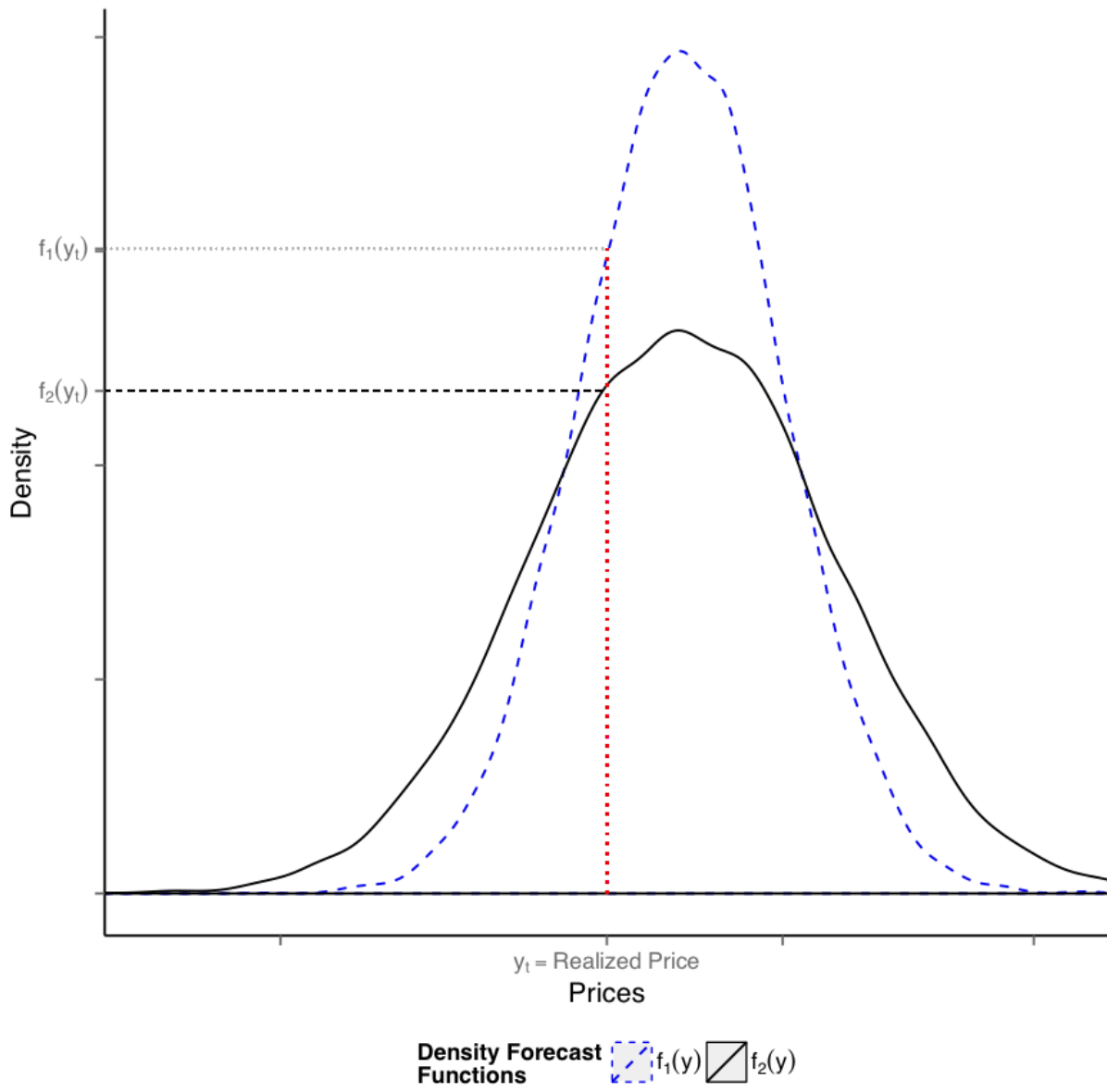
**Figure 4.2:** Data used in vector autoregression models. 1975.I - 2010.IV.



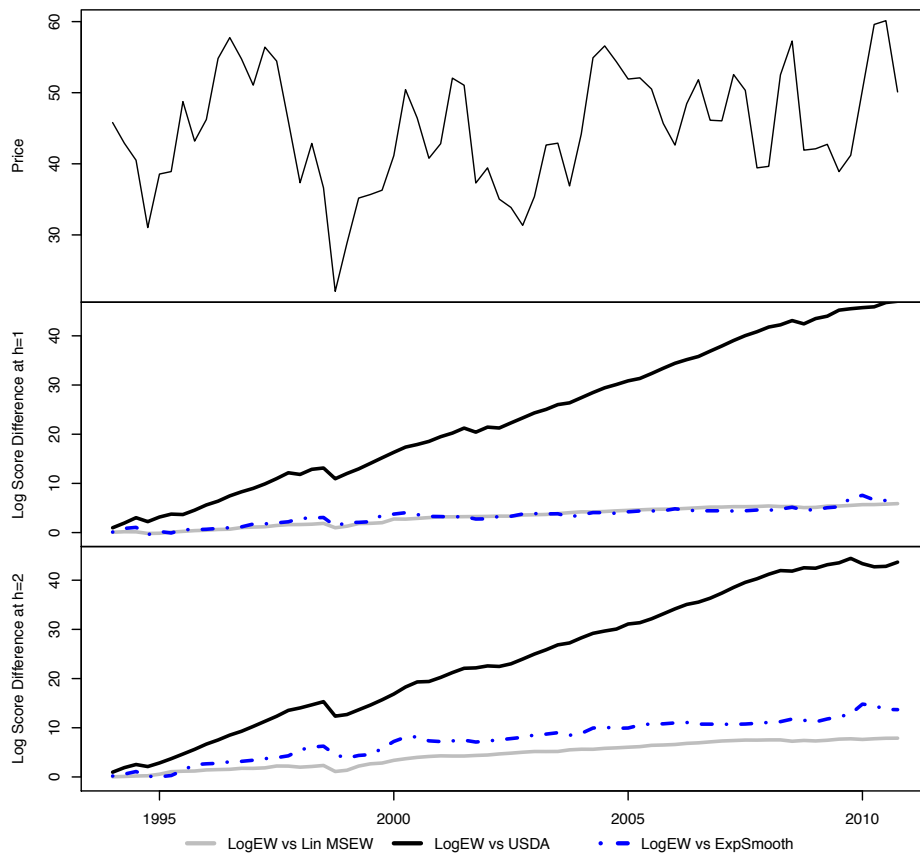
**Figure 4.3:** Cullen and Frey graphs for outlook programs forecast errors at one-quarter-ahead horizon



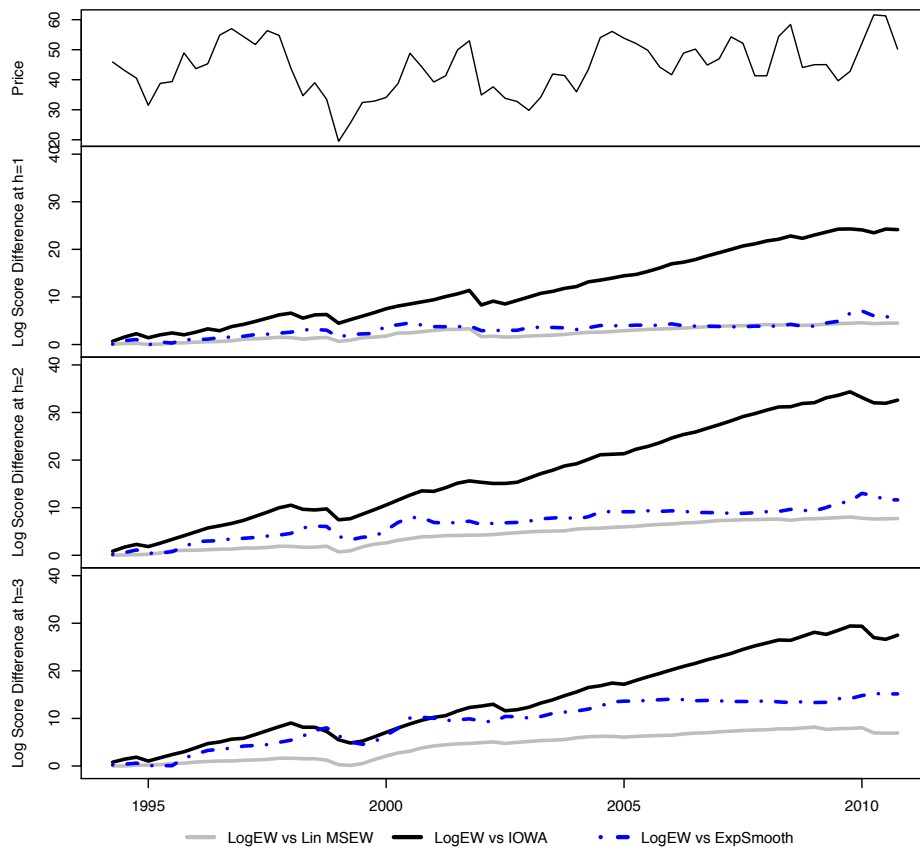
**Figure 4.4:** Cullen and Frey graphs for outlook programs forecast errors at two- and three-quarter-ahead horizon



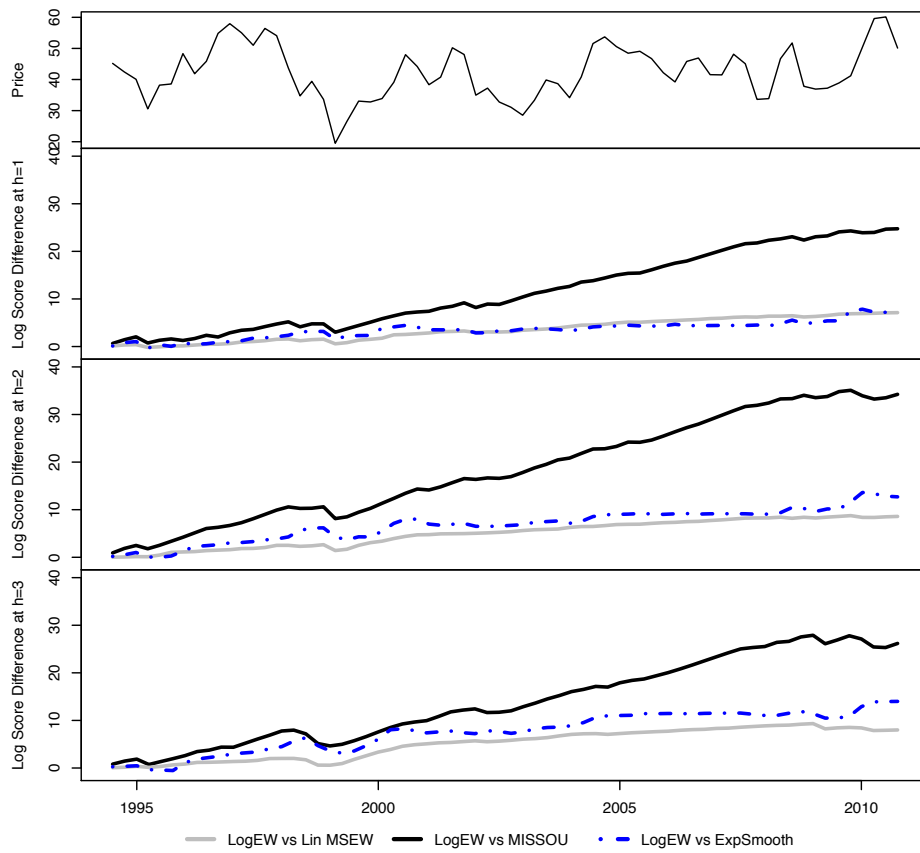
**Figure 4.5:** Density forecast functions at realized price,  $f_i(y_t)$



**Figure 4.6:** Cumulative difference of log scores with USDA forecasts



**Figure 4.7:** Cumulative difference of log scores with Iowa State University forecasts



**Figure 4.8:** Cumulative difference of log scores with University of Missouri forecasts

# Chapter 5

## Conclusions

Price variability has been the most salient characteristic of commodity markets in recent years. Sharp price changes increase uncertainty for market participants, complicating price discovery and business planning. It also potentially affects the livelihood of agricultural producers and the consumption of food, particularly for vulnerable groups in low-income populations in developing countries. In addition, commodity trading in futures markets has been growing strongly. It is evident that many stakeholders are directly affected by commodity price variability, raising the need to understand market fundamentals and the drivers of price variability. Further, many governments are currently engaged in developing food security policies that include planning and coordination of supply, management of inventories, and support of agricultural producers. Therefore, decision makers require prediction tools that take into account the increased uncertainty generated by strong price variability.

This dissertation consists of three papers that investigate price variability from different perspectives. In the first paper, I study relationships between energy and agricultural commodity prices. In particular, volatility price spillovers from crude oil to corn and ethanol. I investigate those markets using futures prices from 2006 until 2011, a period characterized by



the financial crisis of 2008 and a strong growth in ethanol production led by biofuels policy in the United States. Since most ethanol in the U.S. is produced from corn and blended into gasoline, this creates a strong link between energy and agricultural markets. Previous literature has been focused on price transmission in levels but relatively less is known about how volatility in the crude oil market may transfer to corn and ethanol markets. Using multivariate GARCH models, I identify conditional volatilities for each of these markets, and develop spillover ratios by calculating the share of volatility in the corn and ethanol markets due to crude oil. Based on the volatility spillover ratios I identify volatility transmission as an important component of price variability in these markets. Spillover ratios from crude oil to corn and ethanol were usually around 10%-20% during the sample period, but increased to almost 45% during the financial crisis. Volatility spillover ratios can help to understand the magnitude and timing of market shocks, which is an important dimension of risk management. They can also help guiding food security policies, given the strong clustering pattern in volatility, and can help monitoring market conditions and anticipating the reaction of agricultural commodities from shocks in the crude oil market.

The second and third papers focus on the development density prediction tools. This analysis is a response to the need to incorporate uncertainty directly into forecasting, an important feature in an environment of high price variability. In the second paper I develop short-term density forecasts (two weeks) in the lean hog futures markets from 2002 until 2012. I build density forecasts using historical data from futures markets, employing GARCH models allowing for different error distributions. Also, I employ a forward-looking approach obtaining the risk-neutral distributions (RND) from option prices using the generalized beta

distribution of the second kind ( GB2). In addition, real-world distributions (RWD) were obtained by calibrating the RND. Then I evaluated the performance of density forecasts in terms of sharpness – forecast accuracy of the forecast, and goodness of fit– the degree to which the forecasted distribution resembles the actual distribution. Results demonstrate that RWD distributions are modestly superior to RND and GARCH generated forecasts. This supports the notion that a risk premium exists even at a two-week horizon and that market participants can use these forecasts to develop a better understanding of the final distribution of prices.

In the third paper I develop and assess density forecasts at longer horizons using quarterly 1975-2010 hog prices from USDA, Iowa State University, and Missouri outlook programs and several commonly used time series models. In the paper I generate and evaluate the predictive accuracy and goodness of fit of the density forecasts, and the effectiveness of density forecasts combination procedures. Forecast composite procedures have been found useful for point forecasts, but only recently has their effectiveness been explored for density forecasts. Results confirm that composite procedures are indeed useful for improving density forecasts out-of-sample performance. . These findings indicate that outlook experts can take advantage of combination procedure to improve their fore- casts by incorporating information from several sources. However the functional form of the combination plays a role in its outcome; here logarithmic pooling dominates linear combinations. Weighting schemes of the individual forecasts also influence the accuracy of the combinations. Evidence suggests that the simplest combination (equal weights) provides the best out-of-sample performance, which is in line with the combination puzzle often found in point forecasting.

This dissertation contributes in the understanding of important dimensions of price variability in commodity markets, including: cross-market relationships, the development of prediction tools that account for forecasting uncertainty, and usefulness of composite procedures. Commodity price variability affects the livelihood of many people in the world economy. Although our knowledge of this phenomena is still limited, findings in this dissertation contribute to a better understanding of drivers, effects, and management of price variability, which can help decision and policy makers to make more informed choices.

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