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Are Futures Prices Good Price Forecasts? Nonlinearities in Efficiency and Risk Premiums in the Soybean Futures Market

Recent research has pointed to a reduction in predictive content in several agricultural futures markets. We investigate short-run forecast in the soybean futures market complex to identify predictive content and the sources of forecast errors. A non-parametric local linear regression framework is first applied to investigate biasness, and to guide the specification of parametric regime-switching models in which we perform statistical testing. To identify effects of risk premiums, we use a nonlinear realized volatility framework. Our non-parametric and parametric findings indicate nonlinearities in efficiency and risk premiums are present. Depending on the level of futures prices, thresholds or regimes of predictive performance exist. Evidence of market exuberance/pessimism emerges as many of the pricing errors occur at the extremes of the price distribution. Our research demonstrates that failure to account for these non-linear relationships can distort our understanding of market effectiveness. Finally, we show that the use of higher frequency data can be useful in identifying the presence and magnitude of risk premiums. This finding may make uncovering risk premiums in agricultural commodity markets more tractable in the future.

Key words: futures markets, forecasting, risk premium.

Introduction

Agricultural futures markets provide information that is vital to decision makers. Users of the information include producers and agribusiness firms who rely on futures prices to inform their production and marketing decisions, and government agencies that employ agricultural price forecasts to understand production and food security issues, and to assist in forecasting commodity market prices (Tomek and Gray 1970; Hurt and Garcia 1982; Allen 1994). Futures prices are also used by crop insurance programs to set their pre-plant and harvest prices (Zulauf, Rettig, and Roberts 2014). Because of their importance, the degree to which futures markets provide accurate forecasts of subsequent prices has been investigated extensively. Prior to 2005, the evidence suggested that futures markets were relatively efficient in the long run, but short-run inefficiencies existed in certain markets for particular periods (Garcia and Leuthold 2004). Recent behavior of agricultural commodity prices has again raised questions of futures markets forecast accuracy. Gutierrez (2013) and Etienne, Irwin, and Garcia (2014) find evidence of explosive futures prices in a variety of markets. Chinn and Coibion (2014) identify differences in the predictive content of commodity futures across and within commodity groups, but document a broad decline in the forecast ability of futures prices since the early 2000s. While a reduction in predictive content has been identified, specific sources of the decline are less well understood. In light of the characteristics of agricultural commodity prices, increased volatility which can influence risk premiums and speculative market exuberance may play an important role.

Here, we investigate short-run forecast in the soybean futures market complex to more clearly identify the predictive content and the sources of forecast errors. Soybean production is a risky enterprise, as many factors such as hard-to-predict weather, the price of corn, the livestock sector, energy markets, currency markets, and domestic and international policies, all play a role in soybean pricing. Among all agricultural futures traded in CBOT and CME, soybeans, soybean oil, and soybean meal represented the second, third, and fourth most traded contracts, respectively, in 2015 (CME Group 2016). Considering the soybean complex as a whole, its trading volume surpasses corn and is the largest. The magnitude of soybean futures trading reflects its importance in the agricultural sector in the U.S. and the world (USDA 2016). As one of the dominating soybeans exporting and financial markets in the world, any biasedness and inefficiency in U.S. soybean complex markets will heavily affect global market participants; hence, examination of this market is warranted.

We concentrate on two-month forecast horizons using a nonlinear realized volatility framework and 1973-2016 data that allow us to identify the effects of market exuberance and risk premiums on prices. A non-parametric local linear regression framework (Fan and Gijbels 1996) is first applied to investigate unbiasedness, and to guide the specification of parametric regime-switching models in which we perform statistical testing. To identify the effects of risk premiums, which have been difficult to estimate in a forecast context (Frank and Garcia 2009), we use a realized GARCH model (Hansen, Huang, and Shek 2012) that has been shown to improve conditional volatility modelling. We focus on the soybean market because of its economic importance. Also, beginning with Rausser and Carter (1983), the forecast accuracy of the soybean complex has been called into question, and use of our long sample period, permits us to gain perspective on the sources of forecast errors.

Our non-parametric and parametric findings indicate nonlinearities exist in efficiency and risk premiums. Depending on the level of futures prices, different regimes of predictive performance exist. Evidence of market exuberance/pessimism emerges in all three markets. When prices are high (low), markets tend to over- (under-) forecast subsequent prices. Differences in the regimes and sources of forecast accuracy also emerge across markets, reflecting that while the markets are linked they can differ in the underlying fundamentals and costs of arbitrage. The results indicate that the recent market booms did affect forecasting performance through exuberance and changing risk premiums. However, they also identify that in periods of low prices predictive content is primarily affected by “pessimism”. These non-linear findings differ substantially from those generated in the conventional linear framework.

On balance, the article highlights the importance of investigating the ability of futures markets to forecast spot prices in a non-linear context. Most research to date has ignored these non-linear price linkages when testing for biasness and the presence of risk premiums. Our article demonstrates that failure to account for these non-linear relationships can distort our understanding of market effectiveness. Finally, we show that the use of higher frequency data to generate realized volatility can assist in identifying the presence and magnitude of risk premiums. This finding may make uncovering risk premiums in agricultural commodity markets more tractable in the future.

Literature review

The forecast performance of agricultural futures contracts has been a subject of intensive research since the pioneering work by Tomek and Gray (1970). They introduce the idea of empirical forecast assessment. The authors regress the futures prices of the new crop corn, soybean and potato futures contracts in the maturity month, on the price of the same contract in the previous spring. They find that futures prices in spring are unbiased forecasts of the futures prices in the maturity month for corn and soybean markets and for the period from 1952 to 1968, but not for potatoes. Many studies on different agricultural commodity futures markets have followed, producing mixed results. While evidence tends to support that non-storable commodity futures markets are more biased or inefficient than storable ones, the forecast performance appears to be highly dependent on the specific time periods and market conditions (Kofi 1973; Martin and Garcia 1981; Kenyon, Jones, and McGuirk 1993; Zulauf et al. 1999; McKenzie and Holt 2002; Garcia and Leuthold 2004).

Researchers have devoted effort to explain the reasons why futures prices are sometimes biased estimates of cash prices. There exist at least two explanations: risk premium and market failure. Risk premium is the compensation required by investors for bearing price risk from hedgers and has been identified as one of the most relevant factors explaining divergence between cash and futures prices (Keynes 1930). However, the existence of a risk premium in agricultural markets is empirically controversial. Measurement of the risk premium requires measurement of price volatility, which is not directly observed. Fama and French (1987), Beck (1993), McKenzie and Holt (2002) and Frank and Garcia (2009) have studied the relevance of agricultural risk premiums in agricultural futures markets using different methods and have derived contrasting conclusions, especially in non-storable livestock markets. Autoregressive Conditional Heteroskedasticity in Mean Models (ARCH-M) and their generalized versions (GARCH-M) (Engle, Lilien, and Robins 1987) have been widely used to model latent volatility and risk premiums (Beck 1993; McKenzie and Holt 2002; Frank and Garcia 2009).

Market bias can also arise from the ineffective assembly, interpretation, and use of information. Much of this research has focused on comparing the accuracy of futures markets to time series forecast models based on either past prices or incorporating other public information (Rausser and Carter 1983; Johnson et al. 1991). Presumably, if the market fails to generate lower forecast errors, the added information in the structure of the model is not being incorporated by the market. Evidence on the inefficiency of markets is also somewhat mixed. Of course, these assessments are influenced by the difficulty in developing models that accurately reflect complex commodity markets, and by the fact that traders are always looking for arbitrage opportunities which shorten the duration of biases (Garcia and Leuthold 2004).

Most research conclusions on agricultural commodity futures forecast ability have been based on linear model specifications. But as noted, forecast ability of agricultural futures may vary under different market conditions so that the forecast performance may be nonlinear. Several studies identify nonlinearities in forecast performance which arise from price changes or basis levels. Martin and Garcia (1981) find that the performance of livestock futures is different between upward and downward trends, between seasons, and when economic conditions (grains market) are more volatile. Kaminsky and Kumar (1990) also find evidence that the forecast bias of futures prices is time-varying and positively correlated to the magnitude of price. Beckmann and Czudaj (2014) suggest the forecast power of the futures spread (between the first and second nearby futures) is more accurate under backwardation than contango.

Forecast accuracy may also be influenced by market exuberance/pessimism and the level of prices. In the presence of herding or exuberance, market participants drive prices to high levels, which are not supported by fundamentals. Recent commodity price fluctuations have raised concerns over bubbles caused by such price exuberance (Gutierrez 2013). Evidence of bubble episodes in agricultural commodity futures markets has been provided by Etienne, Irwin, and Garcia (2014). They show how markets over-react generating both positive and negative explosive episodes. In these scenarios, prices are likely to continue drifting away from fundamentals in the short run and affect the ability of futures prices to predict spot prices. In effect, traders wrongly believe prices will continue to increase (decrease) even when the price is extremely high (low) if exuberance/pessimism occurs.

Most literature not only overlooks the nonlinearities in market efficiency, but also omits the nonlinearities of risk premiums. This article makes a contribution to previous literature by conducting an ex-post forecast assessment in the soybean complex using nonlinear approaches and a bimonthly forecast horizon. Local linear regression methods are adopted, which consist of a data-driven nonparametric method that does not impose any a priori assumption on the behavior of data. This highly flexible approach may allow us to uncover hidden nonlinearities which are not revealed by traditional methods. Theories and practices for the local linear regression are well established in the literature (Fan and Gijbels 1996; Li and Racine 2007), but these techniques have not been applied in agricultural commodity price analysis until recently (Serra, Gil, and Goodwin 2006; Serra and Goodwin 2009; Hassouneh et al. 2012). However, they have not been yet applied to study futures market unbiasedness and efficiency. Therefore, one of the main contributions of this article is the application of local linear regression methods in identifying nonlinearities of market unbiasedness in agricultural markets. After nonlinearities are identified, nonlinear GARCH-M models allow statistical tests of unbiasedness and risk premium to be conducted. This framework permits us to assess more carefully the role that risk premiums play in forecasting and to distinguish information inefficiency from risk premiums.

Methods

The main objective of this article is to characterize unbiasedness, efficiency, and risk premiums for different price levels in the U.S. soybean complex futures markets. To do so, a conditional mean and a conditional volatility model are estimated. The conditional mean model captures the dynamics of the relationship between futures and spot price levels, as well as the role of the risk premium in explaining possible deviations of the futures prices from spot prices. Since the risk premium represents the amount that hedgers are willing to pay to reduce price risk, derivation of the risk premium requires an estimation of price volatility. The conditional volatility model's main role is to estimate price volatility which is incorporated into the conditional mean model to quantify the risk premium. To capture the different response of volatility to positive and negative market shocks, a leverage function is also included in the model. Because the capacity of futures prices to forecast spot prices may change with market conditions, nonlinearities are allowed for in the conditional mean model by introducing multiple regimes.

The method used takes the specification by Tomek and Gray's (1970) as a starting point to study efficiency and unbiasedness in futures markets. It then adds flexibility to this specification to allow for nonlinear price adjustments and risk premiums. Tomek and Gray's (1970) model adopts the following form:

$$S_t = \alpha + \beta F_{t-1} + \varepsilon_t \quad (1)$$

where S_t is the spot price in period t, F_{t-1} is the futures price in period $t-1$ with contract maturity in period t, and u_t is the OLS error term. If $\alpha = 0$ and $\beta = 1$, futures prices are unbiased and efficient. The method used in this article builds on this classic model to include all the important extensions. It allows for the futures forecast power to change depending on market conditions. Further, it attempts to explain deviations from the unbiasedness as inefficiency or risk premium (or both).

First, to allow for nonlinear price links, the Tomek and Gray's model is estimated by local linear techniques (Fan and Gijbels 1996). These techniques are especially useful if the suitable functional form describing price links is unknown. Local estimation methods allow for multiple regimes and contain threshold and smooth threshold models as a special case. Data inform and determine the shape of the relationship. While nonparametric models are highly flexible, interpretation and inference are less clear-cut than in parametric approaches. Therefore, the role of local linear regression models here is to assess the behavior of the prices studied and to inform specification and estimation of the parametric models, which are used to test for biasedness.

Following the literature (Fan and Gijbels 1996; Li and Racine 2007; Silverman 1986; Serra and Goodwin 2009), let $m(x_k) = E(Y_t|X_{t-1}=x_k)$ be the nonparametric regression problem. The main idea behind local linear regression is to estimate function m at point x_k, using the observations that are relatively close to x_k. The process is evaluated for each point in the sample, though one can also choose to evaluate the estimators at grid points of X_{t-1}. As recommended by Fan and Gijbels (1996), a Taylor series expansion of order one is used to approximate function m, which results in a local linear regression. Since the local linear regression method uses those observations with most information about $m(x_k)$, in order to estimate the function, weighted least squares are used to give more weight to close observations, relative to more distant ones. Weights are determined by a kernel function k_h as follows:

$$\sum_{t=1}^{n}\left(Y_t - \alpha - \beta(X_{t-1} - x_k)\right)^2 K_h(X_{t-1} - x_k) \quad (2)$$

where $K_h(X_{t-1} - x_k) = \prod_{j=1}^{d} K\left(\frac{X_{j,t-1} - x_{j,k}}{h_j}\right) h_j^{-1}$ is a kernel function that weights data points in the given local neighborhood and h_j is the bandwith that controls for the size of the neighborhood of x_k. The kernel reduces the contribution of observations away from x_k in the local least squares problem. $K_h(X_{t-1} - x_k)$ can be either a univariate or a multivariate kernel depending on how many (j) independent variables are used in the regression analysis.

Local polynomial fitting techniques require taking several important decisions. First is the specification of the kernel function. Following Fan and Gijbels (1996), who characterize the Epanechnikov (1969) as an optimal weighting function, the kernel is specified as follows: $K\left(\frac{X_{j,t-1} - x_{j,k}}{h_j} = z\right) = 0.75(1 - z^2) I_{[-1,1]}(z)$. A second relevant decision is the bandwidth parameter, which is chosen to be $h_j = h_{base} s_x n^{-0.2}$, where s_x is the standard deviation of covariate X_j and n is the number of observations. h_{base} is the constant base bandwidth and is selected by a least squares cross-validation method that minimizes the in-sample leave-one-out squared prediction error: $\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2$. In the context of Equation (1), $Y_t = S_t$, i.e., the dependent variable is the spot price in period *t* and the independent variable is the futures price in period $t-1$, i.e., $X_{t-1} = F_{t-1}$. The model is essentially a weighted least squares version of Tomek and Gray's (1970) OLS specification.

The results of the local linear regression are used to guide specification of the conditional mean model. The conditional mean model can be specified as follows:

$$S_t = \sum_{k=1}^{K}(\alpha_k + \beta_k F_{t-1}) I_{k,t} + \varepsilon_t, \tag{3}$$

where $I_{k,t}$ is a dummy that takes the value of one when futures price F_{t-1} is in the *k* regime, otherwise it is zero. If $\alpha_k = 0$ and $\beta_k = 1$, futures prices are considered unbiased in the *k* regime.

GARCH effects have been widely documented in agricultural commodity markets (Goodwin and Schnepf 2000; Holt and Aradhyula 1998). It is thus important to allow for time variation in the conditional volatility. Further, to assess the presence of time-varying risk premiums in the soybean complex futures markets, we follow Hansen, Huang, and Shek (2012) and use a realized GARCH-M model with a log-linear specification to jointly model the conditional mean, the conditional volatility and the realized volatility. Conventional GARCH models have been shown to poorly capture rapid volatility changes because of the slow GARCH model adjustment. In this context, realized volatility measures are likely to be more informative about current volatility levels than squared error terms, turning them into a very useful instrument for modeling volatility.

Engle (2002) first proposed to use realized volatility to model conditional volatility through the GARCH-X model that considers realized variance as a purely exogenous measure. As a result, GARCH-X models are only capable of forecasting returns and volatility beyond a single period into the future. Later, the literature changed to modeling realized volatility measures as latent volatility processes (Engle and Gallo 2006; Shephard and Sheppard 2010; Hansen, Huang, and Shek 2012). From an empirical perspective, this article represents the first attempt at using a realized GARCH-M specification to assess the existence of risk premiums in agricultural futures markets. It is also the first article to jointly estimate a regime-switching conditional mean model and a realized GARCH-M model. The joint conditional mean and volatility model is specified as follows:

$$S_t = \sum_{k=1}^{K}(\alpha_k + \beta_k F_{t-1} + \theta_k h_t) I_{k,t} + \varepsilon_t \tag{4a}$$

$$log h_t = c_0 + \sum_{i=1}^{p} c_i log h_{t-i} + \sum_{j=1}^{q} r_j log v_{t-j} \tag{4b}$$

$$log v_t = w_0 + w_1 log h_t + \tau(z_t) + u_t \tag{4c}$$

$$\tau(z_t) = w_2 z_t + w_3(z_t^2 - 1) \tag{4d}$$

$$\varepsilon_t = z_t\sqrt{h_t},\ z_t \sim i.i.d.(0,1),\ u_t \sim i.i.d.(0, \sigma_u^2). \tag{4}$$

The first Equation, (4a), models the conditional mean by considering *k* different regimes. h_t is the conditional volatility and θh_t is interpreted as the time-varying risk premium (McKenzie and

Holt 2002). Our specification does not include seasonal variables as they were found to be non-significant. If $\alpha_k = 0$, $\beta_k = 1$, and $\theta_k = 0$, futures prices are considered unbiased and efficient in the *k* regime. The second Equation, (4b), models conditional volatility, h_t, as an autoregressive process of order i. Variable v_{t-j} is the lagged realized volatility and is expected to improve the estimation of h_t. The third Equation, (4c), contemporaneously relates the observed realized volatility v_t, to the latent volatility h_t . Function $\tau(z_t)$ allows for a leverage effect, i.e., it allows different responses of volatility to negative or positive shocks. The leverage function is specified following Hansen, Huang, and Shek (2012) using Hermite polynomials of $\tau(z) = w_1 z + w_2(z^2 - 1) + w_3(z^3 - 3z) + w_4(z^4 - 6z^2 + 3) + \cdots$, and taking, as a baseline, a simple quadratic form $\tau(z) = w_1 z + w_2(z^2 - 1)$. This specification is similar to an EGARCH structure and yields $E\tau(z_t) = 0$ for any distribution with $E(z_t) = 0$ and $var(z_t) = 1$.

Key to the specification is determining the thresholds, $I_{k,t}$. Based on nonparametric results, the number of price behavior regimes needed to capture nonlinearities are defined. Following Balke and Fomby (1997), we then conduct a grid search procedure whereby thresholds are chosen to maximize the log likelihood function of the parametric specification, using the futures price level as threshold variable. Quasi maximum-likelihood estimation (QMLE) is used to estimate jointly the conditional mean and conditional volatility models. The log-likelihood function is $l(\varepsilon, v) = -\frac{1}{2}\sum_{t=1}^{n}[\log(2\pi) + \log(h_t) + \varepsilon_t^2/h_t] - \frac{1}{2}\sum_{t=1}^{n}[\log(2\pi) + \log(\sigma_u^2) + u_t^2/\sigma_u^2]$, as detailed in Hansen, Huang, and Shek (2012).

Empirical analysis

Data description

CBOT futures prices of soybeans, soybean meal and soybean oil from 1973 to 2016 are obtained from the Commodity Research Bureau (CRB). The starting date of the analysis is chosen so as not to include the structural break in 1972 identified by previous research (Zulauf et al. 1999; Frank and Garcia 2009). This article focuses on a non-overlapping two-month-ahead forecast horizon, which allows working with a sufficiently large dataset and prevents the overlapping data problem (Hansen and Hodrick 1980; Fama and French 1987; Harri and Brorsen 2009). By using non-overlapping data, this article follows McKenzie and Holt (2002) and Frank and Garcia (2009).

Non-convergence problems have occurred in agricultural commodity markets, that is, futures prices sometimes do not converge to the spot price at maturity, so that futures prices do not represent subsequent spot prices (Irwin et al. 2011; Garcia, Irwin, and Smith 2014). To avoid this problem and focus on the research objective, futures prices are used to represent spot prices. Following Fama and French (1987), futures settlement prices on the first trading day of expiration month are used to represent the spot price. The futures settlement price on the first trading day in the month which is two months prior to expiration is used as the futures price and paired to spot prices. January, March, May, July, September and November soybean futures contracts are selected. For soybean meal and soybean oil, March, May, July, September and December futures contracts are chosen. There are six observations a year for soybeans and five observations a year for soybean meal and oil. All prices are transformed into natural logarithms. The plots for spot and futures price series from 1973 to 2016 are presented in figure 1.

From 1973 to 2006, prices move within a rather constant range, characterized by substantial volatility. Several events contributed to the observed fluctuations including severe weather events in the U.S. Corn Belt in 1973, 1974, 1980, 1983, and 1988, the oil crises in 1973 and 1979, and the entrance of Russia into the global grain and oilseeds market in the early 1970s. The huge price increase from 2006 to 2008 took prices beyond that range because of the surging domestic demand for biofuel and the foreign demand for soybeans especially from China. Later, prices fluctuated for several years because of the global financial crisis and undesirable weather in the U.S. Corn Belt. In 2014 prices started to decline when bumper crops finally built enough inventory. Summary statistics are reported in table 1. Note spot prices (at time t) and futures prices (at time $t-1$) have similar patterns, and are highly correlated.

Unit root tests were performed on the prices and realized volatilities and suggest stationarity of all the series,[1] a finding compatible with Wang and Tomek (2007) who suggest that, in the long-run, agricultural prices are likely to be stationary. To measure the risk premium in the markets, an estimate of price volatility is needed is produced through Equation (4), the realized GARCH-in mean model by Hansen, Huang, and Shek (2012).[2] The conditional volatility is expressed on a bimonthly basis and the realized volatility is expressed on a daily basis. The daily realized volatility is used for improving the estimation of the bimonthly conditional volatility. A five-day average squared daily return is considered to estimate realized volatility:

$$\hat{v}_t = \frac{1}{5}\sum_{d=0}^{4}(logF_{t,d} - logF_{t,d+1})^2 \tag{5}$$

where $F_{t,d}$ is the futures closing price d days before t. Since the futures price is from the first trading day two months prior to the expiration month, the five daily returns used for computing realized volatility are from the five trading days before the day when the futures price is observed.

This realized volatility measure leaves significant ARCH effects in the standardized residuals of the soybean oil model. As an alternative for the soybean oil model, an efficient range-based volatility estimator, the Parkinson (1980) estimator, is used as the realized volatility. The five-day average version is:

$$\tilde{v}_t = \frac{1}{5}\sum_{d=0}^{4}\frac{1}{4ln2}(logH_{t,d} - logL_{t,d+1})^2 \tag{6}$$

where $H_{t,d}$ is the intraday high of futures price in logs, d days before F_t, and $L_{t,d}$ is the intraday low of futures price in logs, d days before F_t. All daily realized volatility estimators are multiplied by 42 to match a bimonthly forecasting interval using an average of 21 trading days in a month.

Preliminary data analysis

The linear model by Tomek and Gray (1970) represents the starting point of the unbiasedness and efficiency analysis. The simple OLS estimation of regression (1) is presented in table 2. Unbiasedness and efficiency tests suggest soybean and soybean meal futures are unbiased and efficient forecasts, while there is evidence of biasedness in soybean oil futures at 1% significance level. Note that no autocorrelation is found in residuals but ARCH effects exist, which reduces reliability of standard errors and conventional tests of hypotheses. ARCH effects are addressed latter on with the estimation of GARCH models.

Nonlinearities cannot be captured by the above OLS model. Therefore, local linear regression techniques are applied to determine whether nonlinear specifications might be informative. Selected by the cross-validation method that minimizes the in-sample leave-one-out squared prediction errors, h_{base} , the constant bandwidth is 4 for soybeans and 3 for soybean meal and soybean oil. As a result, the widths of the Epanechnikov kernel are 0.83, 0.67, and 0.70 for soybeans, soybean meal, and soybean oil, respectively. On average, 175, 121, and 121 observations are used to produce the local estimations for soybeans, soybean meal and soybean oil models, respectively. In the left [right] tail, the minimum number of observations used for soybeans, soybean meal, and soybean oil is 121 [28], 33 [15], and 46 [15], respectively.

Soybean, soybean meal and soybean oil local linear regression results are presented in figures 2, 5, and 4, respectively. The X-axis measures the futures price at time $t-1$ (F_{t-1}) and the Y-axis measures the predicted spot price at time t (S_t). Blue dots are predicted spot prices from local linear regressions. The 45-degree line is a reference for unbiasedness, as it corresponds to equation (1) when $\alpha = 0$ and $\beta = 1$. The distance of blue dots from the 45-degree line is thus an indicator of the local degree of biasedness of futures prices.

For soybeans (figure 2), predicted values (blue dots) have two pronounced tilted ends, which implies departure from unbiasedness in both extremes of the futures price distribution. More specifically, for low futures price levels, futures prices tend to under-forecast subsequent spot prices. In contrast, for high futures price levels, futures prices tend to over-forecast subsequent spot prices. In the central region of the futures price distribution, the predicted values are close to the 45-degree line, indicating futures prices are generally unbiased predictors of subsequent spot prices. For soybean meal (figure 3), deviations from the 45-degree line in the tails are less pronounced. The left tail again indicates under-forecasting of subsequent spot prices, but the deviations from the 45-degree line are not large. For the right tail, most of the observations are very close to the 45 degree line, except for one largely over-forecasting observation that may be an outlier. In the middle, predicted values again are close to unbiasedness. For soybean oil (figure 4), the right tail is pronounced and also indicates over-forecasting. The left tail suggests low futures prices generally under-forecast subsequent spot prices, but it is less pronounced (except for two observations). In the middle, predicted values are close to the 45 degree line, indicating unbiasedness.

On balance, these results suggest that while the three markets appear to be unbiased in the central region of the distribution, they are not always unbiased in the extremes. The three figures show that more observations cluster together in the left tail than in the right tail, but the right tails have several larger deviations. Despite differences in the degree and number of observations, left extremes indicate some under-forecasting behavior across the soybean complex. Since the deviations in the left for soybean meal and soybean oil are less pronounced, there may not form statistically different regimes. The right extremes show some over-forecasting behavior, which is pronounced for soybeans and soybean oil, so statistically different regimes are expected to be found there.

While local linear regressions are fully flexible in that they allow derivation of a new set of parameters for Equation (1) for each observation in the sample, they complicate statistical inference. To facilitate inference and interpretation, the information provided by the local linear analysis is used to define a discrete regime-switching parametric model.[3] As suggested by the local linear regression, the futures price is used as the threshold variable in the regime-switching model specification. More specifically, different regimes are considered to reflect the different forecast ability of futures prices.

Research results

Figure 2 suggests that for soybeans, observations in the two tails deviate from the 45 degree line, but in the central part observations are close to the 45 degree line. A three-regime realized GARCH-M (1,1) model (equation (4) for *i*=*j*=1) is specified.[4] To ensure a minimum number of observations in the lower regime, the search for the lower threshold is constrained between the tenth lowest futures price and the 75th percentile of the price distribution with increases of 0.01. The second threshold is constrained between the 25th percentile and the tenth highest futures price with increases of 0.01. The estimated thresholds 6.45 and 7.15 (6.33 and 12.74 dollars per bushel when transformed to original price levels) maximize the likelihood function and define the three regimes. There are 121, 118 and 20 observations in the low, middle and high price regimes, respectively. The average absolute forecast error in percentage terms is: 1.9%, 0.6% and 3.3% in the low, middle and high price regimes, respectively, compared to 1.4% for the entire sample. Estimates of the three-regime realized GARCH-M (1,1) model are presented in the first column in table 3. Conditional volatility is positively related to its own lag (c_1) and the lag of realized volatility (r_1). A significant and positive w_1 suggests that realized volatility positively depends on the contemporaneous conditional volatility. A non-significant w_2 and a significant w_3 suggest there is no leverage effect in the soybean market, i.e., volatility responses to shocks only depend on the size of the shock but not on the sign.

In table 4, the test for nonlinearities in the soybean model suggests that the coefficients (α, β, θ) differ significantly between the three soybean regimes at 1% level of significance. Simple observation of coefficient estimates suggests that the soybeans market is biased ($\alpha \neq 0$, $\beta \neq 1$, and/or $\theta \neq 0$) in all three regimes. θ_2 and θ_3 support a time-varying risk premium in the middle and high price regimes. The signs of the coefficient of risk premiums (θ) are indicative of the composition of the futures market, with short hedgers dominating when theta is positive, and long hedgers dominating when theta is negative (McKenzie and Holt 2002; Frank and Garcia 2009). Given the negative sign of theta in all three regimes, one can conclude that, in the soybean futures market, long hedgers (crushers or index funds) pay risk premiums to short sellers. The signs of the risk premiums are consistent with Beck (1993) findings for the soybean market for the period 1974-1987.

In the first column of table 4, formal tests of unbiasedness and efficiency are conducted and suggest that soybeans futures prices provide biased and inefficient forecasts in all three regimes. In both the middle and the right tail regimes, α_k is far from 0, β_k, (k=2,3) is far from 1, and the risk premium is significant, the biasedness is caused by risk premiums and inefficiency. In the left tail of the market, the biasedness is likely to come from inefficiency, given the non-significance of the risk premium. As noted, results of local linear regressions in figure 2 suggest the right tail is over-forecasting and the left tail is under-forecasting. Given such scenarios exist in both tails, market participants either don't account for mean reversion in actual prices, or traders are caught up in the enthusiasm of high prices or in the panic/pessimism of low prices thinking current high prices or low prices will continue. Considering market exuberance is usually relatively short-lived and mean reversion is a longer-term process, it is likely that extreme price regimes primarily represent short-run market sentiment.

Figure 5 provides several figures related to conditional volatility and risk premium for soybeans. The predicted conditional volatility (h_t) for soybean is shown in the top panel. Conditional volatility reached the highest level in the early 1970s. Substantially high volatility levels were also reached in the late 1970s, the mid 1980s, and the 2000s. However, the highest conditional volatility period may not have the highest risk premium because the size of the coefficient of risk premiums (θ) depends on price levels. Noteworthy is the fact that the absolute values of theta coefficients increase with increases in futures prices ($|\theta_1| < |\theta_2| < |\theta_3|$); hedgers are willing to pay more for every unit of risk as prices increase. Beck (1993) also suggests risk premiums are larger (in absolute value) when futures prices become larger. The middle panel of Figure 5 presents the risk premiums ($\theta * h_t$) over time. Note that risk premiums became extremely large (in absolute value) in 2008, which reflects the turmoil in the global grain and oilseeds market (the food crisis). There are several peaks after 2008, which are significantly higher than the peaks in previous periods. Hedgers were concerned about price risks and were willing to pay more premiums in these periods. The proportion that risk premiums represent of futures prices (log prices) is shown in the bottom panel of figure 7, with risk premiums usually around 1% of futures prices and increasing to nearly 6% in 2008.

Soybean meal local linear regression identifies that biasness is not pronounced in the middle and right tail of the futures price distribution (figure 3), where all the observations are close to the 45 degree line, except for one observation that may be an outlier. In contrast, the left tail departs from the 45 degree line. As a result, a two-regime realized GARCH-M (1,1) model is specified. The lower threshold is constrained between the tenth lowest observation and the 75th percentile (notice that the 75th percentile is 5.50 and located in the center of figure 3) by increments of 0.01. The threshold that maximizes the likelihood function is 5.29 (198 dollars per short ton in the original prices). There are 126 observations in the left regime and 89 in the right regime. The average absolute forecast error in percentage terms is: 1.3% for the left regime, 0.6% for the right regime, compared to 1.0% for the entire sample. Estimates of the two-regime realized GARCH-M are presented in the second column in table 3. The final soybean meal model is verified to have the lowest AIC, no autocorrelation, and no ARCH effects in the standardized residuals.

Conditional soybean meal volatility depends positively on its own lag (c_1) and on the lag of realized volatility (r_1). A significant and positive w_1 suggests that realized volatility positively depends on the conditional volatility contemporaneously. Both w_2 and w_3 are significant and positive, identifying a leverage effect in which positive shocks increase volatility more than negative shocks. Considering soybean meal is non-storable, the capacity to use inventories as a buffer is limited. A positive shock, which usually reflects unexpected tight supply or strong demand, causes higher volatility than a negative shock which can be temporarily cushioned through increases in inventory.

In table 4, the test for nonlinearities in the soybean meal model suggests that the coefficients (α, β, θ) differ significantly in the two regimes at the 1% level. The test of unbiasedness (a joint test of $\alpha = 0, \beta = 1$ and $\theta = 0$) suggests that only the lower price regime is biased, which is consistent with figure 3. θ_1 shows a time-varying risk premium in the first regime. The sign of θ_1 is negative, with long hedgers paying risk premiums to short sellers. The results of the joint test provide some evidence the left regime is biased, and separate examination of coefficients suggests bias is caused by both inefficiency and risk premium.

Figure 6 provides the conditional volatility and risk premiums for soybean meal. The predicted conditional volatility (h_t) is shown in the top panel, which suggests soybean meal price's conditional volatility was significantly high in early 1970s. The middle panel presents the risk premiums ($\theta * h_t$) over time. Risk premiums are found to be significantly higher in the 1970s. To the extent they exist, these premiums are likely to be paid by feed mills and large animal farms, but not by index funds whose presence has increased recently, as premiums have declined. Notice that zero (or insignificant) risk premiums do not mean that hedgers don't participate in the market. Rather, it may simply reflect a balancing effect when long- and short-hedgers operate in the two sides of the market. The proportions of the risk premium to futures price (log price) are shown in the bottom panel and fluctuate around 1-2% of the futures prices, but reach 5% in the early 1970s. This contrasts with McKenzie and Holt (2002) and Frank and Garcia (2009), who find no evidence of time-varying risk premium for the 1959-1995 period and the 1972-2004 period, respectively.

Soybean oil local linear regression shows that observations in the tails of the price distribution deviate from the 45 degree line (figure 4). Hence, we may separate the central part from the two tails and estimate a three-regime model. As a result, a three-regime realized GARCH-M (1,1) model is first estimated.[5] Not-presented results suggest no statistically significant difference between the first and the second regime. Notice that these results are consistent with figure 4, where the right tail (high price) is more pronounced, and the left tail (low price) is close to the 45 degree line. Therefore, the low and middle price regimes are combined and the single threshold separating the two regimes is specified between the 25th percentile of the futures prices to the tenth highest futures price. The estimated threshold is 3.79, the first regime consists of 197 observations in the left and center of the distribution, and the second regime consists of 19 observations in the right tail. The average absolute forecast error in percentage terms is: 2.0% for first regime, 6.5% for the second regime, compared to 2.4% for the entire sample.

Estimates of the two-regime realized GARCH-M model for soybean oil are presented in the third column of table 3. Residuals of the estimated model show no signs of autocorrelation and ARCH effects. GARCH coefficients and a test for nonlinearity show this model is appropriate. Conditional volatility positively depends on its own lag (c_1) and on the lag of realized volatility (r_1). A significant and positive w_1 suggests that realized volatility positively depends on the conditional volatility contemporaneously. A non-significant w_2 and a significant w_3 identify there is no leverage effect. In table 4, the test for nonlinearity suggests that the coefficients ($\alpha, \beta,$ θ) are significantly different in the two regimes at 1% level.

In table 4, tests of unbiasedness show that the first regime of the soybean oil model is unbiased and the second regime is biased. In the first regime, coefficients α_1, β_1, and θ_1 are not significantly different from 0, 1, and 0, respectively, which reflects that the predicted values are close to the 45-degree line in the left and middle of the price distribution (figure 4). In the second regime, α_2 and β_2 are significantly different from 0 and 1, respectively, and θ_2 is not significant, which are consistent with the pronounced right tail in figure 4. No evidence of time-varying risk premium is found in either regime. This finding contrasts with Fama and French (1987) who found evidence of premiums for the 1966-1984 period. The biasedness in the second (high price) regime arises from inefficiency.[6]

Conclusion

Assessing the capacity of futures markets to forecast spot prices and the existence of a risk premium in futures markets, constitute important research topics in the agricultural commodity market literature. To date, research has widely ignored nonlinear price links between futures and spot prices when testing for risk premiums or efficiency. Recent research has identified both positive and negative bubbles characterized by explosive price behavior in agricultural commodity futures markets (Gutierrez 2013; Etienne, Irwin, and Garcia 2014). In the presence of this behavior, traders may believe that price will continue to increase (decrease) even when it is already extremely high (low). If so, over-forecasting (under-forecasting) may occur, limiting the price discovery function of futures markets. This may be reflected in futures markets by different (nonlinear) forecasting ability at different price levels.

This article studies the short-run forecasting ability of futures markets in the soybean complex. We allow for differences in predictive performance at different price levels and identify the sources of forecast errors. We concentrate on two-month forecast horizons and 1973-2016 data that allows us to identify the effects of market sentiment and risk premiums on prices. A non-parametric local linear regression framework (Fan and Gijbels 1996) is first applied to investigate biasness, and to guide the specification of parametric regime-switching models in which we perform statistical testing. To identify effects of risk premiums, which have been difficult to estimate in a forecasting context, we use a realized GARCH model (Hansen, Huang and Shek 2012) that has been shown to improve conditional volatility modeling. The use of both local linear regression methods and the realized GARCH framework to investigate forecast performance and the presence of risk premiums in agricultural futures markets is novel.

Major findings indicate the forecast performance of futures markets is nonlinear, since it depends on price levels and time-varying risk. Evidence of inefficiency and time-varying risk premiums is found in the soybean complex. The magnitude of the biasness varies by market and regime, but can be large in economic terms. For instance, for soybeans the average absolute forecast error in percentage terms is: 1.9% for the low price regime, 0.6% for the middle price regime and 3.3% for the high price regime. In part, this may reflect the notion that bubbles and market-moving sentiment occur somewhat infrequently in these markets. There also is much less evidence of a risk premium in these two markets.

Results also reveal the relevance of nonlinear modeling of time-varying risk premiums based on a realized GARCH framework. Evidence of time-varying risk premium is identified in the soybeans market in two of the three price regimes, and in the soybean meal market in one of the two regimes. Informatively, the signs of coefficients for the risk premium are negative, which is an indicator that long hedgers are dominating. These long hedgers are likely soybean crushers (and maybe index funds) in the soybean market and feed mills or animal producers in the soybean meal market. The absence of a time-varying risk premium in the soybean oil market may reflect that users (food processors, vegetable oil producers, and other industrial users) have a high degree of flexibility in adjusting to changing price because of the wide range of available substitutes for soybean oil. Our evidence on bias is consistent with the findings of Rausser and Carter (1983), Fama and French (1987), Kenyon, Jones, and McGuirk (1993), and Frank and Garcia (2009). In contrast, our evidence of risk premium is more at odds with previous literature (McKenzie and Holt 2002; Frank and Garcia 2009; Fama and French 1987). It is not easy to identify specific explanations for differences from our findings, but it clearly reflects the difficulty that agricultural economists have encountered in finding market risk premiums. Based on our results, part of the differences may arise from the improved volatility modeling (i.e.,the nonlinear realized GARCH-M model) used in the analysis.

An implication of our general results that forecast performance is nonlinear and dependent on price level is that when market prices take values close to the middle of the distribution, futures prices have more forecast power and are more reliable. However, if the market price is close to the extremes of the distribution, futures prices tend to be less reliable and are more likely to be subject to over-forecasting or under-forecasting. These findings are relevant to market participants. For example, potential short hedgers should lock their profit in the high price region instead of waiting to lock at a higher price, and potential long hedgers should lock their profit in the low price region instead of waiting to lock at a lower price. In addition, speculators and risk bearers can be more confident of making profit in light of the results that confirm that long hedgers are willing to pay a risk premium, especially in the soybean market. In this situation, the premium may increase when price level and risk are higher. Finally, the findings are also relevant to policy makers who need to be cautious when using futures prices as efficient and unbiased forecasts when prices are either extremely high or low. Since errors in futures markets appear to occur when prices are at extreme levels a more moderate in nature policy response may be needed.

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Table 1. Descriptive statistics

Variable	Mean	Standard Error
Soybeans Spot price	6.56	0.32
Soybeans Futures price	6.56	0.31
Soybeans Realized volatility	2.34E-4	2.45E-4
Soybean - Correlation Spot - Futures		0.94
Soybean meal Spot price	5.34	0.35
Soybean meal Futures price	5.33	0.32
Soybean meal Realized volatility	4.81E-4	7.19E-04
Soybean meal - Correlation Spot - Futures		0.92
Soybean oil Spot price	3.24	0.34
Soybean oil Futures price	3.24	0.34
Soybean oil Realized volatility	9.01E-4	7.96E-4
Soybean oil - Correlation Spot - Futures		0.91

Note: Prices are transformed into natural logs. Number of observations is 259 (soybeans) and 215 (soybean meal and soybean oil).

Table 2. OLS estimates of Tomek and Gray (1970) model

$$S_t = \alpha + \beta F_{t-1} + u_t$$

	Soybeans	Meal	Oil
α	0.279*	0.121	0.268***
	(0.148)	(0.157)	(0.090)
β	0.958***	0.978***	0.918***
	(0.023)	(0.029)	(0.028)
Unbiasedness test	1.803	0.463	4.389**
$H_0: \alpha = 0, \beta = 1$	(0.167)	(0.630)	(0.014)

Note: Level of significance: 1% (***), 5% (**) and 10% (*). *p*-values are shown in parentheses for tests. No autocorrelation is found in residues, but ARCH effects are identified.

Table 3. Nonlinear realized GARCH-M

	Soybeans	Meal	Oil
α_1	1.053***	1.619***	0.107
(first low price regime)	(0.355)	(0.420)	(0.110)
β_1	0.836***	0.699***	0.952***
(first low price regime)	(0.053)	(0.081)	(0.033)
θ_1	-0.125	-4.455**	2.839
(first low price regime)	(3.220)	(2.134)	(1.781)
α_2	-0.821***	0.096	3.755***
(second middle price regime)	(0.271)	(0.262)	(0.913)
β_2	1.133***	0.988***	0.026
(second middle price regime)	(0.042)	(0.046)	(0.234)
θ_2	-7.086***	-0.632	8.797
(second middle price regime)	(2.510)	(2.687)	(9.310)
α_3	4.714***	NA	NA
(third high price regime)	(0.111)		
β_3	0.384***	NA	NA
(third high price regime)	(0.015)		
θ_3	-30.896***	NA	NA
(third high price regime)	(9.758)		

Table 3. Nonlinear realized GARCH-M (continued)

	Soybeans	Meal	Oil
c_0	0.068	-0.063	0.039
	(0.146)	(0.409)	(0.228)
c_1	0.610***	0.622***	0.678***
	(0.041)	(0.085)	(0.064)
r_1	0.211***	0.179***	0.187***
	(0.028)	(0.054)	(0.026)
w_0	-3.991***	-3.245**	-1.812**
	(0.612)	(1.493)	(0.833)
w_1	1.056***	1.241***	1.334***
	(0.131)	(0.361)	(0.202)
w_2	0.076	0.187**	0.066
	(0.062)	(0.077)	(0.043)
w_3	0.125***	0.165***	0.092***
	(0.033)	(0.045)	(0.021)
σ_u^2	0.836***	1.124***	0.309***
	(0.061)	(0.106)	(0.029)
First threshold	6.45	5.29	3.79
Second threshold	7.15	NA	NA
# observations in the first regime	121	126	197
# observations in the second regime	118	89	19
# observations in the third regime	20	NA	NA

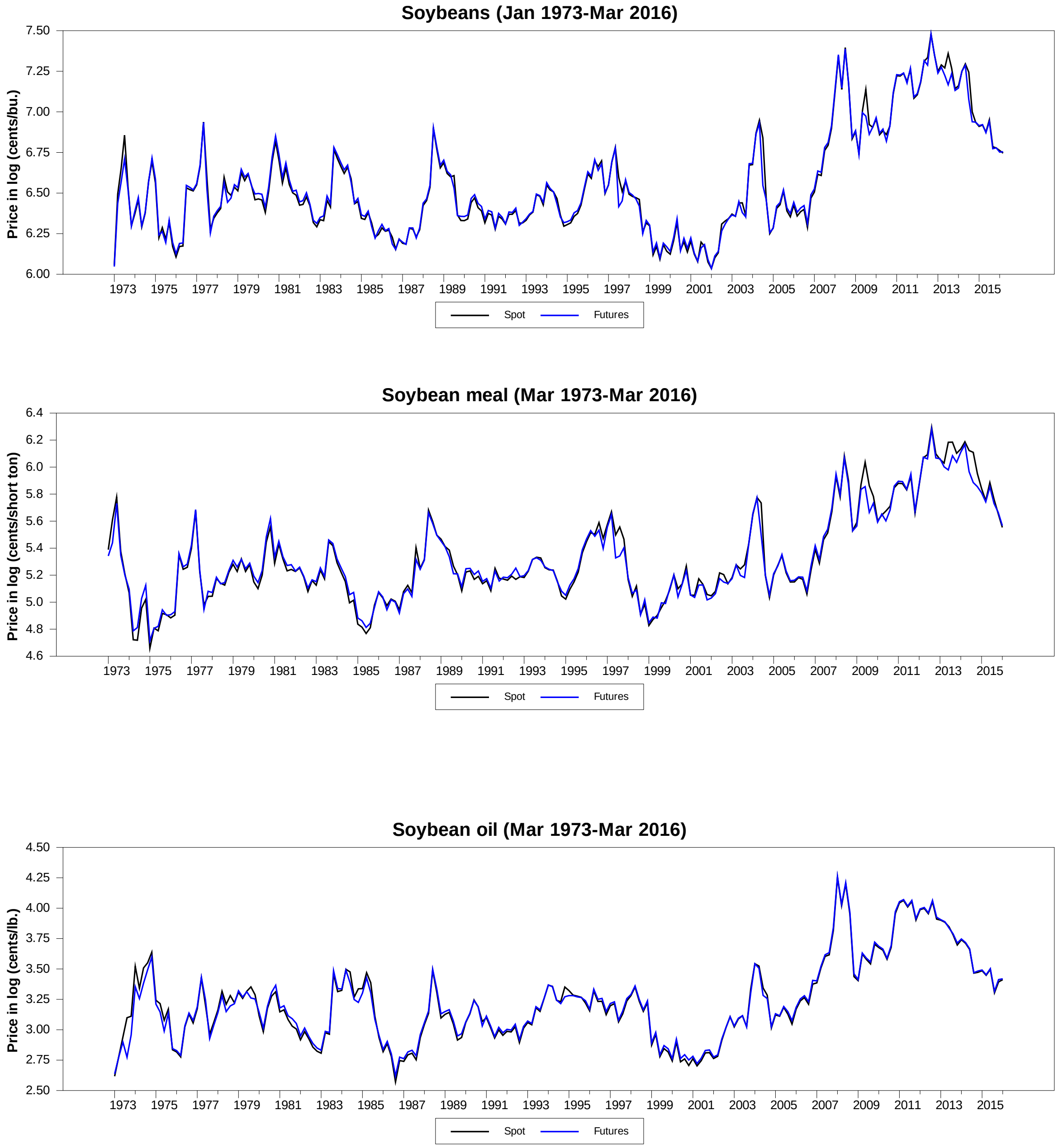
Note: Based on Equation (4). Level of significance: 1% (***), 5% (**) and 10% (*). Standard errors are shown in parentheses for parameters.

Table 4. Statistical tests for nonlinear realized GARCH-M

	Soybeans	Meal	Oil
Test of nonlinearity	113.416***	4.944***	6.088***
H_0: $\alpha_1 = \alpha_2 = \alpha_3$,	(0.000)	(0.002)	(0.000)
$\beta_1 = \beta_2 = \beta_3$,			
$\theta_1 = \theta_2 = \theta_3$			
Test of unbiasedness	5.831***	6.002***	1.656
H_0: $\alpha_1 = 0, \beta = 1, \theta_1 = 0$	(0.001)	(0.000)	(0.174)
Test of unbiasedness	4.600***	0.495	5.829***
H_0: $\alpha_2 = 0, \beta_2 = 1, \theta_2 = 0$	(0.003)	(0.686)	(0.001)
Test of unbiasedness	663.7***	NA	NA
H_0: $\alpha_3 = 0, \beta_3 = 1, \theta_3 = 0$	(0.000)		
Q(5)	3.176	4.476	0.727
	(0.529)	(0.345)	(0.948)
LM ARCH (5)	1.433	6.699	2.339
	(0.921)	(0.244)	(0.801)

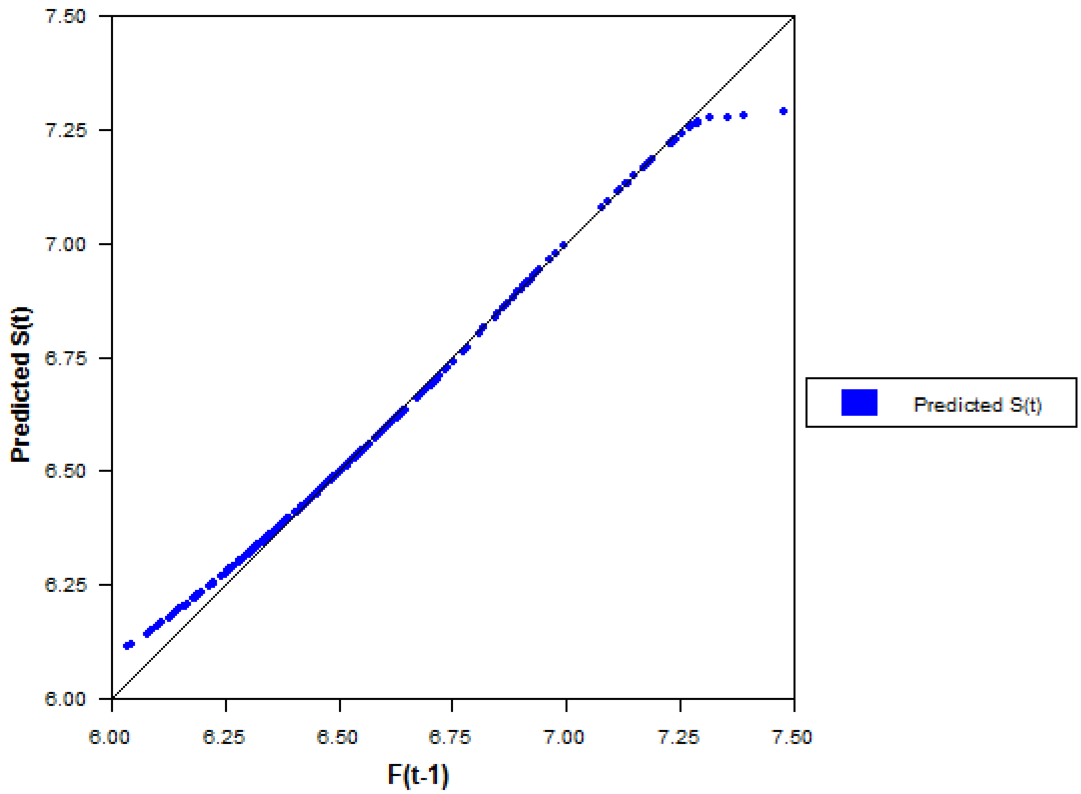
Note: Based on Equation (4). Level of significance: 1% (***), 5% (**) and 10% (*). *p*-values are shown in parentheses for tests.

Figure 1. Soybean complex price series, 1973-2016



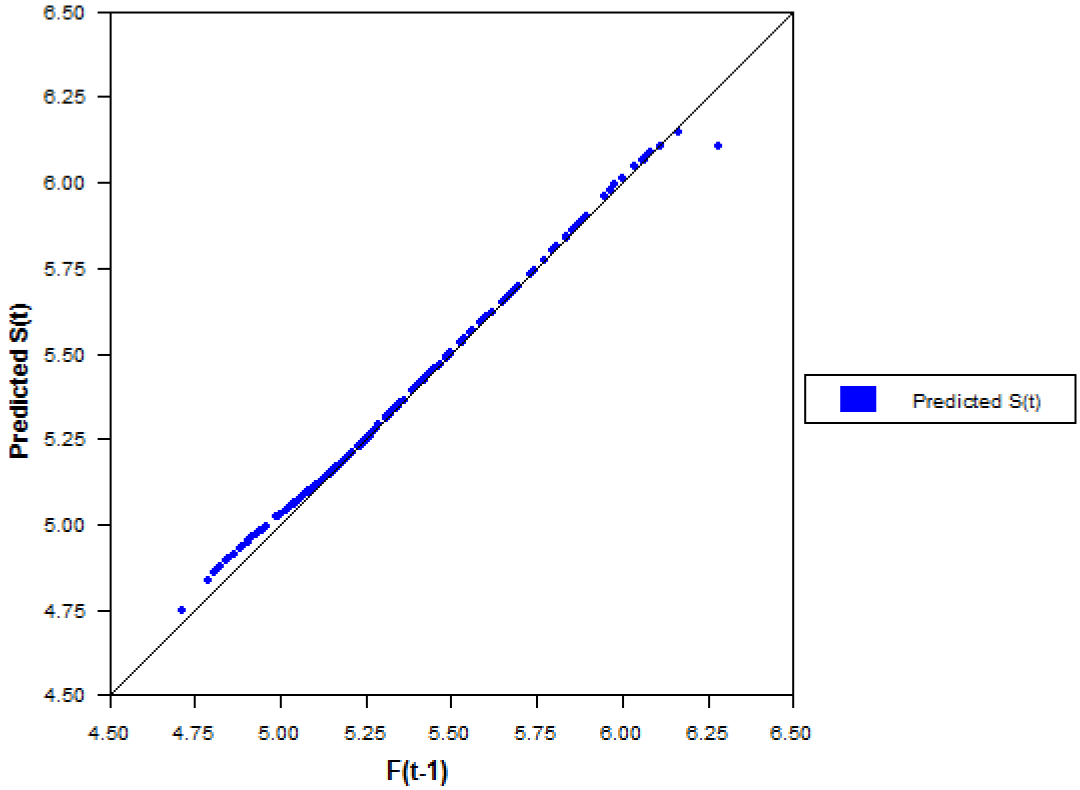
Note: All prices are in natural logs.

Figure 2. Local linear regression (soybeans)



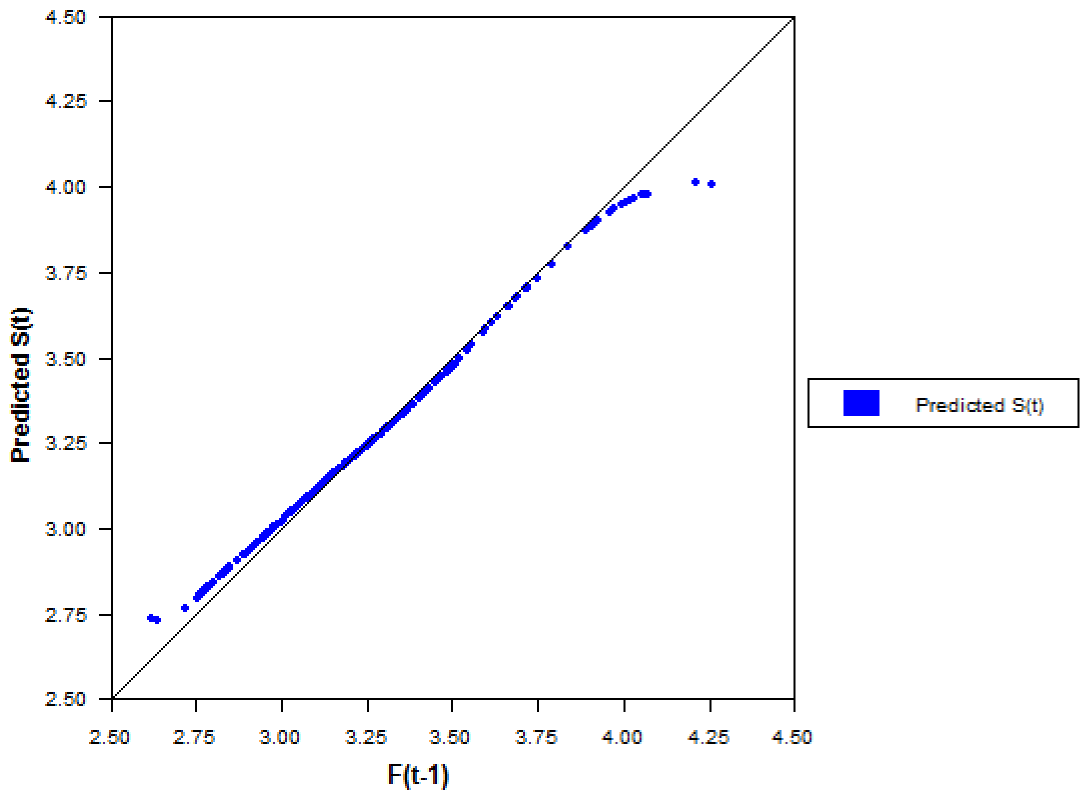
Note: The X-axis is the futures price at time *t*-1 (F_{t-1}) and the Y-axis is the predicted spot price at time *t* (S_t). The blue dots are predicted spot price from local linear regressions, and the 45-degree line represents Y=X.

Figure 3. Local linear regression (soybean meal)



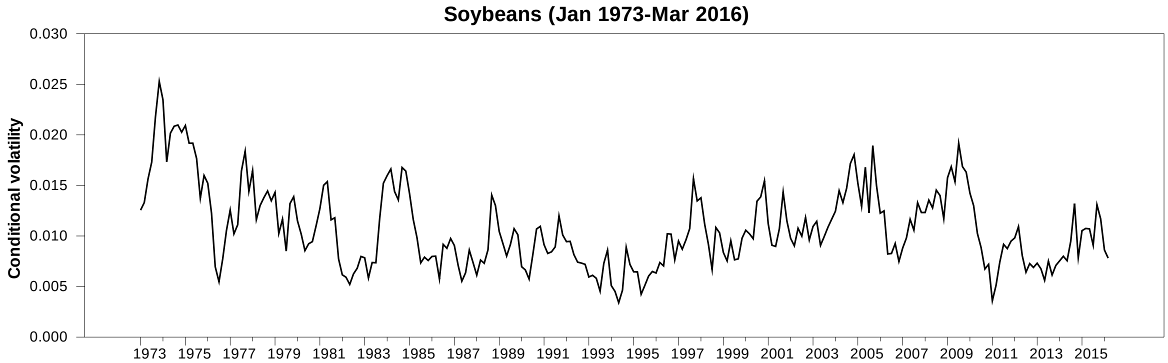
Note: The X-axis is the futures price at time *t*-1 (F_{t-1}) and the Y-axis is the predicted spot price at time *t* (S_t). The blue dots are predicted spot price from local linear regressions, and the 45-degree line represents Y=X.

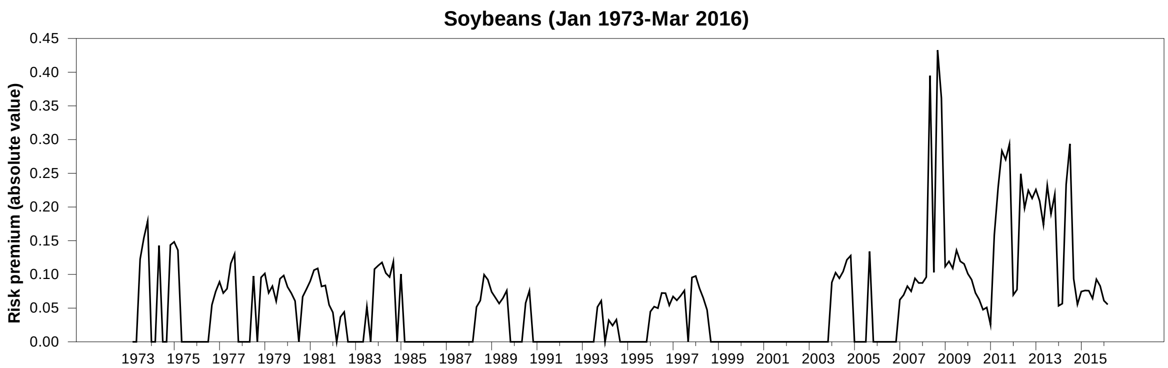
Figure 4. Local linear regression (soybean oil)



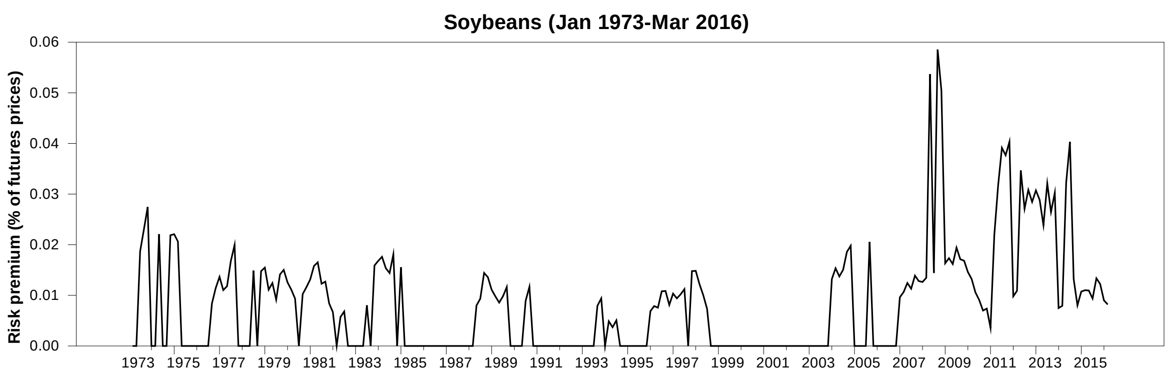
Note: The X-axis is the futures price at time *t*-1 (F_{t-1}) and the Y-axis is the predicted spot price at time *t* (S_t). The blue dots are predicted spot price from local linear regressions, and the 45-degree line represents Y=X.

Figure 5. Soybean Conditional Volatility, Risk Premium, Risk Premium/Futures



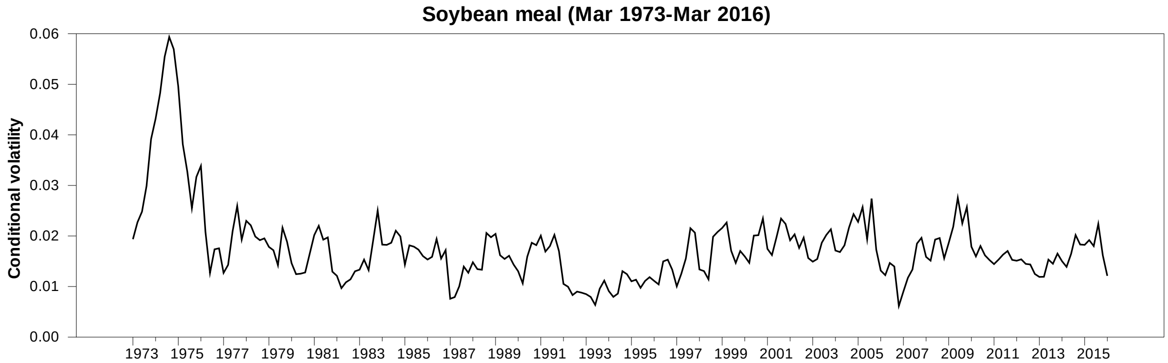


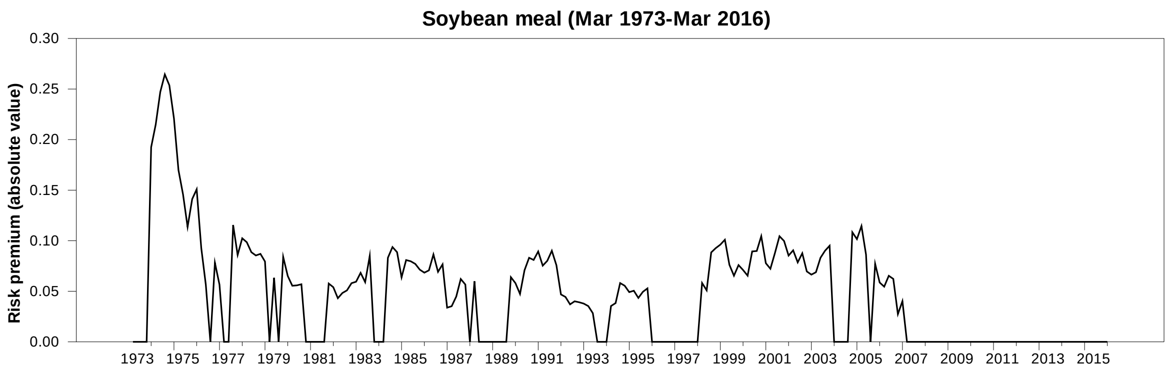
Note: Risk premiums are reported in absolute values. The original signs are negative.



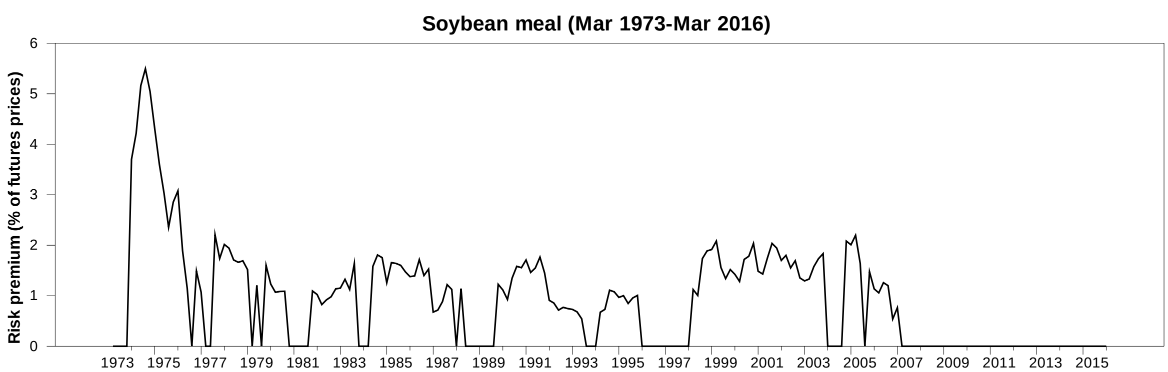
Note: Risk premiums are reported in absolute values. The original signs are negative. Futures prices are in natural logs.

Figure 6. Soybean Meal Conditional Volatility, Risk Premium, Risk Premium/Futures





Note: Risk premiums are reported in absolute values. The original signs are negative.



Note: Risk premiums are reported in absolute values. The original signs are negative. Futures prices are in natural logs.

Statistical Appendix

A1. Log-likelihood of GARCH-M and partial log-likelihood of realized GARCH-M

	Soybeans	Soybean Meal	Soybean Oil
Linear GARCH-M	207.592	128.746	129.750
Linear realized GARCH-M	211.175	128.896	127.879
Nonlinear GARCH-M	219.833	135.546	132.442
Nonlinear realized GARCH-M	224.051	133.250	133.092

Endnotes:

[1] To preserve space, these tests are not presented, but are available from authors upon request.

[2] We focus on the nonlinear realized GARCH-M models presented in the text because overall they are most consistent with nonparametric analysis and produced similar or more intuitively attractive models. Comparisons of the value of the log likelihood function across the standard GARCH-M, and across the realized GARCH-M models for the three markets favored the nonlinear specification (Statistical Appendix A1). Similarly, except in soybean meal market, comparisons of the log-likelihood of the GARCH-M and corresponding conditional volatility components (i.e., the partial log-likelihood) of the realized GARCH-M favored the realized model (Statistical Appendix A1). In the soybean meal case, the linear and nonlinear GARCH-M produced virtually identical corresponding coefficients, and tests for bias and efficiency.

[3] Smooth transition specifications were also considered but models failed to converge for all commodities.

[4] This specification has the lowest AIC and is free from autocorrelation and time-varying volatility in the standardized residuals.

[5] The first threshold is restricted between the tenth lowest futures price and the 75th percentile. The second threshold is restricted between the 25th percentile and the tenth highest futures price. Threshold increments are equal to 0.01.

[6] The conditional volatility for soybean oil is somewhat similar to that of soybean mean. Since the risk coefficients are not found to be statistically significant for soybean oil, the conditional volatility and risk premiums are not presented.