We develop a theoretical model of optimal hedging that nests expected utility and expected target utility theories. We use this model to characterize optimal hedging with and without reference price dependence. The model’s theoretical predictions are tested with a unique database consisting of every forward contract written with a major grain marketing firm by Iowa corn producers over a five-year period. Our results suggest that a current December futures price higher than a reference price triggers hedging activity. A likely candidate for producers’ reference price is a rolling average of the current futures price. We then use trading activity implied by the producers to determine if they benefit from the way they hedge. The evidence is mixed. Finally, we compare the producer forward contract data to the only publicly available data on producer hedging: The Commodity Futures Trading Commission Disaggregated Commitment of Traders Report (DCOT) for Short Hedgers. A hedge ratio constructed from the open interest in new futures contracts of the DCOT report is highly correlated with the producer hedge series in the Iowa data, providing evidence that DCOT data represent farmers’ hedging behavior reasonably well. This work has important implications for future research that uses the DCOT data, and provides new evidence about producers’ hedging behavior that marketing specialists and extension agents can use to enhance their educational efforts related to risk management.

Key words: Expected utility, forward contracting, corn hedging, production risk, reference dependence, subjective beliefs.

JEL codes: D8, Q12, Q13.

Expected utility (EU) theory, as it applies to a producer’s hedging decision, posits that risk aversion drives hedging and that if a producer believes the futures market is efficient, hedging strategies should be independent of the level of futures prices. Agricultural economists have found limited support for this EU optimal hedging theory, and there is no consensus on how useful other utility theory paradigms are in this context. One alternative to EU theory is reference dependence (RD), a central feature of alternative utility theory paradigms that asserts an agent’s utility derives from gains and losses relative to a reference value rather than a measure of final wealth (Tversky and Kahneman 1991). While we understand relatively little about how producers formulate hedging strategies and respond to price changes, we understand well that the impact of hedging practices on farm income and the stability of farm income is a key issue for farmers. Beyond the farm, extension economists and grain marketers (elevators) have a stake in understanding how and when producers hedge.

The goal of this article is two-fold. First, we develop a model of optimal hedging that nests within it EU hedging and RD hedging for symmetric utility functions. Second, we explore empirically the hedging activities of producers for evidence of RD behavior. From the theoretical model, we derive empirical hypotheses with implications for the consistency of observed hedging behavior with EU and RD expectations. These are tested using a dataset of corn producers’ pre-harvest forward contracts written by a major Iowa
Expected Utility, Hedging and Price-Position Relationships

In the EU context, hedging is a mitigation mechanism for price risks, and risk aversion is the primary motive for a producer's hedging behavior (Johnson 1960; Holthausen 1979; Feder, Just, and Schmitz 1980; Grant 1985; Castelino 1992; Lapan and Moschini 1994). Abstracting from basis risk, the EU optimal hedge ratio is equal to 1 and independent of the underlying futures price if producers believe the futures price is unbiased. This result is robust to any concave utility function that incorporates production decisions because of the separation theorem (Feder, Just, and Schmitz 1980). Lapan and Moschini (1994) incorporate yield risk in a utility framework and show, using a mean-variance approach, that the optimal hedge ratio is the regression coefficient of random revenue on the futures price. In a dynamic setting, the optimal hedge ratio increases at the inverse of the interest rate and time to maturity (Myers and Hanson 1996). To the extent that the correlation between expected spot prices and forward prices varies over time, the EU optimal hedge ratio can change; however, McNew and Fackler (1994) find little variation in the correlation using corn prices within a GARCH framework.

Theoretical models of hedging, including those above, recognize that the optimal hedge ratio is dependent on producers' risk attitudes. However, the empirical evidence for this is mixed, and other factors may contribute. In survey-based studies, Sartwelle et al. (2000) find no evidence that self-identified risk attitudes impact hedging practices, while Goodwin and Schroeder (1994) find a negative relationship between risk aversion and the use of forward contracts. An alternative explanation to risk as the motivation to hedge is the potential for price enhancement through market-timing strategies (Schroeder et al. 1998); however, these strategies have little support in the literature (Irwin, Good, and Martines-Filho 2006). Further, there is conflicting evidence of the use of forward contracting by grain producers, regardless of the motivation. Survey-based studies of grain producers find that the use of forward contracting in the 1990s ranged from as low as 12% to 38% of producers (Davis et al. 2005; Velandia et al. 2009) to approximately 70% (Musser, Patrick, and Eckman 1996; Schroeder et al. 1998; Sartwelle et al. 2000). Other studies focus on the proportion of crop forward contracted, finding that producers using these contracts hedge just 15% to 40% of their harvest (Schroeder et al. 1998; Davis et al. 2005). One explanation, which relates directly to the topic of this investigation, is that hedging is not only risk dependent but also affected by current prices and expectations of future prices relative to a target or reference price.

Mounting empirical evidence inconsistent with the traditional EU hedging theory prompted the exploration of alternative theoretical frameworks (e.g., Collins, Musser, and Mason 1991; Musser, Patrick, and Eckman 1996; Lien 2001; Mattos, Garcia, and Pennings 2008; Kim, Broersen, and Anderson 2010). A common alternative framework is reference dependence (Tversky and Kahneman 1991); broadly, this includes prospect theory (Kahneman and Tversky 1979) and regret theory (Loomes and Sugden 1982). The literature that explores reference dependence in hedging suggests the potential for price-based triggers in hedging, including price changes from a prior period and the price level itself. Kim, Broersen, and Anderson (2010) explore an expected target utility framework in which a producer’s reference may be a targeted profit margin. These authors show that producers will hedge more of their crop when prices move above the targeted profit margin. Kim, Broersen, and Anderson’s (2010) theoretical construct draws on the work of Fishburn (1977), who reconciles the RD and EU models under certain conditions. Broersen, Coombs, and Anderson (1995) find that producers lack an interest in forward contracting when prices are low, but otherwise do not define the high crop prices that would motivate hedging. McNew and Musser (2002) use a hedging game with producers and discover their...
hedge ratios respond to changes in the futures price relative to the previous year’s high price.

Market advisory services commonly promote strategies that utilize profit margin hedging (e.g., Parcell and Pierce 2009). Motivated by this, Mattos and Zinn (2016) carry out an experimental study on crop marketing decisions of producers, finding that decisions depend, in part, on the difference between the current futures price and a reference price that weights the current futures price and the highest price in the marketing year. These authors’ work provides evidence that reference prices may update during the marketing period in response to changing market conditions.

An early insight into hedging motivated by factors other than risk aversion was offered by Working (1962). His paper on futures markets and prices describes two forms of hedging in which producers respond to price expectations and hedge incompletely: selective hedging and anticipatory hedging. As Working states, “Business hedging is done for a variety of reasons, which differ according to circumstance.” This insight was contrary to a prominent idea that hedging was motivated by risk transfer alone. Selective hedging involves “...hedging or not hedging according to price expectations.” This behavior emerges when hedging occurs ahead of an expected price decline. Anticipatory hedging, which is also guided by price expectations, includes hedging behavior that “...serves as a substitute for a forward sale of the specific goods that are in the course of production.” In the context of our model, selective hedging occurs when producers hedge because they expect prices to decline, that is, they believe the futures price is biased upward. Anticipatory hedging occurs when a producer presells his expected crop because s/he believes the price today is better than the expected spot price at harvest.

Beyond crop marketing, there is evidence of reference effects in markets for insurance, securities, and real estate. Using crop insurance premiums as a reference, Babcock (2015) shows that cumulative prospect theory generates crop insurance purchase decisions that are consistent with observed low participation rates, a result that is anomalous to expected utility maximization. In a study of the stock market, Grinblatt and Keloharju (2001) find evidence of reference price effects in securities trading activities of individual investors, citing their higher propensity to sell if a stock rises above its high of the past month. Moreover, Odean (1998) and Shefrin and Statman (1985) find that individual investors in general have a greater tendency to sell stocks with positive returns than losses, indicating that their purchase price is their reference price. In real estate markets, reference effects manifest as decisions to rent more expensive apartments by those who move from expensive cities (Simonsohn and Loewenstein 2006), and the use of original purchase prices as references in setting sales prices of homes (Genesove and Mayer 2001).

Finally, there is a growing body of literature exploring price-trade relationships in the CFTC trader positions and positions held by producers (in agricultural) and others for cases outside of agriculture. Price-trade position correlations have been examined to better understand traders’ behavior (Wang 2003), risk flows between speculators and hedgers (De Roon, Nijman, and Veld 2000; Sanders, Boris, and Manfredo 2004; Cheng, Kirilenko, and Xiong 2015), and market efficiencies (Irwin, Sanders, and Merrin 2009; Irwin and Sanders 2012; Fishe, Janzen, and Smith 2014). Our research fits within and contributes to this literature by providing evidence of the relationship, for corn, between trader data and producer activities. The correlation between DCOT and producer hedge series in new crop hedging is consistent with a passive role of a marketing firm who provides forward contracting services to producers and lays off that risk in the futures markets.

Theoretical Framework

We begin with a standard EU framework where a crop producer maximizes the expected utility of terminal wealth, \( w^T \), which includes the producer’s initial wealth, \( w^0 \), and the price received for one (normalized) unit of crop. The producer maximizes \( w^T \) by optimally choosing to hedge a portion of crops in the pre-harvest period, \( h \). The producer’s objective function is

\[
max_h E[U_{EU}(w^t + F^T(1 - h) + F'h)]
\]

where \( U_{EU} \) is a concave and symmetric utility function such that \( U'_{EU} > 0 \) and \( U''_{EU} < 0 \).\(^1\) Further, \( F^T \) is the price of the futures

---

\(^1\) We derive theoretical results under an assumption of symmetric utility; results may not hold in the case of non-symmetry.
contract at maturity and will be higher or lower than the current futures price $F^t$, by $\epsilon \in (0, F^t)$, with probabilities $\pi \in [0, 1]$ and $1 - \pi$, respectively:

$$F^t = \begin{cases} F^t + \epsilon, & \text{with probability } \pi \\ F^t - \epsilon, & \text{with probability } 1 - \pi \end{cases}$$

Here, $\pi$ represents the producer’s belief about the likelihood of the price difference. When $\pi = 0.5$, the producer believes the futures price is unbiased.

Hedging occurs prior to harvest, and production uncertainty affects the producer’s hedging decision. Consider a simple form of production risk, independent of price risk, such that with probability $1 - \beta \in (0, 1)$ the crop is lost. In this form, production uncertainty—the likelihood a crop is lost—gradually resolves during the growing season. We formalize the impact of production risk on the producer’s optimal hedge ratio in proposition 1.

**Proposition 1.** If the producer believes the futures price is unbiased or biased upward such that $\frac{\pi}{1 - \pi} \leq g(w^t, F^t, h^*, \epsilon)$, then the marginal impact of resolving production risk on the producer’s optimal hedge ratio is positive:

$$\frac{\partial h^*}{\partial \beta} \geq 0, \quad \text{if } \frac{\pi}{1 - \pi} \leq g(w^t, F^t, h^*, \epsilon)$$

where $g(w^t, F^t, h^*, \epsilon) = \frac{U_{EU}(w^t + F^t \epsilon) - U_{EU}(w^t + F^t(1 - h^*) \epsilon)}{U_{EU}(w^t - h^* \epsilon) - U_{EU}(w^t + F^t + (1 - h^*) \epsilon)} < 1$.

**Proof:** See appendix A in the online supplementary materials.

The impact of production uncertainty on the optimal hedge ratio incorporates producers’ subjective beliefs about the futures price, and this is because a producer’s hedge includes pure and speculative hedge components. When the producer believes the futures market is unbiased, proposition 1 states that as production uncertainty resolves, the optimal hedge ratio increases, a result that is consistent within the literature (see, e.g., Lapan and Moschini 1994).

In what follows, we abstract from production risk and the initial wealth condition to facilitate a comparison of the optimal hedging decision between an EU producer and an RD producer. In particular, while the objective of the EU producer is to maximize the expected utility of the crop price received, the RD producer’s objective is to maximize utility of the crop price relative to a reference price.

Letting $P \equiv F^t (1 - h) + F^t h$ be the crop unit price received by the producer, an expected utility function that nests reference dependence is

$$U(h; R, \alpha, \epsilon, F^t, P^t) = \begin{cases} [P - R]^{1 - \alpha} / 1 - \alpha & \forall \ P \geq 0 \\ -[R - P]^{1 - \alpha} / 1 - \alpha & \forall \ 0 < P < R \end{cases}$$

where $R$ is the reference price, and $\alpha$ is a risk aversion parameter. When $R$ is greater than zero, equation (4) describes an expected target utility function such that the producer’s utility derives from gains or losses relative to the reference price. When $R = 0$, the utility function is an EU function with constant relative risk aversion $0 < \alpha < 1$. In this framework, the RD producer is risk averse in gains but risk seeking in losses, and the utility function is symmetric with respect to the reference point. The lower bound of the hedge ratio is normalized to zero to abstract from the possible but unlikely scenario where the producer’s natural long position is increased using futures contracts, which arises because initial wealth is not modeled.

With the general utility model set forth above, we compare RD and EU optimal hedge ratios for producers who believe the futures price is biased or unbiased. We offer two further propositions.

**Proposition 2.** If the producer believes the futures price is unbiased, the optimal hedge ratio is

$$h^* = \begin{cases} 1 & \forall \quad F^t > R \geq 0 \\ 0 & \forall \quad 0 < F^t < R \\ [0, 1] & F^t = R \end{cases}$$

--

2 If the producer is risk averse over total wealth while being reference-dependent on the hedged portfolio as described in equation (4), then there exists a weighting parameter such that the optimal hedge ratio that maximizes the convex combination of the two sources of utilities will be non-negative. Appendix B in the online supplementary material provides an expansion and proof of this.
Proposition 3. If the producer believes the futures price is biased, a change in beliefs about the biasedness of the futures price changes the optimal hedge ratio. The marginal impact on the optimal hedge ratio from a change in \( \pi \) is given by

\[
\frac{\partial h^*}{\partial \pi} = \begin{cases} 
-F'g_1(\pi) & \text{if } R=0 \\
-(F' - R)g_1(\pi) & \text{if } F' > R > 0 \\
-(R - F')g_2(\pi) & \text{if } R > F' > 0 \text{ and } g_3(\pi) < \epsilon/(R - F') \\
0 & \text{if } R > F' > 0 \text{ and } g_3(\pi) > \epsilon/(R - F') 
\end{cases}
\]

where

\[
g_1(\pi) = \frac{2}{\alpha} \frac{[(1 - \pi)^{1-\alpha}/s]}{[\pi^{1/s} + (1 - \pi)^{1/s}]},
\]

\[
g_2(\pi) = \frac{2}{\alpha} \frac{[(1 - \pi)^{1-\alpha}/s]}{[\pi^{1/s} - (1 - \pi)^{1/s}]}, \text{ and } g_3(\pi) = \frac{\mu^{1/2} + (1 - \pi)^{1/2}}{(1 - \pi)^{1/2} - \mu^{1/2}}.
\]

Proof: See appendix A in the online supplementary materials.

Equation (5) shows that when the beliefs are of an unbiased futures price, an EU producer will fully hedge, \( h^* = 1 \), but an RD producer will only hedge when the futures price is higher than the reference price. The RD producer responds to the relative level of the futures price, whereas the EU producer’s hedge is constant.

Equation (6) shows the marginal effect of a change in beliefs \( \pi \) about futures prices on the optimal hedge ratio for an EU producer (line one), and for an RD producer when the futures price is above the reference price (line two). Note that \( g_1(\pi) \) is positive and largest when \( \pi = 0.5 \) and monotonically decreases as \( \pi \) becomes larger or smaller than 0.5. By proposition 3, a producer who believes the futures price is biased upward will increase the hedge ratio, and vice versa.

The magnitude of \( \frac{\partial h^*}{\partial \pi} \) for both EU and RD producers depends on beliefs about size of the bias in the futures price, which is captured within \( g_1(\pi) \). For a given futures price level, \( g_1(\pi) \) is symmetric around \( \pi = 0.5 \), mapping linearly to \( \frac{\partial h^*}{\partial \pi} \). The hedge response to a change in price expectations is greatest at \( \pi = 0.5 \) and declines as the strength of the belief about biasedness increases. In other words, the marginal adjustment to the producer’s optimal hedge ratio declines as the strength of the belief about biasedness increases.\(^3\) The intuition is that a risk-averse producer has already chosen not to fully hedge as the result of belief about bias in the futures price. The producer’s price risk exposure increases as the producer moves away from a full hedge, leading to lower expected utility. This limits the magnitude of deviations from a full hedge.

The third and fourth lines of equation (6) show that when the current futures price is below the reference price, the RD producer who believes the futures price is biased will either hedge or not, and this depends on the strength of the belief that the futures price at maturity will be lower than the current futures price. If the probability that the future price is biased upwards is large enough, such that \( \pi < g_3^{-1}(F_t/C_0) \), s/he will hedge. Note that \( g_3(\pi) \) is continuous and monotonically increasing when \( \pi \in [0, 0.5] \). In other words, \( g_3(\pi) \) is invertible, with \( g_3^{-1}(\cdot) \) denoting its inverse function. When \( \pi > g_3^{-1}(F_t/C_0) \), the producer will not hedge even when s/he believes the futures price may be lower at contract maturity than it currently is. The intuition is that when the futures price is below the reference price, an RD producer is risk seeking and will not hedge because hedging at a loss limits the upside of the price s/he can receive.

Empirical Investigation of Reference-Dependent Hedging

Proposition 3 gives rise to empirical implications for producer hedging when producers hold beliefs that the futures price may be biased. Though producers’ subjective beliefs about futures prices are unobserved, we carry forward an assumption that an increase in the futures price proxies for an upward bias in futures prices. Given this, we explore the following issues: (a) Under EU hedging, the hedge ratio response to futures price changes will be symmetric given the absolute futures price level; however, when RD behavior is present, an asymmetric price response in hedging emerges such that the response to

\(^3\) This property of \( g_1(\pi) \) is a result of an inelastic utility function that has a negative third-order partial derivative.
price changes will be larger when the futures price is above the reference price and smaller when the reference price is above the futures price. 

(b) An EU producer will hedge more than an RD producer (compare lines 1 and 2 of equation [6]) if s/he believes futures prices are biased upward, and the marginal hedge response will decline as the belief about bias in futures prices gets stronger.

An empirical investigation of these issues relies on identifying the impact of a futures price change on the hedge ratio change, and we explore this empirically in what follows.

Data

We analyze the pre-harvest hedging activities of Iowa corn producers using daily forward contract data from a major grain-marketing firm with more than thirty grain-receiving locations in Iowa. The data include over 115,000 forward contracts for corn during January 2009 through August 2013, and contain the contract date, bushels contracted, and delivery date. We limit our analysis to forward contracting in the pre-harvest period from January 1 to August 31, as harvest grain bids are commonly available between January and the end of August (Mallory, Zhao, and Irwin 2015). Restricting our analysis in this way separates the decision to hedge anticipated production from storage hedges and post-harvest contracts used to lock in favorable prices or basis for planned deliveries.

In addition to the individual forward contract data, the data also include the firm’s annual total receipts of corn from producers in each year from 2009 to 2013. These data are without individual producer identifiers, so it is not possible to link behavior to a single producer. Thus, we assume producer homogeneity in hedging following Katchova and Miranda (2004), who provide evidence that farm characteristics influence the decision to use futures and forward contracts but not how much to hedge.

We construct a hedge ratio, $h$, in week $t$ from our contract data. The numerator is total bushels contracted from January through week $t$ for delivery in the period September 1 to August 31 of the following year. Following the CFTC, our hedge ratio is constructed for Tuesday in each week. Expected production is the ideal denominator for the weekly hedge ratio but is not observable. We proxy expected production using the corn (in bushels) received by the firm in each year. The proportion of corn hedged in our data varies considerably from year to year: more than 20% of corn receipts were forward priced in the high price years of 2011–2012, while only 3.75% was hedged by the same time in 2013—a year when prices fell significantly from 2012 levels. This empirical observation is consistent with our model’s theoretical predictions of hedging behaviors of RD producers.

Empirical Procedure

Figure 1 plots the weekly change in the producers’ pre-harvest hedge ratio within each crop year. Note that seemingly large differences in pre-harvest hedging occurs within and across years. Our RD hedging theory, specifically equation (5), prescribes two states of producers’ hedging activities: “hedge” and “not hedge.” The “not hedge” state corresponds to periods when the futures price is below the producer’s reference, and the “hedge” state is triggered when the futures price is above the producer’s reference price. Since we do not observe reference prices, we employ a Markov Switching (Hamilton 1989)
model to infer them from the data, the details of which are presented below.

Testing for State Switching in the Producer Hedge Series

Let \( h_t \) be the cumulative hedge ratio, the percentage of the total crop forward contracted up to week \( t \), and \( \Delta h_t \) be the proportion of total harvest hedged in week \( t \). The unobserved state variables are identified by \( s = 1, 2 \). An empirical model of hedging is

\[
\Delta h_t = \alpha_s + \beta_1 time + \beta_2 vol_t + \beta_3 \Delta F_t + \epsilon_t, \quad \epsilon_t \sim iidN(0, \sigma_s^2).
\]

(7)

The variable \( time \) measures the weeks left until harvest. Following Irwin and Sanders (2012), we include a price volatility measure, \( vol_t \), which is constructed from the weekly change in the annualized implied volatility in the December futures contract from Barchart.com (http://acs.barchart.com/). Both \( time \) and \( vol_t \) are control variables and assumed to be state-independent.

The crop marketing literature considers spatial basis as a unique feature of agricultural forward contracts (Nelson 1985; Musser, Patrick, and Eckman 1996; Garcia and Leuthold 2004; Taylor, Tonsor, and Dhuyvetter 2014) and identifies that increased forward contracting is related to a widening basis (Elam and Woodworth 1989; Elam 1992; Schroeder et al. 1993). Basis and basis risk may be determinants of hedging in our data; however, we are unable to model spatial basis because we do not observe the location of the grain contracts nor the basis levels during the contract periods in our data.

The state-dependent covariates in equation (7) are the intercepts and price change. The intercepts, \( \alpha_s \), are the conditional average weekly portion of production forward contracted during the pre-harvest season. If the producer is reference-dependent, proposition 1 implies that more of the crop will be hedged in weeks when the futures price is above the reference price, such that

\[
\alpha_s = \begin{cases} 
\alpha_{s1}, & F_t \geq R_t \\
\alpha_{s2}, & F_t < R_t
\end{cases}, \quad \text{and} \quad \alpha_{s1} \geq \alpha_{s2}
\]

(8)

where \( F_t \) is the current futures price and \( R_t \) is the producer’s reference price.

The price change, \( \Delta F_t \), is the weekly difference in the logged price of the December futures contract, and its coefficient, \( \beta_s \), estimates the responsiveness of the hedge ratio to price changes. By proposition 3, an RD producer’s hedge is more responsive to prices above the reference price and less responsive below, such that

\[
\beta_s = \begin{cases} 
\beta_{s1}, & F_t \geq R_t \\
\beta_{s2}, & F_t < R_t
\end{cases}, \quad \text{and} \quad \beta_{s1} \geq \beta_{s2}
\]

(9)

Finally, we allow the variance of residuals, \( \sigma_s^2 \), to be state-dependent,
recognizing that the hedge ratio may exhibit larger variation in the hedge state.

To understand the transition between states, we begin by denoting $\mathbf{P}_t$ as a two-by-two matrix that governs the transition between no hedging and hedging. The $i$, $j$th element of the matrix, $p_{ij} = Pr(s_t = j | s_{t-1} = i)$, represents the probability of state $j$ being realized in the current period $t$ given the last period’s state $i$. The transition matrix $\mathbf{P}_t$ is unobservable, but we infer it from the observed hedging activities, conditional on the explanatory variables specified in equation (7). If the difference between the state-dependent coefficient estimates is significant, (i.e., $\alpha_1 \neq \alpha_2$ and $\beta_1 \neq \beta_2$) and the transition matrix $\mathbf{P}_t$ of the Markov process is not singular and symmetric, then there is empirical support for switching. The null hypotheses, that is, no state-dependent hedging, we associate with EU optimal hedging. However, statistically significant evidence of state-dependent hedging is consistent with RD behavior.

Exploring Possible Reference Prices

The empirical hedging literature noted previously suggests a number of candidate reference prices producers may have in mind when choosing their hedging strategy, and we empirically explore the common ones. Consider a modification of regression equation (7) to incorporate reference prices

$$
\Delta h_t = \alpha_0 + \alpha_1 \mathbb{1}_{(F_t - R_t < 0)} + \beta_1 \text{time} + \beta_2 \text{Vol}_t + \beta_3 \Delta F_t + \beta_4 \Delta F_{t-1} \mathbb{1}_{(F_t - R_t < 0)} + \beta_5 \Delta F^2_t + \epsilon_t
$$

(10)

where $\mathbb{1}_{(F_t - R_t < 0)}$ is a reference-price binary variable equal to one if the current futures price is below the reference price, and zero otherwise. As an interaction term, the reference price indicator captures asymmetry in the hedge ratio responses to prices. The intercept term $\alpha_0$ estimates the average proportion of the crop hedged per week when the futures price is above the reference price, and $\alpha_1$ is the estimated average difference in the hedge ratio when the futures price is below the reference price. The inclusion of the intercept term connects our empirical specification with proposition 1, which indicates that the optimal hedge ratio will increase as production uncertainty resolves during the pre-harvest period. We include a quadratic price term, $\beta_5 \Delta F^2_t$, to capture potential non-linearities in hedging that may result from belief changes. If hedging is done in response to changes in beliefs about bias in futures prices as a result of price changes, the coefficient estimate on this term should be negative and significant. The error term, $\epsilon_t$, is an identically, independently, and normally distributed (i.i.d.) shock, with mean zero and variance, $\sigma^2$.

The choice of a reference price influences the binary variable in equation (10). Following the literature, we consider three static references prices (static within a year) and one dynamic reference price, though one can imagine a number an infinite number of candidate reference prices. The Risk Management Agency’s (RMA) projected harvest price used to establish revenue guarantees in crop insurance and the estimated corn production costs per bushel are references that producers might naturally use. This insurance price may serve as a lower bound below which a producer has no incentive to enter into a forward contract. Similarly, a producer may be reluctant to hedge when the futures price is below production cost because it means locking in a loss. A third static reference price is last year’s average marketing price, which may anchor expectations for hedging decisions. Finally, we model a dynamic reference price—the thirty-day moving average of the December corn futures contract.

The statistical validity of regression equation (10) hinges on the i.i.d. assumption of the error term. We check the validity of this assumption by examining the autocorrelation and variance of the realized residuals, and we calculate the standard errors for estimates using a Heteroskedastic-Autoregressive-Consistent (HAC) estimator. If we reject the null hypothesis of no reference price effect, different candidate reference prices can be compared using a goodness-of-fit estimate.

---

7 The log likelihood function is: $\log (|h_1, h_2, \ldots, h_T; \Theta|) = \sum_{t=1}^T \log (f(h_t; \Theta), \text{ where } f(h_t; \Theta) = \sum_{i=1}^2 \sum_{j=1}^2 p(h_t | h_{t-1}) \times \text{Pr}(s_t = j | s_{t-1} = i)$ is the $i, j$th element of the two-by-two transition matrix $\mathbf{P}_t$, and $f(h_t; \Theta)$ represents the density function under regime $j$. $\text{Pr}(s_t = j | s_{t-1} = i)$ is the inferred probability of the state $i$ occurred in period $t-1$ based on the observations $\Omega_{t-1}$ and parameters of interest $\Theta$.

8 We refer to calendar days: thirty calendar days is equivalent to twenty-two trading days.
Table 1. Quasi-Maximum Log-Likelihood Parameter Estimates, Weekly Pre-harvest Forward Contracting, 2009–2013

\[
\Delta h_t = \alpha_s + \beta_1 \text{time} + \beta_2 \Delta \text{vol}_t + \beta_s \Delta F_t + \epsilon_t
\]

\[\epsilon_t \sim iidN(0, \sigma^2_t)\]

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<tr>
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<th>State 2 (Active Hedging)</th>
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<td></td>
<td>(0.0013)</td>
<td>(0.0017)</td>
</tr>
<tr>
<td>(\sigma_s)</td>
<td>0.0019***</td>
<td>0.0081***</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0009)</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Difference in Hedging Response between States 2 &amp; 1</th>
<th>State 1 (No Active Hedging)</th>
<th>State 2 (Active Hedging)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\beta_2 - \beta_1)</td>
<td>0.0825***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0248)</td>
<td></td>
</tr>
<tr>
<td>(\alpha_2 - \alpha_1)</td>
<td>0.0079***</td>
<td></td>
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<tr>
<td></td>
<td>(0.0015)</td>
<td></td>
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</table>

<table>
<thead>
<tr>
<th>Specification Check</th>
<th></th>
<th>Transition Probabilities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Obs.</td>
<td>169</td>
<td>(p_{11})</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>730</td>
<td>(p_{12})</td>
</tr>
<tr>
<td>Autocorrelation</td>
<td>0.18</td>
<td>(p_{21})</td>
</tr>
<tr>
<td>ARCH Effect</td>
<td>0.59</td>
<td>(p_{22})</td>
</tr>
</tbody>
</table>

Transition Probabilities:

- \(p_{11} = 0.93\)
- \(p_{12} = 0.07\)
- \(p_{21} = 0.24\)
- \(p_{22} = 0.76\)

\(\text{Jacobs, Li, and Hayes Reference-Dependent Hedging: Theory and Evidence from Iowa Corn Producers}\)

\(\text{9}\)

\(\text{Downloaded from https://academic.oup.com/ajae/advance-article-abstract/doi/10.1093/ajae/aay035/5046062}\)

\(\text{by Iowa State University user}\)

\(\text{on 03 August 2018}\)

**Results**

Table 1 contains the quasi-maximum log-likelihood estimates and transition probabilities for equation (7), where State 1 is no active hedging and State 2 is active hedging. Note that Lagrange multiplier tests for autocorrelation and autoregressive conditional heteroscedasticity (Hamilton 1996) indicate that the estimated residuals exhibit neither heteroscedasticity nor serial correlation.

The state-independent variables—time-to-harvest and change in implied volatility—are statistically significant in both states. The estimated time-to-harvest effect has the expected negative sign. On average, producers increase their hedge ratio by 0.01 percentage points per week, thereby pricing their upcoming expected harvest as yield uncertainty diminishes towards harvest. The coefficient estimate on the change in implied volatility indicates that an increase in volatility moves hedge ratios higher.

Asymmetry of hedging responses is detected in the two states as the intercept estimates, \(\alpha_s\), are positive and statistically significant: the additional proportion hedged in State 1 is 0.4 percentage points, while in State 2 it is 1.2 percentage points, three times more than in State 1. This and the time-to-harvest effect is consistent with proposition 1, which indicates the optimal hedge ratio will increase as production uncertainty resolves. We find that producers’ responses to futures prices changes also differ across states, with producers in State 2 increasing their hedge ratio by 0.1 percentage points for a 1% increase in the futures price, which is nine times greater than in State 1.

Figure 2 shows the change in producers’ weekly hedge ratio against the smoothed probability that the producer is in the active hedging state \((p[s = 2])\). Recall that the estimates of regression equation (7) presented in table 1 produce state probabilities based on current and past information in the data. To get a more complete picture of the probabilities of producers’ hedging states by week, we use a smoothed probability-estimator on the full sample of data to estimate producers’
switching routine. This is what we illustrate in Figure 2. The producers’ hedge series exhibits clear shifts between the “hedge” and “not hedge” states. Consistent with our intuition, State 2 is associated with periods where larger weekly hedges take place, but the timing of the hedging state does not seem to follow a consistent pattern year-to-year. In particular, the active hedging state can prevail close to harvest, as in 2009 and 2012, in early spring as in 2011, or not at all, as in 2013. The estimated Markov transition probabilities, given in Table 1, provide more insight. There is a 93% chance that a realization of State 1 follows a prior State 1. If the producer starts in State 2, there is a 76% chance that s/he will continue to actively hedge in the next period. This suggests that economic stimuli may trigger shifts between the states, which we explore further in regression equation (10).

Testing Alternative Reference Prices

Table 2 presents the OLS estimates and model fit statistics for equation (10) and a base regression where no reference price specification is included. Robust standard errors are estimated because we reject the assumption of homoscedasticity of the residuals at the 5% significance level for all candidate reference prices. This is consistent with the Markov Switching regression results indicating that sample variances differ across states.

Regression equation (10) is an empirical framework for exploring asymmetry in hedging. At least two empirical conditions present challenges in identifying the suitability of reference prices. First, for stable candidate references (i.e., the RMA projected harvest price, estimated production cost, last year’s average marketing price), we ideally need to observe a futures price that oscillates around the reference price in order to identify reference price effects in both high- and low-price periods. In our producer hedge series, the corresponding annual estimated production cost is always below the December futures price, and therefore we exclude that from our presented results. Second, to draw inferences about which reference price performs best among them, there should not be too much overlap of the high- and low-price periods for each. The high- and low-price periods in the RMA prices and last year’s marketing prices have significant overlap, so we caution against using model goodness-of-fit measures such as the adjusted $R^2$ to compare the two reference price performances. Conversely, by virtue of being a dynamic price within a marketing year, we believe there is more information about hedging responses to price movements and high- and low-price states in thirty-day moving average reference price specification. All three reference prices appear to be an improvement over the base case, as measured by the adjusted $R^2$ values.

Across model specifications in Table 2, the estimated time-to-harvest estimated effects are negative and statistically significant for all
Table 2. OLS Estimates with Robust Standard Errors, Pre-harvest Weekly Forward Contracting, 2009–2013

Equation 10: \( \Delta h_t = \alpha_0 + \alpha_1 1_{(F_t - R_t < 0)} + \beta_2 \text{time} + \beta_3 \Delta F_t + \beta_4 \Delta F_t 1_{(F_t - R_t < 0)} + \beta_5 \Delta F_t^2 + \epsilon_t \)

<table>
<thead>
<tr>
<th>No Reference Price</th>
<th>Nonlinear Price Response</th>
<th>Last Year's Avg Price</th>
<th>RMA Forecast Price</th>
<th>30-day Moving Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha_0 )</td>
<td>0.007***</td>
<td>0.006***</td>
<td>0.009***</td>
<td>0.007***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>( \beta_1 )</td>
<td>-0.0002**</td>
<td>-0.0002**</td>
<td>-0.0001**</td>
<td>-0.0001**</td>
</tr>
<tr>
<td></td>
<td>(&lt;0.0001)</td>
<td>(&lt;0.0001)</td>
<td>(&lt;0.0001)</td>
<td>(&lt;0.0001)</td>
</tr>
<tr>
<td>( \beta_2 )</td>
<td>0.026</td>
<td>0.026</td>
<td>0.040</td>
<td>0.032</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.028)</td>
<td>(0.026)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>( \beta_3 )</td>
<td>0.054***</td>
<td>0.057***</td>
<td>0.066**</td>
<td>0.085**</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.019)</td>
<td>(0.033)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>( \beta_4 )</td>
<td>-0.034</td>
<td>-0.065</td>
<td>-0.094***</td>
<td>-0.102***</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.043)</td>
<td>(0.041)</td>
<td>(0.042)</td>
</tr>
<tr>
<td>( \beta_5 )</td>
<td>0.412</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.251)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \alpha_0 + \alpha_1 )</td>
<td>0.006***</td>
<td>0.006***</td>
<td>0.003***</td>
<td>0.004***</td>
</tr>
<tr>
<td>( \beta_3 + \beta_4 )</td>
<td>0.032*</td>
<td>0.020</td>
<td>-0.099</td>
<td>-0.013</td>
</tr>
<tr>
<td></td>
<td>0.089</td>
<td>0.103</td>
<td>0.163</td>
<td>0.163</td>
</tr>
<tr>
<td>Year*time</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Year fixed effects

- BP test: 0.0007 0.0007 0.0087 0.010 0.001 0.002 0.007 0.009
- DW test: 0.542 0.389 0.391 0.359 0.339 0.338 0.3188 0.262
- Adj-R²: 0.21 0.24 0.27 0.31 0.34 0.34 0.34 0.42
- F-test: 0.007 0.007 <0.001 0.77 0.26 0.003

Note: Asterisk * denotes the 10% level, ** denotes the 5% level, and *** denotes the 1% level. Robust standard errors appear in parentheses. P-values reported for the Wald tests of joint significance, Breusch-Pagan (BP) tests and Durbin-Watson (DW) tests as well as F-test that compares model fit.
our candidate reference prices, and this is consistent with the Markov Switching model results in table 1. However, our estimations of equation (7) and equation (10) are not consistent for the other state-independent variable, implied volatility: in table 2 its coefficient estimates are not statistically significant. We believe this suggests a sensitivity of second-order price effects to the reference price specification and is not necessarily evidence that producers are indifferent about or unresponsive to price volatility. Producers may use a volatility measure other than the implied volatility or focus on volatility over a much longer window, such that a short-term change in implied volatility does not affect their week-to-week hedging decision.

Results for regressions using static reference prices are in the third and fourth results columns in table 2. Based on the intercept estimates, $x_0$ and $z_1$, producers on average hedge 0.9% of their total harvest in weeks when the futures price is above the reference price, but when the futures price is lower than the candidate reference price, producers hedge 0.3 percentage points less. Note that the coefficient estimates are statistically significant across model specifications, providing empirical evidence supporting proposition 1—that the optimal hedge ratio increases as production uncertainty resolves—and the Markov Switching model estimates in table 1. Using static reference prices, we do not detect asymmetry in the hedge ratio response to price changes: the hedge ratio appears to respond positively to futures price changes above the static reference prices, and the estimated effects when the futures price are below the reference prices are not statistically different.

Results using a dynamic reference price—the thirty-day moving average of the December corn futures contract—along with yearly fixed effects and time-year controls, occupy the last four columns of table 2. In addition to a significant threshold response in the weekly average hedge, we detect asymmetric hedging responses to price changes when the futures price fluctuates around the dynamic reference price, and this is consistent with an RD producer’s hedging behavior according to our theoretical model. In particular, a 1% increase in price when the price is above the thirty-day moving average results in a 0.09 percentage point increase in the hedge ratio. On the other hand, in weeks when the futures price is below the thirty-day moving average price, producers do not increase their hedge position in response to price changes, indicated by a lack of statistical significance in the joint parameter estimate on price changes, $\beta_3 + \beta_4$.

Our strategy to detect RD hedging relies on the interaction terms when futures prices are below reference prices, $x_1$ and $\beta_3$, and we control for the role of changing price expectations, which are unobserved, by including a quadratic price term. In all our specifications, the coefficient estimates on the quadratic price term variable, $\beta_5$, are statistically insignificant, and $x_1$ and $\beta_4$ are statistically significant and of the expected sign. We interpret this as evidence in support of RD hedging—asymmetry of a hedging response to price changes above and below the reference prices—and against hedging as a response to changing beliefs about bias in futures prices. Hedging behavior reflects unobserved beliefs, and we acknowledge that because we do not observe the true reference price we cannot conclusively identify this behavior as reference dependence.

One of the empirical implications of proposition 3 is that belief effects in hedging are greater for an EU producer than for an RD producer when beliefs are of upward biased prices. In order to test whether an EU producer hedges more than the RD producer in this case, we modified equation (10) to include an interaction term between the squared price changes and the reference price indicator. The coefficient estimate of this variable is -0.073 with a t-statistic of -0.544. Due to its lack of significance, we do not report the term in our versions of the model and their estimates.

Regression results using the thirty-day moving average price as a reference price are consistent with findings from the Markov Switching regression of asymmetric hedging behavior. If shifts between the hedging and non-hedging states are indeed triggered by futures prices moving across the thirty-day moving average price, then periods when the futures price is above the thirty-day average price will also be accompanied by high probabilities of State 2, as inferred from the Markov Switching model. Referring again to figure 2, we observe a high correlation between the probability of State 2 behavior and the price change from its thirty-day moving average. This strengthens our support for using the thirty-day moving average of the futures price as a likely candidate reference
price in understanding producers’ hedging behavior. It is worth highlighting from table 2 that the weekly hedge ratio change as a percentage of the total crop is small, even when the futures price is above the reference price. However, as producers continue to hedge throughout the pre-harvest period, the cumulative reference price effect is economically significant. Figure 3 plots the December futures thirty-day moving average and the level of the observed hedge ratio. Visually, the hedge ratio increases at a faster pace when the futures price trends up, leading the producer to hedge a greater portion of the harvest at the end of the pre-harvest season in years when the price trends higher.

Finally, the thirty-day moving average price parameter is robust to adding longer-dated price changes such as sixty-day, ninety-day, and six-month moving average prices, and to small changes in the number of days used to calculate a moving average. Yearly seasonality may also play a role in explaining variations in producers’ hedging behaviors, since the uncertainty of harvest may be resolved at different paces in different crop years. We test for such seasonality, augmenting the regression equation with year fixed effects as well as interaction of the weeks-to-harvest and year fixed effects. Tests of joint significance suggest a significant role of unobserved yearly fixed effect in producers’ hedging, and the parameters of interest are robust to the inclusion of seasonality measured this way.

**Importance of Production Risk**

The observed hedge ratios are low, particularly at the beginning of the growing season. This can be explained, in part, by the use of futures rather than forward contracts by some producers. When corn is hedged using futures it will not show up in our hedge ratio, but when this corn is eventually delivered it will show up in the total carry of the firm. Later we show that the behavior of hedgers who use short futures is remarkably similar to those who use forward contracts.

Also important in explaining the low hedge ratios is the gradual elimination of production risk. If a corn producer pre-sells, either on futures or forward markets, and then fails to produce the quantity sold due to low yields, they will face penalties on the oversold portion of production in years when the harvest time price is greater than the price at which they presold. In forward contracting cases, they essentially buy the missing corn on the local cash market. For futures contracts, they lose the difference between the harvest futures price and the price at which they sold on the futures without having an offsetting amount of corn to sell at the higher harvest price. The importance of the gradual elimination of production uncertainty can be seen by the magnitude and significance of $\beta_0$.
and \( z_1 \). There are 35 weeks between January 1 and August 31, suggesting that \( 35(z_0+z_1) \) is an estimate of the cumulative impact of resolving production uncertainty on the hedge ratio. Using estimates from the first sub-column of the thirty-day moving average results in Table 2 as the reference price, the proportion of total production forward contracted based on these two terms is 17.5%.

**Does the Observed Hedging Pattern Result in a Higher Marketing Price?**

Our results suggest that producers’ hedges respond to price changes, which in turn suggests that hedging may be driven in part by an attempt to time the market. This raises the question as to whether the hedging pattern we observe performs better than other common marketing strategies. Our producer data series is too short for a meaningful comparison between hedging strategies; instead, we rely on estimates from our empirical model along with futures price data from 1960 to 2015 to simulate price outcomes for common marketing strategies, including selling at harvest, hedging in January or March, equal monthly hedging, and RD hedging. We use estimates from the thirty-day moving average price model without year fixed effects and seasonal interactions and construct October and January monthly average prices of the December futures contract to approximate the harvest and planting prices, respectively. Prices are per-bushel weighted-average prices, where the weights are the weekly change in pre-harvest hedge ratios, \( \Delta h_t \), and we assume the unhedged portion, \( \Delta h_T \), is sold at the harvest price.

\[
P = \sum_{t=1}^{T} (\Delta h_t + F_t).
\]

Table 3 presents the simulated prices received for different hedging strategies using DCOT data from 1960 to 2015. Note that to facilitate this simulation and comparison we ignore transaction costs and basis risk and assume the producers are able to adjust their hedge ratio weekly. With the exception of the “Sale at Harvest” strategy, which has the lowest expected selling price and relatively high variability, the average prices across the other non-RD strategies are similar. Hedging in January or March, on average, result in higher prices and lower variability compared with selling everything at harvest. The weather premium in U.S. corn markets (Li, Hayes, and Jacobs 2017) may result in this premium for selling in spring. The RD hedging strategy over the period yields the highest average price but also with a relatively high variance. This result is intuitive based on the model explored here: an RD producer only hedges in relatively high-price periods. In our data, producers forward contract on average only 14% of production, leaving their marketing plans susceptible to greater price variability at harvest and therefore not fully realizing the intended benefit of hedging, which is a reduction of price variability.

**Comparison of Producers’ Hedging to the DCOT New Crop Hedging Data**

The DCOT data include a variety of hedging activities that traders pursue, and the data have been criticized because reported positions are aggregated in a way that limits researchers’ ability to classify traders’ activities (CFTC 2006). However, the DCOT report does separate open interest into new and old futures.

<table>
<thead>
<tr>
<th></th>
<th>Sale at Harvest</th>
<th>Hedge in January</th>
<th>Hedge in March</th>
<th>Hedge Monthly</th>
<th>RD Hedge</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>257</td>
<td>262</td>
<td>265</td>
<td>264</td>
<td>269</td>
</tr>
<tr>
<td>Median</td>
<td>230</td>
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<td>258</td>
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<td>253</td>
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<tr>
<td>Std. Dev</td>
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<td>119</td>
<td>122</td>
<td>125</td>
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</tr>
<tr>
<td>Min</td>
<td>106</td>
<td>110</td>
<td>110</td>
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<td>112</td>
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<tr>
<td>Max</td>
<td>747</td>
<td>589</td>
<td>595</td>
<td>647</td>
<td>674</td>
</tr>
</tbody>
</table>

*Note: In the comparison of common marketing strategies, we assume that producers market their entire crop by harvest. The prices used for the “Sale at Harvest,” “Hedge in January,” and “Hedge in March” strategies are the monthly average prices of the December futures contract in October, January, and March, respectively. The “Hedge Monthly” strategy assumes hedging an equal amount of crop each month, and the price received is the average price of the December futures contract between January and October. The “RD Hedge” price is simulated using the thirty-day moving average estimates from Table 2 without year fixed effects and time-year interactions.*

---

**Table 3. Comparison of Selling Prices (cents per bushel) Received for Different Hedging Strategies, 1960–2015**
The new futures open interest corresponds to the first contract of the next marketing year and later, which presumably contains information about pre-harvest hedging. We are interested in understanding how well the producers’ hedge and DCOT series mirror each other. If the series are closely related, then DCOT data may serve as a good proxy for producer hedging in the pre-harvest period. For an accessible summary of markets and hedging strategies, see Carter (2017). Chapter 1 describes the CFTC report and data, while chapter 7 provides a detailed description of hedges typically used by corn market participants. Carter (2017) uses the term “anticipatory hedge” to describe the pre-harvest hedging that is the focus of our work and also aligns with Working’s (1962) intuition for hedging.

We construct the commercial pre-harvest hedge ratio as the ratio of the weekly short hedgers’ open position in new futures contracts to the USDA’s report of U.S. corn production from Quick Stats (USDA NASS 2017). Figure 4 shows the producer and DCOT hedge ratio series (in levels) for the producer data periods, and figure 5 plots the weekly changes in the producer and commercial hedge ratio series during the pre-harvest period. The correlation coefficients between the two series in levels and differences are 0.93 and 0.68, respectively, evidence that CFTC DCOT short hedgers’ positions in new futures are a good representation of producers’ hedging activities. This is intuitive: corn producers can hedge their expected crop either by taking a short position in the futures...
market or by forward contracting with a local grain dealer or marketing firm that in turn hedges this exposure on futures markets. We note the possibility that producers may switch their method of hedging between forward contracting with the elevator to taking a position in the futures market, and vice versa, depending on the trend in prices. Producers who hedge directly on the CME maintain margin accounts and must pay margin calls when the market price increases, and this is not true with forward contracts. Producers may be more likely to use forward contracts when they believe a price increase is more likely, and more likely to hedge with futures when a price decrease is more likely. Our data do not allow us to identify switching between the two hedging methods.

Summary and Conclusions

This article explores the role of reference dependence in producers’ pre-harvest hedging of corn. To that end, we develop a utility framework that incorporates reference dependence and we derive testable empirical hypotheses from it. We analyze a dataset of every forward contract between a large grain-marketing farm and grain producers over a five-year period, and construct weekly producer hedge ratios, regressing changes in hedge ratios on changes in futures prices and prices relative to candidate reference prices commonly known by producers.

Our theoretical model and empirical results, including asymmetric hedging around a reference price, highlight issues that broadly relate to the motivations for hedging described by Working (1962). His support for selective and anticipatory hedging comes from surveys of industry, and it would seem that the triggers that motivated the types of hedging that Working describes are those that motivate hedging in our data. What is novel in our work is an attempt to identify a likely reference price used to determine whether prices are high or low; therefore, it is unclear if the behavior he has in mind includes asymmetric hedging around a reference price and non-linearity in hedging price responses.

Our data show that when prices trended higher in the period from 2011 to 2012, producers forward contracted as much as 24% of the crop. In 2013, when prices trended lower, producers forward contracted only 4% of the crop. Using regression analysis and a simple Markov Switching model, we demonstrate the presence of asymmetric behavior in hedging when prices are above and below reference prices, consistent with the theoretical predictions. Producers who hedge using forward contracts respond to price changes, and in particular, they sell more when the current futures price is above the contract’s thirty-day moving average. The tendency of hedgers to sell into a price rally will, in the short run, help to stabilize futures prices. However, the tendency to sell more corn in the pre-harvest period in drought years may exacerbate harvest time price volatility because a smaller proportion of the crop will be uncommitted at the end of the season. The reduction in hedging behavior in years when prices trend down is problematic from a risk management perspective.

Lastly, we examine whether the price-induced hedging activity of producers results in higher average marketing prices than a few of the prescriptive, less active hedging strategies. Using a longer times series of futures prices, we find evidence of higher expected prices under RD hedging, but also increased variability in prices, something that our model predicts. We also find that spring sales strategies—selling in January or March—have the highest expected selling prices with the lowest variability. In light of our evidence that DCOT data for corn is representative of producer hedging behavior, we can examine whether this holds for other commodities. Further evidence of the usefulness of the DCOT data as a proxy for hedging behavior in a longer series and for other commodities is needed.

This work, particularly the empirical evidence, will be valuable to researchers who consider using the DCOT data as a proxy for producers’ hedging behavior. Our analysis suggests a number of future investigations that with new data—particularly a longer series—will be fruitful. Importantly, the demonstration of reference price effects—even if the thirty-day moving average we explored is not the holy grail of reference prices—should

9 We thank an anonymous reviewer for suggesting this as a potential explanation. This makes an excellent idea for future research that is unfortunately beyond the capability of the data we possess.
inform conversations about marketing and risk management. Our comparison of marketing strategies is practical evidence that marketing and extension professionals can use to assist producers in managing price risk.

**Funding**

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**Supplementary Material**

Supplementary material is available online at http://oxfordjournals.org/our_journals/ajae/online.

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