# CROP INSURANCE, COMMODITY FUTURES PRICES, AND COMMERCIAL TRADER POSITIONS IN CORN AND SOYBEAN MARKETS*

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## ABSTRACT

We examine the impacts of price changes on commercial traders' aggregate net positioning in grains and oilseed futures markets during the pre-harvest periods from 2007-2019. We proceed in two steps. We use first an extension of the reference-price hedging model of Jacobs, Li, and Hayes (*AJAE* 2018), and then a Structural Vector Auto-Regressive Model (SVAR) that accounts for possible endogeneity between the variables, to analyze the respective impacts of futures prices and of market uncertainty and sentiment (proxied by the VIX) on commercial trader positioning in grains and oilseeds markets. The results from Impulse Response Functions (IRFs) retrieved from the SVAR show that futures price changes drive position changes, shedding new light on whether commercial traders hedge or instead speculate in agricultural markets.

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# SECTION 1: INTRODUCTION

Whether commodity prices drive commercial traders' hedging decisions is an important topic that has drawn the attention of many researchers. There exist many studies documenting a high correlation between futures prices and producers' positions in agricultural futures markets. In particular, commodity producers go short more often when futures prices are trending up (Wang, 2003; Cheng and Xiong, 2014; Fishe, Janzen, and Smith, 2014; Bessec, Le Pen, and Sevi, 2017; Jacobs, Li and Hayes, 2018). In a recent article, Jacobs, Li, and Hayes (*AJAE* 2018) propose a theoretical model to explore the role of price history ("reference-dependence") in agricultural producers' hedging decisions, and they test the model's predictions using a proprietary dataset of Iowan farmers' pre-harvest hedging of their corn crops. Their empirical results show that, during pre-harvest time in 2009-2013, corn producers sell more forward when the current futures prices are trending above reference prices, and that changes in futures prices statistically significantly impact the producers' hedge ratios.

In the present paper, we first modify and extend their empirical study to longer time periods and more commodities. Jacobs *et al*. (2018) focus the corn market in 2009-2013. That five-year period is atypical, in that it covers the financial crisis and Great Recession (2009-2011) and then droughts in 2011-2012. Thus, it is not obvious that the results can be generalized to a longer period or to other commodities. By augmenting their model to include (i) additional proxies for market fundaments, (ii) corn and beans, and (iii) a much longer sample period, we confirm their original findings that agricultural producers and other commercial traders use past prices as references.

Second, we revisit the statistical insignificance of the corn option-implied volatility (IVol) in Jacobs, Li, and Hayes (2018). That result is puzzling since volatility expectations should matter to farmers' hedging decisions. We hypothesize that, because the near-dated corn IVol is seasonal (Adjemian, Bruno and Robe, *AAEA* 2017) and is sensitive to USDA announcements (Cao and Robe, *AAEA* 2020), it may not be the ideal uncertainty indicator. We therefore use the VIX as a potentially better proxy for demand-side market uncertainty. The VIX has three advantages: (i) it captures both heightened uncertainty about global macroeconomic conditions and risk aversion among investors (Bekaert *et al., JME* 2013); (ii) it is not affected by agricultural seasonality or scheduled USDA report releases; (iii) it has a close relationship with agricultural option-implied volatilities (Adjemian *et al*., *AAEA* 2017). Using the VIX generates more intuitive findings. In particular, while in OLS regressions inspired by Jacobs *et al*. (2018) we find (as they do) that the VIX does not have any significant effect on commercial traders' aggregated net short positions in 2009-2013, we find that the VIX variable is significant for the full sample (2007-2019). In a similar vein, while the impulse response functions (IRF) from an SVAR suggest that the VIX changes do not significantly affect hedging decisions, we find evidence of an indirect effect through short-term impacts on soybeans futures prices. The mixed results with the SVAR analysis point to the need to use a different empirical approach that allows for asymmetric responses of trader positions depending on whether reference prices are exceeded or not.

Third, we investigate the usefulness of publicly available data on producer positioning in agricultural derivative markets. Jacobs *et al*. (2018) use proprietary over-the-counter (OTC) data on farm-level forward contracts to calculate a "producers' hedge ratio" for their empirical analysis. As an alternative, they suggest calculating a "producer hedge ratio" using as a numerator the aggregate short position of commercial traders in new-crop futures contracts—based on data from the US Commodity Futures Trading Commission's weekly DCOT or Disaggregated Commitments of Trader reports—and as denominator the annual expected crop production from the USDA. They show graphically that their non-public “producers’ hedge ratio” and the DCOT “commercials’ hedge ratio” exhibit similar patterns over time, and they argue (using correlation coefficients between the two series in levels and differences) that DCOT data is representative of producers hedging behavior in the corn futures market. We first verify their intuition, using a “commercials’ hedge ratio” calculated by their suggested formula to analyze the optimal hedging model in corn and soybeans markets during the sample period of 2009-2013, and in a longer period of 2007-2019. Our results are consistent with their proprietary-data findings, suggesting that the DCOT data are an acceptable substitute to the proprietary data for examining commercial traders’ hedging behavior in the agricultural futures market. Next, we propose an alternative hedging ratio. Instead of using the expected crop size (which is a physical variable measured in bushels), we use the open interest (which is a financial variable, measured in contracts) from the DCOT as a scaling factor. The results from the newly proposed hedge ratio calculation method are qualitatively the same as those estimated by using the “old” hedge ratio calculation method, suggesting the ability of using such a measure for all commodities for which DCOT data exist but expected production figures are not readily available (unlike in grain and oilseed markets).

Our final contribution to the literature is to use a structural VAR to account for possible endogeneity issues in the analysis of the effects of futures prices and of the VIX on commercial futures-market positioning. Precisely, we ask whether (during pre-harvest period from January 2007 to August 2019 for corn, and to July 2019 for soybeans) the changes in commercial traders’ aggregate net short positions are affected by changes in futures prices and/or changes in the macroeconomic uncertainty (captured by the VIX) after accounting for exogenous factors that capture seasonality and crop insurance protection. The SVAR results indicate that, although a VIX increase boosts producers’ net short position in both grains and oilseeds markets (which matches the intuition that hedging increases as uncertainty increases), the direct relation is not statistically significant at the 95% confidence level.[1] Changes in futures prices, in contrast, have highly statistically significant impacts on changes in commercial traders' aggregated short positions in grain and oilseed futures markets. The findings therefore suggest that commercial producers not only hedge but also speculate, in the sense that their aggregate net short futures position increases when futures prices rise.

The paper proceeds as follows. Section 2 reviews the literature. Section 3 essentially replicates Jacobs *et al*. (2018) using DCOT data. Sections 4 and 5, respectively, motivate and test our modifications of the basic model. Section 6 describes the SVAR model. Section 7 summarizes the results of our SVAR analysis from the impulse-response functions, and results from robustness tests. Section 8 concludes. Appendix 1 and Appendix 2 include figures and tables, respectively, for the replication modifications and extensions, as well as the robustness analyses.

## SECTION 2: CONTRIBUTION TO THE LITERATURE

Being an independent agency of the U.S. government regulating the U.S. derivatives markets, the CFTC records all positions held by large derivative market participants. The CFTC publishes a summary in the weekly Commitment of Traders (COT) reports, which contain aggregate information on open trading position, net long positions, net short positions, and spread positions for several types of traders.

In the historical COT reports, commodity market participants are categorized into two main groups: commercial traders and noncommercial traders. Beginning in June 2009, and retroactively

[1] As noted earlier, we do find evidence of an indirect effect through short-term impacts on soybeans futures prices.

back to June 2006, the CFTC has released weekly Disaggregated Commitment of Traders Reports (DCOT), which are a more-detailed version of COTs in terms of categorizing market participants: commercial traders are separated into two sub-groups ( “Producers/Merchant/Processor/User” and “Swap Dealers”) and noncommercial traders are divided into two subgroups (“Managed Money” traders and “Other Reportable” traders).

The (D)COT data have been used by many researchers to examine the relationship between price changes and position changes among market participants in the commodity futures market. Fishe, Janzen, and Smith (*AJAE* 2014) use DCOT data for six high-volume agricultural commodities: corn, cotton, lean hogs, live cattle, soybeans, and wheat to regress position change on prices change for all subgroups in DCOT data from June 2006 to March 2012. Cheng and Xiong (*JLS* 2014) employ DCOT data from June 2006 until December 2012 to investigate the correlation between the change in prices and the change in producers' short positions in wheat, corn, soybeans, and cotton. Bessec, Le Pen, and Sevi (*IAEE* 2017) use DCOT data from June 2006 until February 2015 to compute weekly changes in the aggregate long and short positions of producers and money managers in four energy markets (crude oil, gas, gasoline, and heating oil) and four non-energy commodity market (copper, wheat, coffee, and live cattle) and to study the explanatory power of prices when modeling trader positions. Most recently, Jacobs, Li and Hayes (*AJAE* 2018) propose to use the DCOT to examine the relationship between producers' position change and price changes in the context of a reference-price model of hedging, but they do not test it.

Many past studies find a high degree of correlation between producers' position changes and price changes. When examining the behavior and performance of speculators and hedgers in 15 U.S. futures markets (including financial markets, agricultural markets, other commodity markets, and foreign currency markets), Wang (*JFutM* 2003) finds that hedgers increase *(decrease)* net positions when the market has turned bullish *(bearish)*. Fishe, Janzen, and Smith *(AJAE* 2014) show that producers short more when prices increase in the corn, cotton, lean hogs, live cattle, soybeans, and wheat markets. Cheng and Xiong (*JLS* 2014) also find a high correlation between futures price change and hedgers' short position changes in wheat, corn, soybeans, and cotton. While Bessec, Le Pen, and Sevi (*IAEE* 2017) do not find evidence that price changes impact hedgers' behavior in energy markets, they argue that prices help predict aggregate commercial positions in non-energy commodity futures markets (copper, wheat, coffee and live cattle). Using daily OTC forward-contract data from a large gain merchandiser in Iowa, Jacobs *et al*. (*AJAE* 2018) document that corn producers short more when futures prices are trending up.

A highly positive correlation between changes in the magnitude of commercial traders' net short futures position and futures price changes raises the question of whether hedgers also speculate. On the one hand, abstracting away from crop insurance, agricultural commodity producers are exposed to changes in the price of the output in their fields. To protect their crops from price drops in the physical market, they must short their positions in the commodity futures market (Keynes, 1923; Hicks, 1939; Hirshleifer, 1988, 1990). Therefore, commercial hedgers' activities in the commodity futures market are conventionally classified as risk hedging[2]. On the other hand, in the report of Farm Services of American in 2017, most producers view themselves as being risk tolerant rather than risk averse. In the same vein, given substantial weekly fluctuations in commercial traders' positions and the highly positive correlation between their net short position and futures prices changes, one may question the real motive of commercial traders – whether they purely hedge their business risk or they also speculate. Cheng and Xiong (*JLS* 2014) provide evidence of speculating by commercial producers in the wheat, corn, soybeans, and cotton as

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[2] For more details, please see "Traders in Financial Futures Explanatory Notes" from CFTC

hedgers short more futures contracts when the futures price rises and reduce their short positions as the futures price falls. In the fixed income space, Fishe, Robe, and Smith (*JFutM* 2016) argue that, even though central banks are "commercial traders" (and as such they ought to be "hedging" their books), the evidence is that they react strongly to interest rate changes in 2009-2012. Raman, Fernando, and Hoelscher (*JBF* 2020) also conclude, from an analysis of corporate announcements regarding changes in firms' hedging policies, that "hedgers" in fact speculate. By confirming commercial traders' aggregate positions react to price changes, our paper further supports the notion that commercial traders also speculate. Importantly, it provides evidence that traders use past price peaks and other references (in particular, crop insurance reference-price levels) in their futures positioning decisions.

Of course, a factor that should matter to hedging decisions is the expectation of volatility. Jacobs, Li, and Hayes (*AJAE* 2018) use corn option-implied volatility (IV) as a measure of price uncertainty in that market. Contrary to what intuition would suggest, however, they do not find a statistically significant impact of implied volatility on hedging decision. One possible explanation is that grain and oilseed implied volatilities are affected by crop seasonality (Adjemian, Bruno, and Robe, *AAEA* 2017) and by USDA scheduled releases (Cao and Robe, *AAEA* 2020), which might hide the effects of price uncertainty on commercial positioning. A good candidate for the replacement of commodity IVols is the equity VIX, which is a proxy for global macroeconomic uncertainty (Bekaert *et al., JME* 2013) that is not affected by agricultural seasonality and USDA news. In addition, its close relationship with commodity IVols is well documented.[3] Regarding the

[3] In the equity space, the VIX index is considered as a good proxy for explaining the dynamics of single-stock implied volatilities and correlations among them (Engle and Figlewski's, *RFS* 2015). In the commodity market, Robe and Wallen (*JFutM* 2016) report the close relationship between the VIX and the IV in the crude oil market; Adjemian, Bruno, and Robe (*AAEA* 2017) find that the VIX is a key driver of implied volatility in three big US agricultural markets: corn, soybeans, and wheat; Covindassamy, Robe and Wallen (*JFutM* 2017) document statistically and economically significant impacts of the VIX on soft commodities' IVols (sugar and coffee).

role of VIX on commercial hedging decisions in the agricultural space, Cheng, Kirilenko, and Xiong (*RoF* 2015) find that, during the *pre*-financial crisis period (January 2001 to September 2008), the VIX did not significantly impact futures prices or commercial hedgers' positions in grains, livestock, and softs markets. *Post*-financial crisis (September 2009 to June 2011), however, its effect on prices is statistically significant. In addition, its effect on commercial hedgers' positions is statistically significant in some markets (but not in corn, lean hogs, and cocoa futures markets). In our paper, we use two statistical methods to examine the role of the VIX on commercial positioning in grains and oilseeds markets over more than a dozen years: (i) OLS regression analyses inspired by the optimal hedging model of Jacobs *et al*. (*AJAE* 2018); (ii) IRFs from a structural VAR model.

The SVAR approach has been employed before to tease out the relationship between market fundamentals and commodity price dynamics. McPhail, Du, and Muhammad (*EnJ* 2012) apply SVAR to measure the contribution of global demand, speculation, and energy prices/policy in explaining corn price variations. Janzen *et al*. (*AJAE* 2014) use SVAR to identify the influences of various factors on wheat prices. Kilian and Murphy (*IER* 2014) and Kilian and Lee (*EnJ* 2014) employ SVAR to examine the impacts of speculation on crude oil prices. Janzen, Smith, and Carter (*AJAE* 2018) use SVAR to identify the main drivers of cotton prices. Bruno, Büyüksahin, and Robe (*AJAE* 2017) use SVAR to document the influence of speculative activity on the strength of co-movements between equity, grains, and livestock markets. Adjemian et al. (*AAEA* 2017) employ SVAR to explore the impact of the VIX on IVols in grain and oilseeds markets. Our paper complements this prior work by using SVAR to tackle endogeneity issues in the analysis of the effects of futures prices and of the VIX on commercial positioning in grains and oilseeds markets.

## SECTION 3: QUASI-REPLICATION STUDY

In their paper published by the *American Journal of Agricultural Economics* in 2018, "Reference-Dependent Hedging: Theory and Evidence from Iowa Corn Producers", Jacobs *et al.* propose a theoretical model of optimal hedging and apply it to identify corn producers' optimal hedging behavior with and without reference-price dependence as follows:

$$\Delta h_t = \alpha_0 + \alpha_1 1_{\{Ft-Rt<0\}} + \beta_1 \text{time} + \beta_2 \Delta Vol_t + \beta_3 \Delta F_t + \beta_4 \Delta F_t 1_{\{Ft-Rt<0\}} + \beta_5 \Delta F_t^2 + \varepsilon_t \qquad (1)$$

where: $\Delta h_t$ is the proportion of total harvest hedged in week t. The variable *time* measures the number of weeks left till harvest. $\Delta Vol_t$ is the weekly change in the annualized implied volatility in the December corn futures contract. The price change, $\Delta F_t$ is the weekly difference in the logged price of the December corn futures contracts. The quadratic price term, $\beta_5 \Delta F_t^2$, is intended to capture potential nonlinearities in hedging that may result from belief changes.

The fourth term (with coefficient $\beta_4$) is meant to capture reference-price dependence, *i.e.*, the possibility that corn producers change their hedge based on whether the current price of corn exceeds a given past reference level. The authors consider three candidate reference dependence prices: the previous year's average marketing price, the Risk Management Agency's (RMA) projected harvest price, and the past-30-day moving average of the December corn futures price.

Hedgers' aggregate hedging decisions are quantified by a weekly hedge ratio,[4] in which the numerator is the total bushels collected from the daily forward contract data from a major grain firm in Iowa, and the denominator is annual total corn received.[5] Some of their empirical findings

[4] The weekly hedge ratio is constructed on every Tuesday, which matches the CFTC's COT report day.
[5] The OTC data are unique and confidential, and collected from over 115,000 forward contracts written by Iowa corn producers with a major grain marketing firm from 01/2009 to 08/2013.

relating to the present paper are that, in their 2009-2013 sample period, (i) uncertainty does not seem to matter to farmers' hedging decisions due to statistically insignificant coefficients of corn option-implied volatility; (ii) corn futures prices are key drivers of commercial hedging behavior in that corn producers sell more forward when prices increase, especially when the current futures price is higher than the reference price. In addition, they submit that (iii) the CFTC's DCOT might be an alternative source of data to estimate the intensity of commercial hedging behavior.

In this Section, we test Model (1) using public DCOT futures position data (as opposed to proprietary farm-level forward sales data) to confirm the value of DCOT data for analyzing examine the impacts of futures prices and implied volatility on commercial traders' decisions in the 2009-2013 period.[6]

Jacobs *et al*. (2018) use their confidential database to calculate hedge ratios, which we are not able to obtain. Therefore, we use an alternative hedge ratio suggested by these authors. Specifically, short producers' open positions for new crops obtained from the CFTC's weekly DCOT report (expressed in bushels) replace the total bushels contracted in the paper as the hedge-ratio numerator, while the annual crop production estimates obtained from USDA reports (from Quick Stats-USDA NASS, also measured in bushels) replace the annual total corn received to be the denominator

$$Producers' \, hedge \, ratio = \frac{Producers' \, short \, open \, position \, for \, new \, crop}{Annual \, crop \, production}$$

[6] Particularly, results from Table 2, which uses equation 10 in Jacobs, Li, and Hayes (2018) are replicated.

In this Section, we keep the replication period unchanged from Jacobs *et al*. (2018): the pre-harvest period from January to August each year, from 01/2009 to 08/2013. To identify and reconfirm the pre-harvest time, the weekly hedge ratio is plotted over years (*See Appendix 1, Figure 1.1*). Note that the hedge ratio, as calculated above, drops tremendously in September each year (because of the start of a new crop cycle in the CFTC futures position data).

Precisely, we replicate Table 2 in Jacobs *et al*. (*AJAE* 2018), using this alternative hedge ratio computation method, using the equation as follows:

$$DHRN_t=\alpha_0+\alpha_1 1_{\{Ft-Rt<0\}}+\mu DHRN\{1\}+\beta_1 time+\beta_2 DVOL_t+\beta_3 DFP_t + \beta_4 DFP_t{*}1_{\{Ft-Rt<0\}} +\beta_5 DFP_t^2+ \varepsilon_t \qquad (2)$$

where, the dependent variable $DHRN_t$ is the weekly change of hedge ratio, in which the hedge ratio is calculated by using annual crop production as a denominator. DHRN{1} is the first lag of $DHRN_t$. The binary variable $1_{\{Ft-Rt<0\}}$ has the value of 1 when the reference price candidate is higher than the current December futures price, and 0 otherwise. The exogenous variable *time* is the number of weeks remaining until harvest. The independent variable $DVOL_t$ is the weekly change in the annualized option-implied volatility of December corn futures contracts and captures the impact of price uncertainty on commercial traders' behavior. The price change $DFP_t$ is the weekly change in the logged price of the December corn futures prices,[7] which measures the impact of futures price movements on commercial traders' behavior. The interaction term $DFP_t{*}1_{\{Ft-Rt<0\}}$ captures possible asymmetries in hedge ratio responses to the changes of price. The quadratic price term $DFP_t^2$ captures potential hedging's nonlinearities when there is a change in producers' beliefs.

The intercept $\alpha_0$ estimates the proportion of crop hedged each week when the current December futures price is above the reference price, and $\alpha_1$ is the difference in the proportion of

[7] December is considered as the biggest month for corn futures contracts

crop hedged per week when the current December futures price is below the reference price. One autoregressive lag for dependence variable is recommended by BIC criterion for eliminating serial correlation.[8]

The error term $\varepsilon_t$ is typically assumed to be an identically, independently, and normally distributed (i.i.d.) shock, with mean zero and variance, $\sigma^2$. Still, we use the Newey-West (1987) construction of the variance-covariance matrix in computing our standard errors to tackle serial correlation and heteroskedasticity in the error terms. Robust standard errors are estimated because the assumption of homoskedasticity of the residuals is rejected at 5% significance level for all candidate references. We use a general Breusch-Godfrey LM test to check for serial correlation in residuals.[9] Candidates for reference dependence prices are compared based on a goodness-of-fit estimate—the adjusted $R^2$.

Table 1 presents our replication results. The coefficient for futures prices is statistically significant across all base cases. The coefficient for corn implied volatility is never statistically significant. In the replication, $\alpha_0$ is statistically significant with positive sign, and $\alpha_1$ is statistically significant in some base cases with a negative sign showing the high correlation between futures prices and hedging behavior: producers short more when the current futures price is above the reference prices

[8] Jacobs *et al*. (*AJAE* 2018) do not discuss the number of lags in their OLS regression. Without including any lag, our results have serial correlation in residuals. To eliminate serial correlation issues, we perform lag selection for the model, and one autoregressive lag is suggested by the BIC criterion.

[9] Jacobs *et al*. (*AJAE* 2018) use Durbin-Watson tests for serial correlation. However, the Durbin-Watson test "is biased towards a finding of no serial correlation when the model contains a lagged dependent variable" (RATS Version 9.0 User Guide).

**Table 1. Replication Result: OLS Estimates, Corn, Pre-harvest Weekly of Producers' Short Position, 2009 - 2013**

Equation 1: $DHRN_t = \alpha_0 + \alpha_1\, 1_{\{Ft-Rt<0\}} + \mu DHRN\{1\} + \beta_1\, time + \beta_2 DVOl_t + \beta_3 DFP_t + \beta_4 DFP_t * 1_{\{Ft-Rt<0\}} + \beta_5\, DFP_t^2 + \varepsilon_t$

| | No Reference Price | Nonlinear Price Response | Last Year's Avg Price | RMA Forecast Price | 30-day Moving Average | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | (1) | (2) | (3) | (4) |
| $\alpha_0$ | 0.005*** | 0.006*** | 0.007*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.004** |
| | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) |
| $\alpha_1$ | | | -0.002** | -0.001* | -0.001 | -0.001 | -0.001 | -0.001* |
| | | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\mu$ | 0.591*** | 0.588*** | 0.525*** | 0.552*** | 0.573*** | 0.561*** | 0.551*** | 0.464*** |
| | (0.061) | (0.061) | (0.065) | (0.061) | (0.060) | (0.061) | (0.063) | (0.073) |
| $\beta_1$ | -0.0002*** | -0.0002*** | -0.0002*** | -0.0002*** | -0.0002*** | -0.0002*** | -0.0002*** | -0.0001 |
| | (<0.0001) | (<0.0001) | (<0.0001) | (<0.0001) | (<0.0001) | (<0.0001) | (<0.0001) | (<0.0001) |
| $\beta_2$ | 0.027 | 0.028 | 0.033 | 0.032 | 0.024 | 0.029 | 0.028 | 0.023 |
| | (0.032) | (0.032) | (0.031) | (0.031) | (0.032) | (0.032) | (0.032) | (0.027) |
| $\beta_3$ | 0.041*** | 0.041*** | 0.045** | 0.052*** | 0.043*** | 0.080*** | 0.077*** | 0.073*** |
| | (0.009) | (0.010) | (0.019) | (0.014) | (0.015) | (0.020) | (0.020) | (0.022) |
| $\beta_4$ | | | -0.013 | -0.028 | -0.018 | -0.088*** | -0.084** | -0.087** |
| | | | (0.022) | (0.018) | (0.023) | (0.033) | (0.033) | (0.037) |
| $\beta_5$ | | -0.078 | | | | -0.542** | -0.508** | -0.519* |
| | | (0.157) | | | | (0.239) | (0.251) | (0.281) |
| $\alpha_0 + \alpha_1$ | | | 0.005*** | 0.005*** | 0.005*** | 0.005*** | 0.005*** | 0.003 |
| | | | (0.000) | (0.000) | (0.001) | (0.000) | (0.001) | (0.298) |
| $\beta_3 + \beta_4$ | | | 0.032*** | 0.024** | 0.025 | -0.008 | -0.007 | -0.014 |
| | | | (0.003) | (0.047) | (0.117) | (0.718) | (0.701) | (0.492) |
| Year*Time | | | | | | | Yes | Yes |
| Year Fixed effects | | | | | | | | Yes |
| BP test | 0.0005 | 0.0004 | 0.0003 | 0.0009 | 0.0003 | 0.0003 | 0.0003 | 0.0000 |
| BGSC test | 0.431 | 0.484 | 0.866 | 0.467 | 0.420 | 0.703 | 0.647 | 0.515 |
| Adj-$R^2$ | 0.57 | 0.57 | 0.58 | 0.58 | 0.57 | 0.58 | 0.57 | 0.58 |

Noted: Significant levels indicated as: * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Robust standard errors reported in the parentheses. P-values reported for the Wald Test of joint 'significance, Breusch-Pagan test, and Breusch-Godfrey SC Test (BGSC). Standard errors reported in brackets are computed using the Newey-West (1987) construction of the covariance matrix with three lags.

## SECTION 4: REPLICATION MODIFICATIONS

In this Section, we modify the model of Jacobs *et al*. (*AJAE* 2018) to enhance its practical application to other agricultural (e.g., soybean) and non-agricultural commodity markets.

The first modification is the replacement of the *time* variable. Jacobs *et al* define *time* as the number of weeks left to harvest. However, that variable is not ideal because the crop progress differs from year to year. To wit, Figures 1.1 to 1.5 illustrate the relationship between hedge ratio and crop progress during the corn pre-harvest period from 2009 to 2013. The crop progress information is released weekly by the United States Department of Agriculture (USDA) during the planting, growing, and harvest season for major crops. It provides market participants critical information about the status of the crop[10] (*USDA Surveys/Crop Progress and Condition)*. Clearly, the percentage planted varies substantially from year to year, making the *time* variable less than ideal.[11]

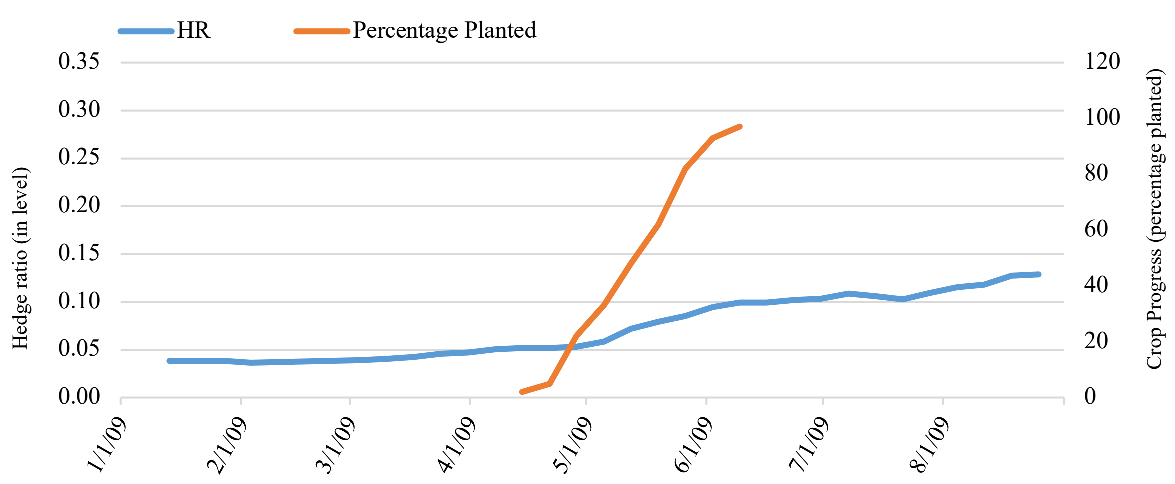


**Figure 1.1. Corn Hedge ratio and Weekly Crop Progress during Pre-Harvest Time in 2009.** *Data Source: Bloomberg*

[10] See USDA Surveys/Crop Progress and Condition: https://www.nass.usda.gov/Publications/National_Crop_Progress/Terms_and_Definitions/index.php

[11] The crop progress patterns also differ from year to year for soybeans market (not displayed)

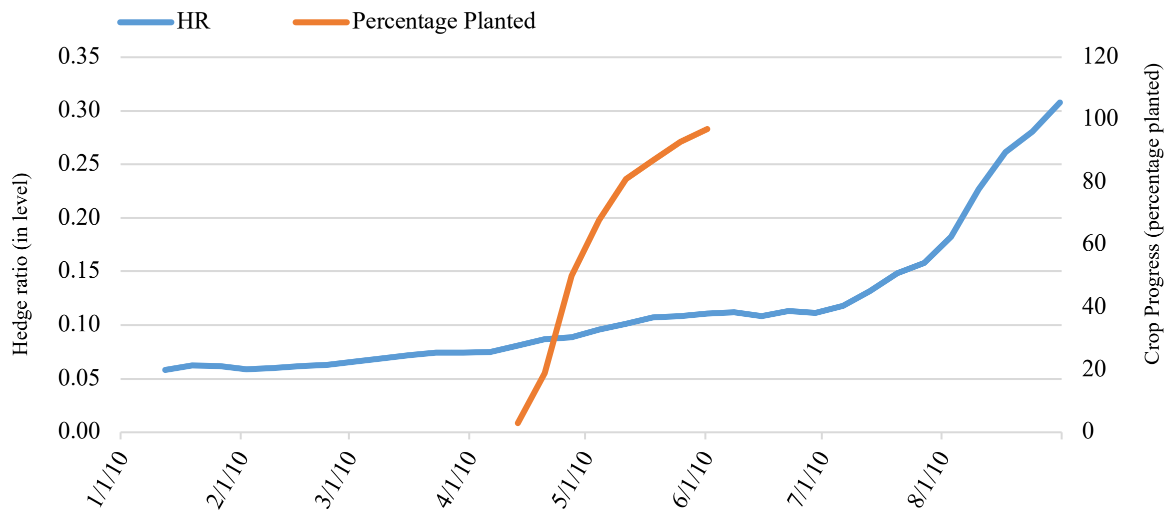


**Figure 1.2. Corn Hedge ratio and Weekly Crop Progress during Pre-Harvest Time in 2010.** *Data Source: Bloomberg*

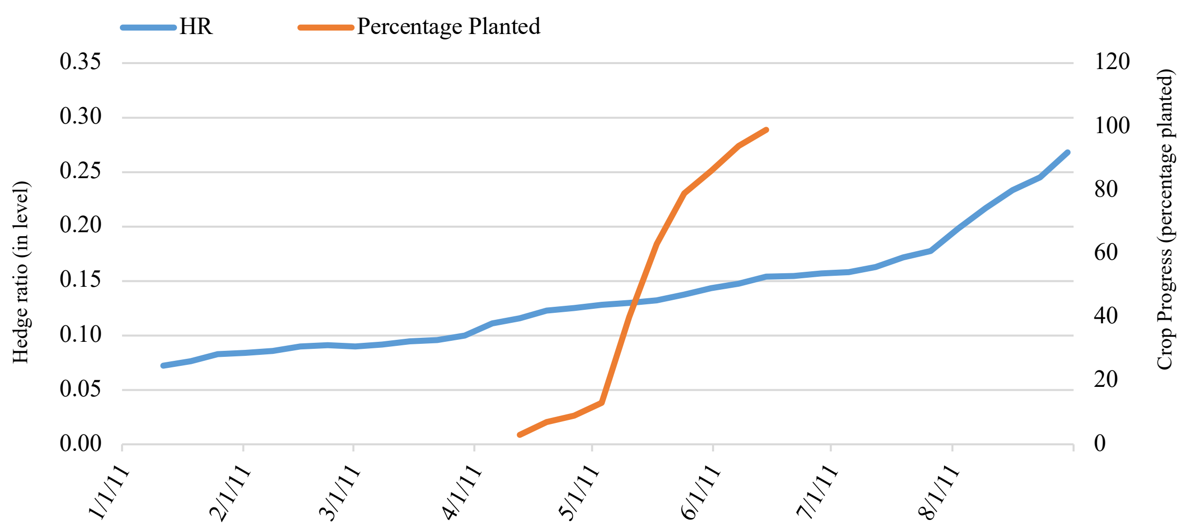


**Figure 1.3. Corn Hedge ratio and Weekly Crop Progress during Pre-Harvest Time in 2011.** *Data Source: Bloomberg*

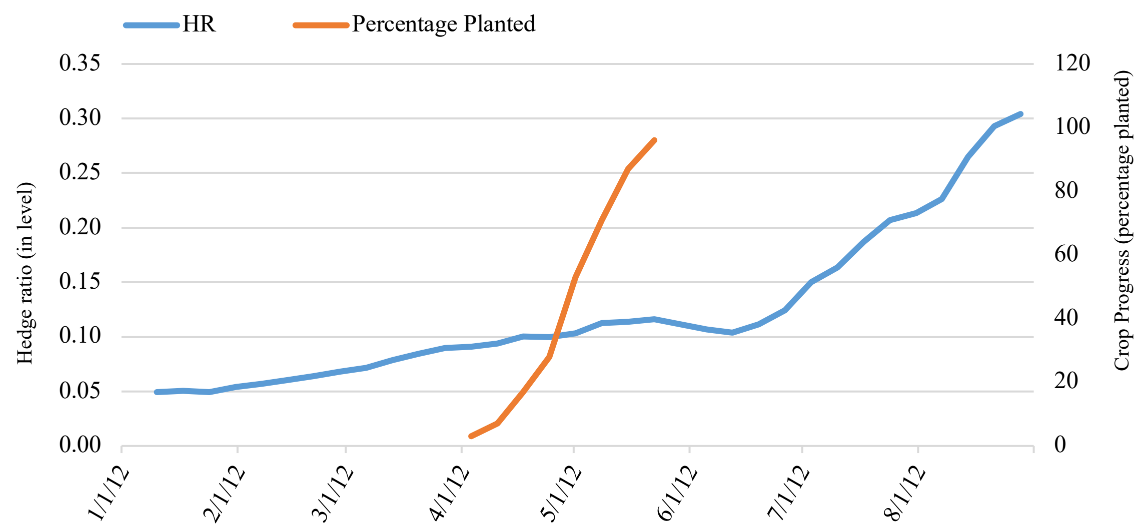


**Figure 1.4. Corn Hedge ratio and Weekly Crop Progress during Pre-Harvest Time in 2012.** *Data Source: Bloomberg*

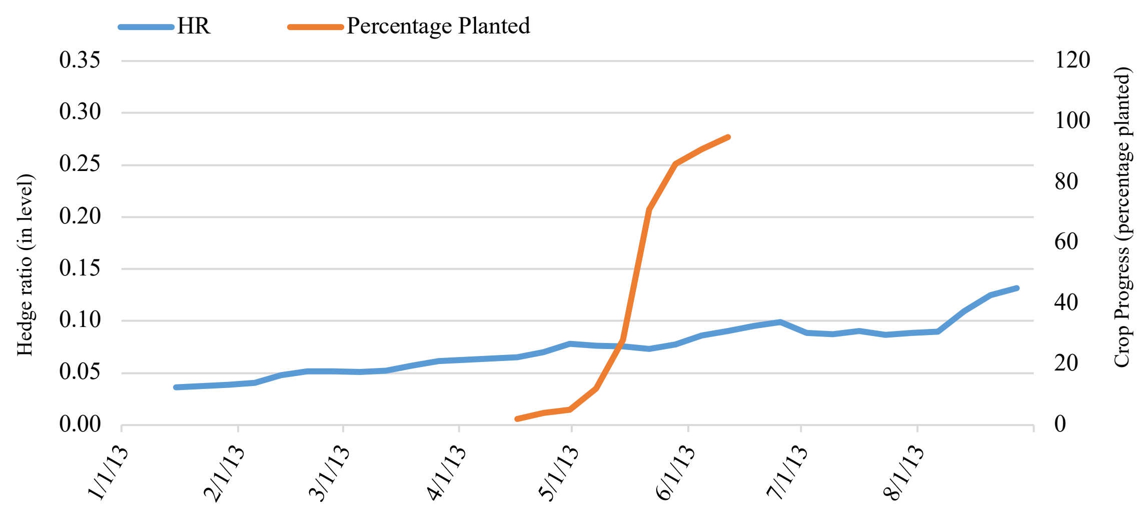


**Figure 1.5. Corn Hedge ratio and Weekly Crop Progress during Pre-Harvest Time in 2013.** *Data Source: Bloomberg*

As an alternative, we divide the pre-harvest period into three periods: the first period (January to February) is when planting has not started yet, and crop insurance parameters have not yet been set up; the second period (March to May) is when the crop is being planted; and the last period (June to August) is when the corn has all been planted and the growing season is fully underway. Our seasonal dummies are: *dummy1* for the first period, and *dummy2* for the second period. Those seasonal dummies capture planting periods and the crop insurance schedule, as alternatives to the *time* variable.

$$DHRN_t = \alpha_0 + \alpha_1 1_{\{Ft-Rt<0\}} + \mu DHRN\{1\} + \beta_0 dummy_1 + \beta_1 dummy_2 + \beta_2 DVOL_t + \beta_3 DFP_t + \beta_4 DFP_t * 1_{\{Ft-Rt<0\}} + \beta_5 DFP_t^2 + \varepsilon_t \quad (2a)$$

in which, $dummy_1$ has value of 1 from January to February, 0 otherwise. $Dummy_2$ has a value of 1 from March to May, 0 otherwise.

$\beta_0$ and $\beta_1$, the coefficients of *dummy1* and *dummy2*, respectively, are expected to be statistically significant with negative signs insofar as producers should increase their futures hedge ratio as yield uncertainty diminishes towards harvest.

Table 2 shows our OLS estimates results, in which the time variable is replaced by two seasonal dummies. As expected, the coefficients of both seasonal dummies are statistically significantly negative. The adjusted $R^2$, a goodness of fit measure, in Table 2 is similar to the adjusted $R^2$ in Table 1 across all base cases, showing that the seasonal dummies are good alternatives.

**Table 2. OLS Estimates, Time Variable is Replaced by Seasonal Dummies, Corn, 2009-2013**

Equation 2a: $DHRN_t = \alpha_0 + \alpha_1 1\{Ft-Rt<0\} + \mu DHRN\{1\} + \beta_0 dummy_1 + \beta_1 dummy_2 + \beta_2 DVOL_t + \beta_3 DFP_t + \beta_4 DFP_t{*}1\{Ft-Rt<0\} + \beta_5 DFP_t^2 + \varepsilon_t$

| | No reference Price | Nonlinear Price Response | Last Year's Avg Price | RMA Forecast Price | 30-day Moving Average | |
|---|---|---|---|---|---|---|
| | | | | | (1) | (2) |
| $\alpha_0$ | 0.004*** | 0.004*** | 0.006*** | 0.005*** | 0.004*** | 0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\alpha_1$ | | | -0.002** | -0.001 | -0.001 | -0.001 |
| | | | (0.001) | (0.001) | (0.001) | (0.001) |
| $\mu$ | 0.622*** | 0.619*** | 0.564*** | 0.590*** | 0.607*** | 0.592*** |
| | (0.059) | (0.058) | (0.061) | (0.057) | (0.059) | (0.060) |
| $\beta_0$ | -0.003*** | -0.003*** | -0.003*** | -0.003*** | -0.003*** | -0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\beta_1$ | -0.003*** | -0.003*** | -0.003*** | -0.003*** | -0.003*** | -0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\beta_2$ | 0.030 | 0.032 | 0.035 | 0.035 | 0.028 | 0.034 |
| | (0.033) | (0.033) | (0.031) | (0.032) | (0.033) | (0.032) |
| $\beta_3$ | 0.041*** | 0.041*** | 0.045** | 0.052*** | 0.044*** | 0.087*** |
| | (0.009) | (0.009) | (0.018) | (0.014) | (0.015) | (0.021) |
| $\beta_4$ | | | -0.012 | -0.027 | -0.019 | -0.097*** |
| | | | (0.022) | (0.018) | (0.023) | (0.033) |
| $\beta_5$ | | -0.099 | | | | -0.613** |
| | | (0.155) | | | | (0.243) |
| $\alpha_0 + \alpha_1$ | | | 0.004*** | 0.004*** | 0.003*** | 0.003*** |
| | | | (0.000) | (0.000) | (0.004) | (0.001) |
| $\beta_3 + \beta_4$ | | | 0.033*** | 0.025** | 0.025 | -0.010 |
| | | | (0.003) | (0.036) | (0.115) | (0.592) |
| BP test | 0.0009 | 0.0006 | 0.0006 | 0.0015 | 0.0005 | 0.0004 |
| BGSC Test | 0.327 | 0.374 | 0.734 | 0.347 | 0.314 | 0.602 |
| Adj $R^2$ | 0.56 | 0.56 | 0.57 | 0.57 | 0.56 | 0.57 |

Noted: Significant levels indicated as: * p<0.1; ** p<0.05; *** p<0.01. Robust standard errors reported in the parentheses. P-values reported for the Wald Test of joint 'significance, Breusch-Pagan test, and Breusch-Godfrey SC Test. Standard errors reported in brackets are computed using the Newey-West (1987) construction of the covariance matrix with three lags

Our second modification is to change the hedge ratio calculation. Jacobs *et al.* (*AJAE* 2018) suggest using hedge ratio calculated by using annual crop forecasts (HRN) of the United States Department of Agriculture's National Agricultural Statistics Service (USDA NASS) as a denominator. Since USDA NASS only gives annual production estimates for agricultural commodities, using HRN limits the application of the optimal hedging model to non-agricultural commodities. We propose replacing annual crop production by the Open Interest from the CFTC's DCOT (HR) so that the scaling factor is reproducible for commodities other than grains and oilseeds. Figure 2 and Figure 3 show the correlations of hedge ratios for corn in levels and in first differences, respectively, with the two different scaling factors during pre-harvest period from 2009-2013. The correlation coefficients between two different calculation methods of hedge ratio in levels and in first differences for corn are 0.93 and 0.87, respectively, providing evidence that our proposed hedge ratio calculation method is a good alternative.[12]

$$DHR_t^* = \alpha_0 + \alpha_1 1_{\{Ft-Rt<0\}} + \mu DHR\{1\} + \beta_0 dummy_1 + \beta_1 dummy_2 + \beta_2 DVOL_t + \beta_3 DFP_t + \beta_4 DFP_t * 1_{\{Ft-Rt<0\}} + \beta_5 DFP_t^2 + \varepsilon_t \quad (2b)$$

in which, $DHR_t$ is the weekly change of hedge ratio where the hedge ratio is calculated using Open Interest from DCOT as a denominator.

[12] Correlation coefficients between two different calculation methods of hedge ratio in levels and in first differences for soybeans are 0.90 and 0.82, respectively.

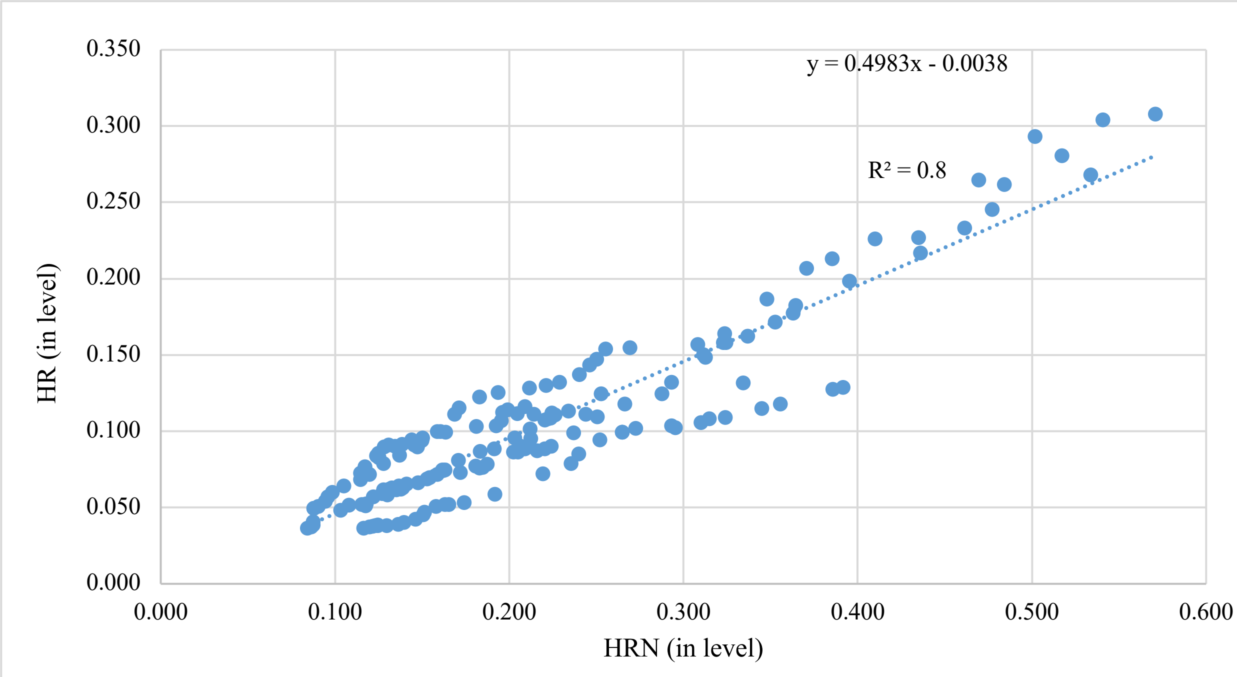


**Figure 2. Coefficient Correlations of Hedge Ratios Calculated by Using Annual Crop Production as Denominator (HRN) and by Using Open Interest as Denominator (HR), Corn, Pre-harvest period 2009-2013**

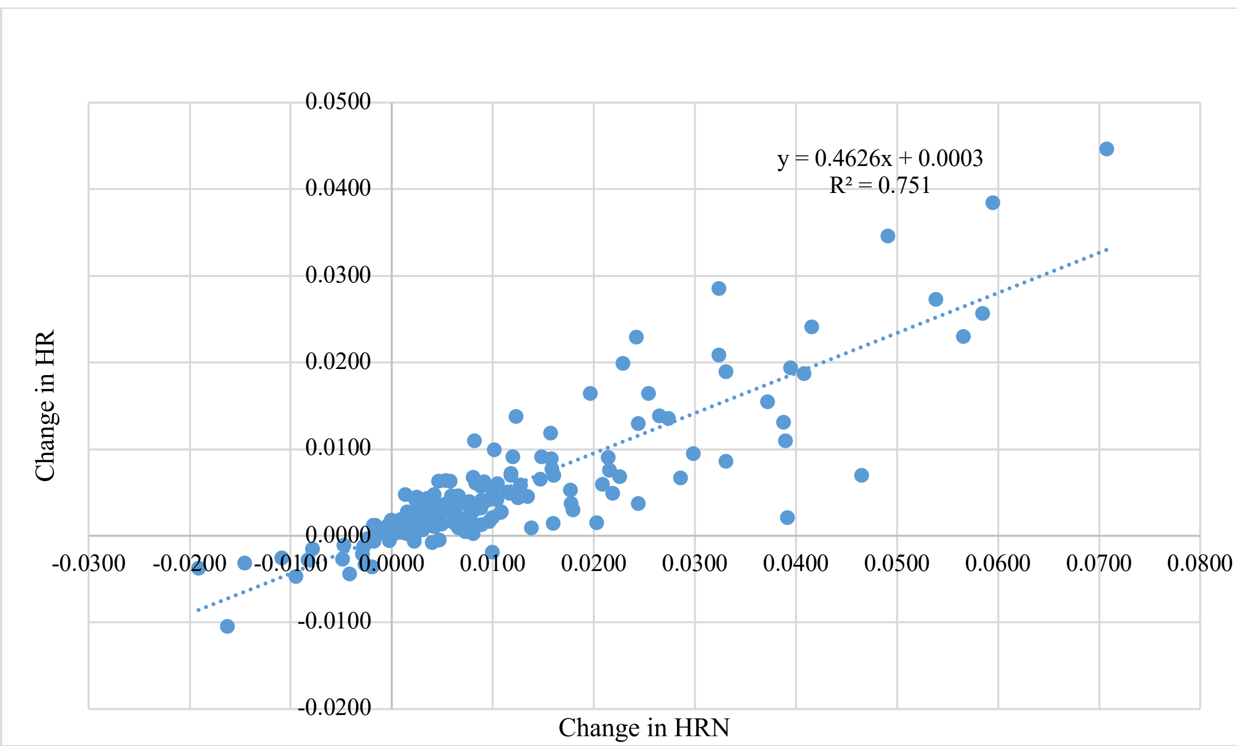


**Figure 3. Coefficient Correlations of the Change in Hedge Ratio, in which Hedge Ratio is Calculated by Using Annual Crop Production as Denominator (HRN) and by Using Open Interest as Denominator (HR), Corn, Pre-harvest period 2009-2013**

**Table 3. OLS Estimates, Hedge Ratio calculated by Open Interest as a Denominator, Corn, 2009-2013**

Equation 2b: $DHR_t = \alpha_0 + \alpha_1 1\{Ft\text{-}Rt<0\} + \mu DHR\{1\} + \beta_0 dummy_1 + \beta_1 dummy_2 + \beta_2 DVOL_t + \beta_3 DFP_t + \beta_4 DFP_t {*} 1\{Ft\text{-}Rt<0\} + \beta_5 DFP_t^2 + \varepsilon_t$

| | No reference Price | Nonlinear Price Response | Last Year's Avg Price | RMA Forecast Price | 30-day Moving Average | |
|---|---|---|---|---|---|---|
| | | | | | (1) | (2) |
| $\alpha_0$ | 0.011*** | 0.011*** | 0.016*** | 0.013*** | 0.012*** | 0.012*** |
| | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) | (0.002) |
| $\alpha_1$ | | | -0.005*** | -0.003 | -0.002 | -0.002 |
| | | | (0.002) | (0.002) | (0.002) | (0.002) |
| $\mu$ | 0.466*** | 0.467*** | 0.420*** | 0.442*** | 0.448*** | 0.445*** |
| | (0.081) | (0.081) | (0.079) | (0.078) | (0.083) | (0.082) |
| $\beta_0$ | -0.009*** | -0.009*** | -0.010*** | -0.010*** | -0.009*** | -0.009*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\beta_1$ | -0.008*** | -0.008*** | -0.008*** | -0.008*** | -0.007*** | -0.008*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\beta_2$ | -0.027 | -0.026 | -0.027 | -0.015 | -0.032 | -0.028 |
| | (0.069) | (0.070) | (0.064) | (0.068) | (0.070) | (0.070) |
| $\beta_3$ | 0.077*** | 0.077*** | 0.010 | 0.057 | 0.073** | 0.106** |
| | (0.023) | (0.023) | (0.031) | (0.038) | (0.035) | (0.052) |
| $\beta_4$ | | | 0.087** | 0.017 | -0.020 | -0.080 |
| | | | (0.041) | (0.049) | (0.051) | (0.078) |
| $\beta_5$ | | -0.068 | | | | -0.478 |
| | | (0.362) | | | | (0.561) |
| $\alpha_0 + \alpha_1$ | | | 0.011*** | 0.010*** | 0.010*** | 0.003*** |
| | | | (0.000) | (0.000) | (0.000) | (0.001) |
| $\beta_3 + \beta_4$ | | | 0.077*** | 0.074** | 0.053 | -0.010 |
| | | | (0.000) | (0.012) | (0.110) | (0.594) |
| BP Test | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0004 |
| BGSC Test | 0.148 | 0.152 | 0.432 | 0.161 | 0.118 | 0.602 |
| Adj $R^2$ | 0.41 | 0.41 | 0.44 | 0.41 | 0.41 | 0.41 |

Noted: Significant levels indicated as: * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Robust standard errors reported in the parentheses. P-values reported for the Wald Test of joint 'significance, Breusch-Pagan test, and Breusch-Godfrey SC Test. Standard errors reported in brackets are computed using the Newey-West (1987) construction of the covariance matrix with three lags

As shown in Table 3, changing the scaling factor for hedge ratio does not change the OLS estimates results qualitatively. Seasonal dummies still have statistically significant negative coefficients across all base cases. The coefficient of the corn IVol is now negative but, crucially, it remains statistically insignificant. The futures prices' coefficient is again positive and highly statistically significant for all four base cases.

One change for the worse is the drop of the adjusted $R^2$ compared to Table 2. This downside is a trade-off, considering the potential benefit of applying the model to a broader set of commodity markets (beyond the agricultural sector).

Our final modification of the empirical model is to replace the commodity IVol by the CBOE Volatility Index, the VIX, as a proxy for market uncertainty and sentiment. As noted in the Introduction, the commodity option-implied volatility (IVol) variable used in Jacobs *et al*. (*AJAE* 2018) is statistically insignificant, which is puzzling because the expected future price volatility should affect hedging decisions. One possible reason could be that commodity grain and oilseed option-implied volatilities drop about 10% for up to a week after scheduled USDA releases (Cao and Robe, *AAEA* 2020), which might affect significance tests. As well, seasonal variations might be an issue. The VIX does not suffer from those drawbacks and has a close relationship with the commodity option-implied volatility (Robe and Wallen, *JFutM* 2016; Adjemian et al., *AAEA* 2017; Covindassamy et al., *JFutM* 2017), in that both the VIX and commodity IVols reflect financial market sentiment and the demand side (macroeconomic) uncertainty that simultaneously permeate both equity (Bekaert *et al., JME* 2013) and commodity markets.

Therefore, the above modification changes Equation 2b as follows:

$$DHR_t = \alpha_0 + \alpha_1 1_{\{Ft\text{-}Rt<0\}} + \mu DHR\{1\} + \beta_0 dummy_1 + \beta_1 dummy_2 + \beta_2 DVIX_t + \beta_3 DFP_t + \beta_4 DFP_t * 1_{\{Ft\text{-}Rt<0\}} + \beta_5 DFP_t^2 + \varepsilon_t \quad (3)$$

The coefficient of the VIX, $\beta_2$, is expected to be statistically significant with positive sign because, the higher the price volatility, the more hedging should take place.

Table 4 represents the OLS estimates for corn during pre-harvest period from 2009-2013 using the VIX as an alternative for implied volatility. Compared to the coefficients' estimates displayed in Table 3, coefficients' estimates of seasonal dummies variables and futures prices' variable are qualitatively the same. Although the VIX is not statistically significant, its sign is now positive as expected. In addition, the replacement of IV with the VIX helps slightly increase the performance of the RMA reference price model, with the increased adjusted $R^2$ from 0.41 in Table 3 to 0.42 in Table 4 (the adjusted $R^2$ for the three other cases are the same as in Table 3).

Finally, we broaden the study by applying Equation 3 to the soybeans market. There are two changes in the case of soybeans. First, November is the most active month of soybeans futures contract. Hence, we use November futures prices as benchmarks. Second, since hedge ratios drop like a stone in August for soybeans (*See Appendix 1, Figure 1.2),* rather than in September for corn, its pre-harvest period is determined from January to July.

Table 5 presents our OLS estimates for the soybean market during a sample period of 2009-2013, in which the commodity IVol is replaced by the VIX, the *time* variable is replaced by our two seasonal dummies, and the hedge ratio is calculated by using open interest as a denominator. The results indicate that the optimal hedging model with these modifications is appropriate for soybeans. The two seasonal dummies' coefficients are statistically significant with the expected negative sign. Futures prices are statistically significant with positive signs. And, while the VIX coefficient has an unexpected negative sign, it is not statistically significant.

**Table 4. OLS Estimates using VIX as an Alternative for IV, Corn, 2009-2013**

Equation 3: $DHR_t = \alpha_0 + \alpha_1 1\{Ft\text{-}Rt<0\} + \mu DHR\{1\} + \beta_0 dummy_1 + \beta_1 dummy_2 + \beta_2 DVIX_t + \beta_3 DFP_t + \beta_4 DFP_t{*}1\{Ft\text{-}Rt<0\} + \beta_5 DFP_t^2 + \varepsilon_t$

| | **No reference Price** | **Nonlinear Price Response** | **Last Year's Avg Price** | **RMA Forecast Price** | **30-day Moving Average** | |
|---|---|---|---|---|---|---|
| | | | | | (1) | (2) |
| $\alpha_0$ | 0.011*** | 0.012*** | 0.016*** | 0.014*** | 0.012*** | 0.013*** |
| | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) | (0.002) |
| $\alpha_1$ | | | -0.005** | -0.003 | -0.002 | -0.002 |
| | | | (0.002) | (0.002) | (0.002) | (0.002) |
| $\mu$ | 0.457*** | 0.459*** | 0.412*** | 0.431*** | 0.438*** | 0.434*** |
| | (0.081) | (0.081) | (0.079) | (0.079) | (0.083) | (0.082) |
| $\beta_0$ | -0.009*** | -0.009*** | -0.010*** | -0.010*** | -0.009*** | -0.009*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\beta_1$ | -0.008*** | -0.008*** | -0.008*** | -0.008*** | -0.008*** | -0.008*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\beta_2$ | 0.027 | 0.027 | 0.023 | 0.031 | 0.029 | 0.031 |
| | (0.029) | (0.028) | (0.027) | (0.029) | (0.027) | (0.026) |
| $\beta_3$ | 0.079*** | 0.079*** | 0.012 | 0.057 | 0.076** | 0.117** |
| | (0.024) | (0.024) | (0.034) | (0.038) | (0.034) | (0.049) |
| $\beta_4$ | | | 0.084** | 0.022 | -0.023 | -0.097 |
| | | | (0.041) | (0.051) | (0.051) | (0.074) |
| $\beta_5$ | | -0.082 | | | | -0.577 |
| | | (0.368) | | | | (0.560) |
| $\alpha_0 + \alpha_1$ | | | 0.011*** | 0.011*** | 0.010*** | 0.003*** |
| | | | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_3 + \beta_4$ | | | 0.096*** | 0.079** | 0.053 | -0.010 |
| | | | (0.000) | (0.012) | (0.145) | (0.612) |
| BP test | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| BGSC Test | 0.137 | 0.145 | 0.390 | 0.158 | 0.109 | 0.149 |
| Adj $R^2$ | 0.41 | 0.41 | 0.44 | 0.42 | 0.41 | 0.41 |

Noted: Significant levels indicated as: * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Robust standard errors reported in the parentheses. P-values reported for the Wald Test of joint 'significance, Breusch-Pagan test, and Breusch-Godfrey SC Test. Standard errors reported in brackets are computed using the Newey-West (1987) construction of the covariance matrix with three lags

**Table 5. OLS Estimates, Soybeans, Pre-harvest Weekly of Producers' Short Position for New Crop, 2009-2013**

Equation 3: $DHR_t = \alpha_0 + \alpha_1 1\{Ft\text{-}Rt<0\} + \mu DHR\{1\} + \beta_0 dummy_1 + \beta_1 dummy_2 + \beta_2 DVIX_t + \beta_3 DFP_t + \beta_4 DFP_t{*}1\{Ft\text{-}Rt<0\} + \beta_5 DFP_t^2 + \varepsilon_t$

| | No reference Price | Nonlinear Price Response | Last Year's Avg Price | RMA Forecast Price | 30-day Moving Average | |
|---|---|---|---|---|---|---|
| | | | | | (1) | (2) |
| $\alpha_0$ | 0.014*** | 0.014*** | 0.015*** | 0.016*** | 0.018*** | 0.018*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| $\alpha_1$ | | | -0.002 | -0.006** | -0.008*** | -0.008*** |
| | | | (0.003) | (0.002) | (0.003) | (0.003) |
| $\mu$ | 0.421*** | 0.425*** | 0.400*** | 0.381*** | 0.356*** | 0.353*** |
| | (0.101) | -0.100 | (0.106) | (0.110) | (0.101) | (0.100) |
| $\beta_0$ | -0.010*** | -0.010*** | -0.010*** | -0.010*** | -0.012*** | -0.012*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| $\beta_1$ | -0.008** | -0.008** | -0.008** | -0.008** | -0.009** | -0.009** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| $\beta_2$ | -0.011 | -0.012 | -0.015 | -0.027 | -0.011 | -0.011 |
| | (0.041) | (0.041) | (0.040) | (0.042) | (0.037) | (0.037) |
| $\beta_3$ | 0.150*** | 0.153*** | 0.205* | 0.190*** | 0.168* | 0.204** |
| | (0.051) | (0.052) | (0.109) | (0.057) | (0.088) | (0.092) |
| $\beta_4$ | | | -0.098 | -0.151* | -0.168* | -0.238** |
| | | | (0.120) | (0.078) | (0.094) | (0.113) |
| $\beta_5$ | | 0.483 | | | | -0.864 |
| | | (0.627) | | | | (0.696) |
| $\alpha_0 + \alpha_1$ | | | 0.013*** | 0.010*** | 0.010*** | 0.010*** |
| | | | (0.000) | (0.001) | (0.001) | (0.001) |
| $\beta_3 + \beta_4$ | | | 0.107** | 0.039 | 0.000 | -0.034 |
| | | | (0.038) | (0.484) | (0.998) | (0.486) |
| BP test | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0004 |
| BGSC Test | 0.389 | 0.455 | 0.609 | 0.446 | 0.578 | 0.504 |
| Adj $R^2$ | 0.36 | 0.36 | 0.37 | 0.39 | 0.41 | 0.40 |

Noted: Significant levels indicated as: * p<0.1; ** p<0.05; *** p<0.01. Robust standard errors reported in the parentheses. P-values reported for the Wald Test of joint 'significance, Breusch-Pagan test, and Breusch-Godfrey SC Test. Standard errors reported in brackets are computed using the Newey-West (1987) construction of the covariance matrix with three lags

# SECTION 5: SAMPLE LENGTH

In this Section, we extend the sample period from 2009-2013 to 2007-2019 for the modified optimal hedging model. Figure 6 and Figure 7 plot the weekly changes in hedge ratio, futures prices, and VIX during pre-harvest period from 2007-2019 for corn and soybeans, respectively.

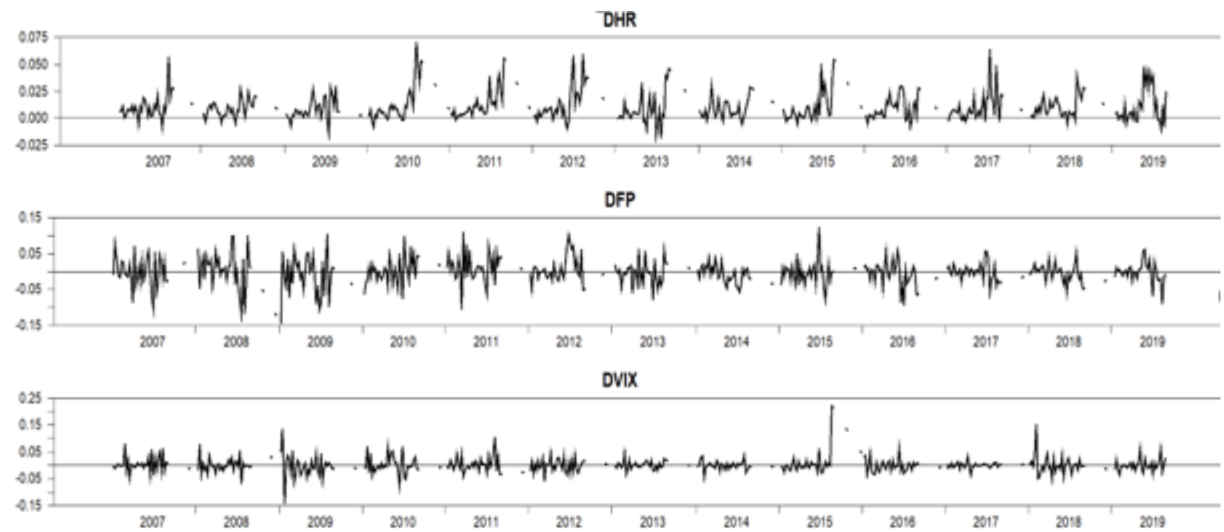


**Figure 4. Weekly Changes in Hedge Ratio, Futures Prices, and VIX in Corn Futures Market, Pre-harvest period from 01/2007-08/2019**

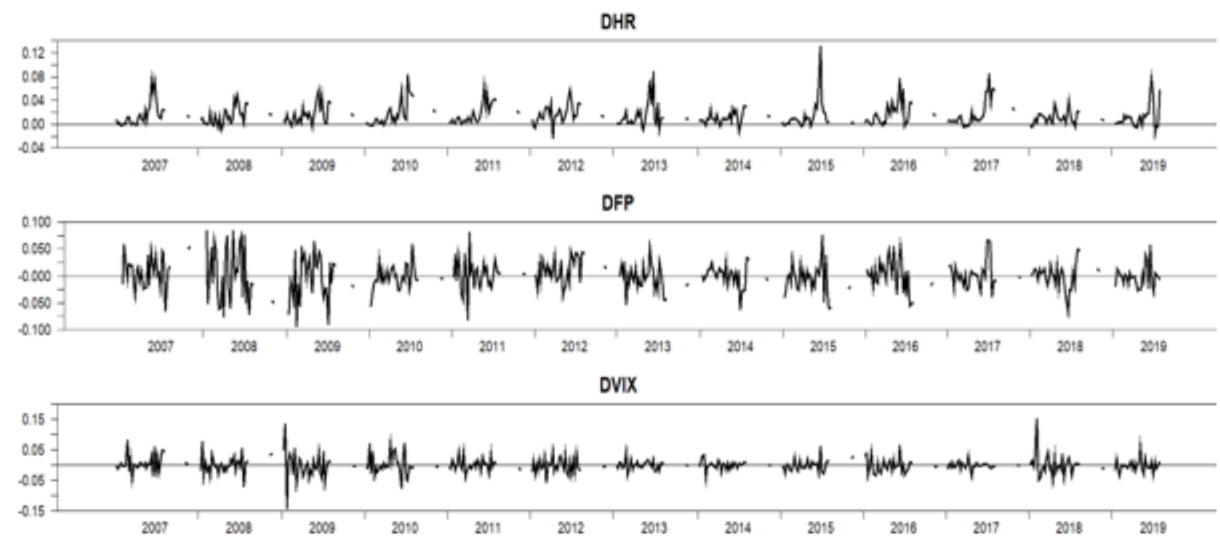


**Figure 5. Weekly Changes in Hedge Ratio, Futures Prices, and VIX in Soybeans Futures Market, Pre-harvest period from 01/2007-07/2019**

The year 2007 is chosen as the starting point because the DCOT data, which we use to calculate commercial traders' hedge ratio, are only available from June 2006 on.

Tables 4 and 5 report our OLS estimates for the optimal hedging model in the corn and soybeans markets, respectively, during pre-harvest time from 2007-2019. In these models, the hedge ratio change uses the futures open interest as a scaling factor to compute the hedge ratio; we use two seasonal dummies; and the VIX acts as a proxy for demand-side uncertainty and financial market sentiment.

Tables 4 and 5 show that prolonging the two seasonal dummies are again statistically significant, with the expected negative sign, and that the futures prices' coefficient maintains its statistically significant with a positive sign in both corn and soybeans markets. Noticeably, there is a change in significance level of the VIX's coefficient. In the corn market, the VIX's coefficient turns statistically significant in five base cases: the only exception is for the model using last year's average price as the producers' reference price. In the soybeans market, the VIX is only statistically significant in the base case of 30-day moving average reference price (the last two columns in Table 7), however, it keeps the expected positive sign across all mosels.

**Table 6. OLS Estimates, Corn, Pre-harvest Weekly of Producers' Short Position for New Crop, 2007-2019**

Equation 3: $DHR_t = \alpha_0 + \alpha_1 1\{Ft-Rt<0\} + \mu DHR\{1\} + \beta_0 dummy_1 + \beta_1 dummy_2 + \beta_2 DVIX_t + \beta_3 DFP_t + \beta_4 DFP_t * 1\{Ft-Rt<0\} + \beta_5 DFP_t^2 + \varepsilon_t$

| | No reference Price | Nonlinear Price Response | Last Year's Avg Price | RMA Forecast Price | 30-day Moving Average | |
|---|---|---|---|---|---|---|
| | | | | | (1) | (2) |
| $\alpha_0$ | 0.011*** | 0.010*** | 0.013*** | 0.013*** | 0.012*** | 0.012*** |
| | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\alpha_1$ | | | -0.002** | -0.003** | -0.003*** | -0.003*** |
| | | | (0.001) | (0.001) | (0.001) | (0.001) |
| $\mu$ | 0.417*** | 0.416*** | 0.397*** | 0.390*** | 0.385*** | 0.385*** |
| | (0.054) | (0.054) | (0.055) | (0.054) | (0.055) | (0.055) |
| $\beta_0$ | -0.008*** | -0.008*** | -0.009*** | -0.009*** | -0.009*** | -0.009*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\beta_1$ | -0.007*** | -0.006*** | -0.007*** | -0.007*** | -0.007*** | -0.007*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\beta_2$ | 0.037* | 0.038* | 0.037 | 0.042* | 0.042* | 0.042* |
| | (0.022) | (0.022) | (0.022) | (0.023) | (0.022) | (0.022) |
| $\beta_3$ | 0.084*** | 0.085*** | 0.053** | 0.073*** | 0.081*** | 0.075** |
| | (0.017) | (0.017) | (0.023) | (0.027) | (0.030) | (0.033) |
| $\beta_4$ | | 0.232 | 0.055* | 0.003 | -0.037 | -0.025 |
| | | (0.270) | (0.032) | (0.035) | (0.038) | (0.052) |
| $\beta_5$ | | | | | | 0.097 |
| | | | | | | (0.380) |
| $\alpha_0 + \alpha_1$ | | | 0.011*** | 0.010*** | 0.009*** | 0.009*** |
| | | | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_3 + \beta_4$ | | | 0.108*** | 0.076*** | 0.044** | 0.050 |
| | | | (0.000) | (0.002) | (0.048) | (0.103) |
| BP test | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| BGSC Test | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Adj $R^2$ | 0.35 | 0.35 | 0.36 | 0.36 | 0.36 | 0.36 |

Noted: Significant levels indicated as: * p<0.1; ** p<0.05; *** p<0.01. Robust standard errors reported in the parentheses. P-values reported for the Wald Test of joint 'significance, Breusch-Pagan test, and Breusch-Godfrey SC Test. Standard errors reported in brackets are computed using the Newey-West (1987) construction of the covariance matrix with three lags

**Table 7. OLS Estimates, Soybeans, Pre-harvest Weekly of Producers' Short Position for New Crop, 2007-2019**

Equation 3: $DHR_t = \alpha_0 + \alpha_1 1\{Ft\text{-}Rt<0\} + \mu DHR\{1\} + \beta_0 dummy_1 + \beta_1 dummy_2 + \beta_2 DVIX_t + \beta_3 DFP_t + \beta_4 DFP_t{*}1\{Ft\text{-}Rt<0\} + \beta_5 DFP_t^2 + \varepsilon_t$

| | No reference Price | Nonlinear Price Response | Last Year's Avg Price | RMA Forecast Price | 30-day Moving Average | |
|---|---|---|---|---|---|---|
| | | | | | (1) | (2) |
| $\alpha_0$ | 0.021*** | 0.020*** | 0.023*** | 0.022*** | 0.022*** | 0.022*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) |
| $\alpha_1$ | | | -0.002 | -0.003** | -0.004** | -0.004** |
| | | | (0.002) | (0.001) | (0.002) | (0.002) |
| $\mu$ | 0.331*** | 0.327*** | 0.325*** | 0.317*** | 0.311*** | 0.317*** |
| | (0.050) | (0.049) | (0.053) | (0.051) | (0.053) | (0.053) |
| $\beta_0$ | -0.017*** | -0.017*** | -0.018*** | -0.018*** | -0.018*** | -0.018*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\beta_1$ | -0.015*** | -0.014*** | -0.015*** | -0.015*** | -0.015*** | -0.015*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\beta_2$ | 0.067 | 0.066 | 0.066 | 0.061 | 0.068* | 0.069* |
| | (0.043) | -0.042 | (0.044) | (0.040) | (0.041) | (0.041) |
| $\beta_3$ | 0.138*** | 0.137*** | 0.104** | 0.196*** | 0.165** | 0.187*** |
| | (0.041) | (0.038) | (0.045) | (0.058) | (0.068) | (0.061) |
| $\beta_4$ | | | 0.065 | -0.136** | -0.140* | -0.185*** |
| | | | (0.081) | (0.059) | (0.072) | (0.067) |
| $\beta_5$ | | 0.528 | | | | -0.569 |
| | | (0.654) | | | | (0.618) |
| $\alpha_0 + \alpha_1$ | | | 0.021*** | 0.020*** | 0.018*** | 0.018*** |
| | | | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_3 + \beta_4$ | | | 0.169** | 0.060 | 0.025 | 0.002 |
| | | | (0.014) | (0.101) | (0.470) | (0.961) |
| BP test | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| BGSC Test | 0.181 | 0.193 | 0.228 | 0.269 | 0.109 | 0.290 |
| Adj $R^2$ | 0.42 | 0.42 | 0.42 | 0.43 | 0.43 | 0.43 |

Noted: Significant levels indicated as: * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Robust standard errors reported in the parentheses. P-values reported for the Wald Test of joint 'significance, Breusch-Pagan test, and Breusch-Godfrey SC Test. Standard errors reported in brackets are computed using the Newey-West (1987) matrix with three lags

During the longer, 13-year, period, there are two effects that should be controlled for. First, we note different initial patterns in hedge ratios in both corn and soybeans markets for some specific years (*Appendix 1, Figure 2.1, and Figure 2.2*). In 2007-2008, the hedge ratios start from a higher level compared to all the other years. This might be explained by the commodity price boom during 2006-2008 period (Janzen, Smith, and Carter, *AJAE* 2018) causing hedgers to sell more in the futures market. To control for the high stating level in the hedge ratio during these years is specified in the model, we create a year dummy (dummy 3) for the 2007-2008 period. Second, the financial crisis period happens from September 2008 until September 2011 should be controlled by using another year dummy (dummy 4) for the 2009-2011 *pre*-harvest periods.

Equation 4 results from adding these two dummies to capture possible outliers in the hedge ratio and financial crisis period

$$DHR_t = \alpha_0 + \alpha_1 1_{\{Ft-Rt<0\}} + \mu DHR\{1\} + \beta_0 dummy_1 + \beta_1 dummy_2 + \beta_2 DVIX_t + \beta_3 DFP_t + \beta_4 DFP_t * 1_{\{Ft-Rt<0\}} + \beta_5 DFP_t^2 + \beta_6\, dummy_3 + \beta_7 dummy_4 + \varepsilon_t \quad (4)$$

Table 8 and Table 9 display our OLS estimates of Equation 4 applied in the corn and soybeans futures markets. The results show that the additional year dummies ($dummy_3$ and $dummy_4$) are not statistically significant for either corn or soybeans. Meanwhile, our two seasonal dummies, the VIX and futures prices maintain their significant level as in Table 6 and Table 7. The goodness of fit does not show any improvement in model performance when using these year dummies. The results from Equation 4 control for the abnormal patterns in hedge ratio level, the commodity price spike during 2007-2008 period, and the financial crisis during 2009-2011 period.

**Table 8. OLS Estimates with Year Dummies, Corn, Pre-harvest Weekly of Producers' Short Position for New Crop, 2007-2019**

Equation 4: $DHR_t = \alpha_0 + \alpha_1 1_{\{Ft-Rt<0\}} + \mu DHR\{1\} + \beta_0 dummy_1 + \beta_1 dummy_2 + \beta_2 DVIX_t + \beta_3 DFP_t + \beta_4 DFP_t 1_{\{Ft-Rt<0\}} + \beta_5 DFP_t^2 + \beta_6 dummy_3 + \beta_7 dummy_4 + \varepsilon_t$

| | **No reference Price** | **Nonlinear Price Response** | **Last Year's Avg Price** | **RMA Forecast Price** | **30-day Moving Average** | |
|---|---|---|---|---|---|---|
| | | | | | (1) | (2) |
| $\alpha_0$ | 0.011*** | 0.010*** | 0.014*** | 0.013*** | 0.012*** | 0.012*** |
| | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\alpha_1$ | | | -0.003** | -0.003** | -0.003*** | -0.003*** |
| | | | (0.001) | (0.001) | (0.001) | (0.001) |
| $\mu$ | 0.416*** | 0.415*** | 0.384*** | 0.389*** | 0.383*** | 0.383*** |
| | (0.053) | (0.053) | (0.053) | (0.053) | (0.054) | (0.054) |
| $\beta_0$ | -0.008*** | -0.008*** | -0.009*** | -0.009*** | -0.009*** | -0.008*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\beta_1$ | -0.007*** | -0.006*** | -0.007*** | -0.007*** | -0.007*** | -0.007*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\beta_2$ | 0.037* | 0.038* | 0.037 | 0.042* | 0.043* | 0.042* |
| | (0.022) | (0.022) | (0.022) | (0.023) | (0.022) | (0.022) |
| $\beta_3$ | 0.085*** | 0.085*** | 0.050** | 0.073*** | 0.082*** | 0.071** |
| | (0.017) | (0.017) | (0.021) | (0.027) | (0.030) | (0.033) |
| $\beta_4$ | | | 0.059* | 0.005 | -0.039 | -0.018 |
| | | | (0.031) | (0.035) | (0.039) | (0.052) |
| $\beta_5$ | | 0.261 | | | | 0.172 |
| | | (0.284) | | | | (0.389) |
| $\beta_6$ | -0.001 | -0.001 | -0.003** | -0.001 | -0.001 | -0.002 |
| | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) |
| $\beta_7$ | 0.0003 | 0.0001 | 0.0001 | -0.0002 | -0.00002 | -0.0001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\alpha_0 + \alpha_1$ | | | 0.011*** | 0.010*** | 0.009*** | 0.009*** |
| | | | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_3 + \beta_4$ | | | 0.109*** | 0.078*** | 0.043* | 0.053* |
| | | | (0.000) | (0.000) | (0.052) | (0.076) |
| BP test | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| BGSC Test | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Adj $R^2$ | 0.35 | 0.35 | 0.36 | 0.35 | 0.36 | 0.36 |

Noted: Significant levels indicated as: * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Robust standard errors reported in the parentheses. P-values reported for the Wald Test of joint 'significance, Breusch-Pagan test, and Breusch-Godfrey SC Test. Standard errors reported in brackets are computed using the Newey-West (1987) construction of the covariance matrix with three lags.

**Table 9. OLS Estimates with Year Dummies, Soybeans, Pre-harvest Weekly of Producers' Short Position for New Crop, 2007-2019**

Equation 4: $DHR_t = \alpha_0 + \alpha_1 1_{\{Ft-Rt<0\}} + \mu DHR\{1\} + \beta_0 dummy_1 + \beta_1 dummy_2 + \beta_2 DVIX_t + \beta_3 DFP_t + \beta_4 DFP_t 1_{\{Ft-Rt<0\}} + \beta_5 DFP_t^2 + \beta_6 dummy_3 + \beta_7 dummy_4 + \varepsilon_t$

| | No reference Price | Nonlinear Price Response | Last Year's Avg Price | RMA Forecast Price | 30-day Moving Average | |
|---|---|---|---|---|---|---|
| | | | | | (1) | (2) |
| $\alpha_0$ | 0.021*** | 0.020*** | 0.024*** | 0.022*** | 0.022*** | 0.023*** |
| | (0.002) | (0.002) | (0.003) | (0.002) | (0.003) | (0.003) |
| $\alpha_1$ | | | -0.004** | -0.003** | -0.004*** | -0.004** |
| | | | (0.002) | (0.001) | (0.002) | (0.002) |
| $\mu$ | 0.330*** | 0.326*** | 0.318*** | 0.317*** | 0.309*** | 0.313*** |
| | (0.051) | (0.050) | (0.055) | (0.051) | (0.054) | (0.054) |
| $\beta_0$ | -0.017*** | -0.017*** | -0.018*** | -0.018*** | -0.018*** | -0.018*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\beta_1$ | -0.015*** | -0.014*** | -0.015*** | -0.015*** | -0.015*** | -0.015*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\beta_2$ | 0.067 | 0.067 | 0.067 | 0.062 | 0.070* | 0.070* |
| | (0.042) | (0.042) | (0.044) | (0.040) | (0.041) | (0.041) |
| $\beta_3$ | 0.138*** | 0.138*** | 0.102** | 0.196*** | 0.167** | 0.184*** |
| | (0.039) | (0.038) | (0.043) | (0.058) | (0.069) | (0.061) |
| $\beta_4$ | | | 0.067 | -0.135** | -0.145* | -0.180*** |
| | | | (0.080) | (0.059) | (0.074) | (0.068) |
| $\beta_5$ | | 0.615 | | | | -0.459 |
| | | (0.731) | | | | (0.725) |
| $\beta_6$ | -0.001 | -0.002 | -0.004 | -0.001 | -0.002 | -0.002 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |

| | | | | | | |
|---|---|---|---|---|---|---|
| $\beta_7$ | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.002) | (0.002) | (0.002) | (0.001) | (0.002) | (0.002) |
| $\alpha_0 + \alpha_1$ | | | 0.020*** | 0.019*** | 0.018*** | 0.019*** |
| | | | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_3 + \beta_4$ | | | 0.169** | 0.061 | 0.022 | 0.004 |
| | | | (0.016) | (0.102) | (0.510) | (0.920) |
| BP test | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| BGSC Test | 0.164 | 0.169 | 0.248 | 0.252 | 0.082 | 0.070 |
| Adj $R^2$ | 0.42 | 0.42 | 0.42 | 0.43 | 0.43 | 0.43 |

Noted: Significant levels indicated as: * p<0.1; ** p<0.05; *** p<0.01. Robust standard errors reported in the parentheses. P-values reported for the Wald Test of joint 'significance, Breusch-Pagan test, and Breusch-Godfrey SC Test. Standard errors reported in brackets are computed using the Newey-West (1987) construction of the covariance matrix with three lags.

In additional robustness checks, we add an interaction term with the VIX. The VIX's coefficient is not statistically significant during the short 2009-2013 replication period for both corn and soybeans markets. Meanwhile, it shows the inconsistent impacts on hedge ratio during longer time for corn and soybeans markets. This issue might come from the decoupling of the VIX and the corn/soybeans IVols during the financial crisis period. Particularly, when looking at the movements of VIX and option-implied volatility during 2007-2019 period (*Appendix 1, Figure 3.1, and Figure 3.2*), we note that (i) the VIX has two big jumps: one is in fall 2008 to summer 2009, and the other one during summer and fall 2012; (ii) although commodity IVols also show spikes during the financial crisis, their spikes are not very large compared to the spikes of VIX. Therefore, an interaction term between the VIX and the VIX dummy is used to capture the possible decoupling of the VIX and corn/soybeans IV during the financial crisis period. Equation 5 is developed from equation 3 by adding a newly proposed variable as follows:

$$DHR_t = \alpha_0 + \alpha_1 1\{Ft\text{-}Rt<0\} + \mu DHR\{1\} + \beta_0 dummy_1 + \beta_1 dummy_2 + \beta_2 DVIX_t + \beta_3 DFP_t + \beta_4 DFP_t * 1\{Ft\text{-}Rt<0\} + \beta_5 DFP_t^2 + \beta_6 \Delta VIX_t * DummyVIX + \varepsilon_t \quad (5)$$

in which $\beta_6$ is the coefficient of the interaction term between the VIX and DummyVIX. DummyVIX has a value of 1 when the VIX is above 30, and 0 otherwise. With this new variable, the VIX is expected to turn statistically significant in both corn and soybeans markets, and the interaction term's coefficient $\beta_6$ is expected to be significant with a negative sign (because the VIX exceeds the IV substantially during those periods, and so the exact VIX value is less "accurate" during those periods than during other periods).

The results in Table 10 and Table 11 show that adding the interaction term of the VIX and its dummy does not provide the expected results. It does not improve the goodness of fit since the adjusted $R^2$ is the same with that from using Equation 3 in Tables 6 and 7. While the futures prices' coefficient continues showing its significantly strong effects on hedgers' positions for both two markets, the VIX coefficient has some changes in the sign and significance level. In the corn market, the VIX now becomes insignificant. In addition, the interaction term does not play well due to its insignificance with positive sign, showing that models work best for the VIX in the corn market should not have the interaction term. Meanwhile, in the soybeans market, the VIX turns significant across all base cases; the interaction term has the expected negative side although it is only significant for cases using 30-day moving average as reference dependence.

**Table 10. OLS Estimates With The Interaction Term of VIX, Corn, 2007-2019**

Equation 5: $DHR_t = \alpha_0 + \alpha_1 1_{\{Ft-Rt<0\}} + \mu DHR\{1\} + \beta_0\ dummy_1 + \beta_1 dummy_2 + \beta_2 DVIX_t + \beta_3 DFP_t + \beta_4 DFP_t 1_{\{Ft-Rt<0\}} + \beta_5 DFP_t^2 + \beta_6 DVIX_t * DummyVIX + \varepsilon_t$

| | No reference Price | Nonlinear Price Response | Last Year's Avg Price | RMA Forecast Price | 30-day Moving Average | |
|---|---|---|---|---|---|---|
| | | | | | (1) | (2) |
| $\alpha_0$ | 0.011*** | 0.010*** | 0.013*** | 0.013*** | 0.012*** | 0.012*** |
| | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\alpha_1$ | | | -0.002** | -0.003** | -0.003** | -0.003** |
| | | | (0.001) | (0.001) | (0.001) | (0.001) |
| $\mu$ | 0.416*** | 0.414*** | 0.395*** | 0.388*** | 0.383*** | 0.383*** |
| | (0.054) | (0.054) | (0.054) | (0.053) | (0.055) | (0.054) |
| $\beta_0$ | -0.008*** | -0.008*** | -0.009*** | -0.009*** | -0.009*** | -0.009*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\beta_1$ | -0.007*** | -0.006*** | -0.007*** | -0.007*** | -0.007*** | -0.007*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\beta_2$ | 0.030 | 0.031 | 0.029 | 0.035 | 0.034 | 0.035 |
| | (0.024) | (0.024) | (0.024) | (0.025) | (0.024) | (0.024) |
| $\beta_3$ | 0.085*** | 0.085*** | 0.053** | 0.074*** | 0.083*** | 0.079** |
| | (0.017) | (0.017) | (0.023) | (0.027) | (0.031) | (0.035) |
| $\beta_4$ | | | 0.055* | 0.003 | -0.038 | -0.031 |
| | | | (0.032) | (0.035) | (0.039) | (0.055) |
| $\beta_5$ | | 0.226 | | | | 0.063 |
| | | (0.272) | | | | (0.398) |
| $\beta_6$ | 0.019 | 0.017 | 0.022 | 0.018 | 0.021 | 0.019 |
| | (0.045) | (0.046) | (0.046) | (0.046) | (0.046) | (0.048) |
| $\alpha_0 + \alpha_1$ | | | 0.010*** | 0.010*** | 0.009*** | 0.009*** |
| | | | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_3 + \beta_4$ | | | 0.108*** | 0.075*** | 0.045** | 0.048 |
| | | | (0.000) | (0.000) | (0.039) | (0.122) |
| BP test | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| BGSC Test | 0.000 | 0.000 | 0.003 | 0.002 | 0.000 | 0.000 |
| Adj $R^2$ | 0.35 | 0.35 | 0.36 | 0.36 | 0.36 | 0.36 |

Noted: Significant levels indicated as: * p<0.1; ** p<0.05; *** p<0.01. Robust standard errors reported in the parentheses. P-values reported for the Wald Test of joint 'significance, Breusch-Pagan test, and Breusch-Godfrey SC Test. Standard errors reported in brackets are computed using the Newey-West (1987) construction of the covariance matrix with three lags

**Table 11. OLS Estimates With The Interaction Term of VIX, Soybeans, 2007-2019**

Equation 5: $DHR_t = \alpha_0 + \alpha_1 1_{\{Ft-Rt<0\}} + \mu DHR\{1\} + \beta_0\,dummy_1 + \beta_1 dummy_2 + \beta_2 DVIX_t + \beta_3 DFP_t + \beta_4 DFP_t 1_{\{Ft-Rt<0\}} + \beta_5 DFP_t^2 + \beta_6 DVIX_t * DummyVIX + \varepsilon_t$

| | **No reference Price** | **Nonlinear Price Response** | **Last Year's Avg Price** | **RMA Forecast Price** | **30-day Moving Average** | |
|---|---|---|---|---|---|---|
| | | | | | (1) | (2) |
| $\alpha_0$ | 0.021*** | 0.020*** | 0.023*** | 0.022*** | 0.023*** | 0.023*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) |
| $\alpha_1$ | | | -0.002 | -0.003** | -0.004*** | -0.004*** |
| | | | (0.002) | (0.001) | (0.002) | (0.002) |
| $\mu$ | 0.332*** | 0.328*** | 0.326*** | 0.319*** | 0.312*** | 0.317*** |
| | (0.050) | (0.049) | (0.053) | (0.052) | (0.053) | (0.053) |
| $\beta_0$ | -0.017*** | -0.017*** | -0.018*** | -0.018*** | -0.018*** | -0.018*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\beta_1$ | -0.015 | -0.015*** | -0.015*** | -0.015*** | -0.015*** | -0.015*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| $\beta_2$ | 0.091* | 0.093* | 0.089* | 0.088* | 0.097** | 0.096** |
| | (0.049) | (0.048) | (0.050) | (0.046) | (0.048) | (0.048) |
| $\beta_3$ | 0.134*** | 0.133*** | 0.103** | 0.194*** | 0.162** | 0.180*** |
| | (0.039) | (0.037) | (0.044) | (0.057) | (0.067) | (0.061) |
| $\beta_4$ | | | 0.059 | -0.139** | -0.145** | -0.182*** |
| | | | (0.080) | (0.059) | (0.073) | (0.070) |
| $\beta_5$ | | 0.611 | | | | -0.461 |
| | | (0.652) | | | | (0.624) |
| $\beta_6$ | -0.094 | -0.101 | -0.087 | -0.100 | -0.108* | -0.104* |
| | (0.068) | (0.067) | (0.068) | (0.062) | (0.060) | (0.061) |
| $\alpha_0 + \alpha_1$ | | | 0.021*** | 0.019*** | 0.019*** | 0.019*** |
| | | | (0.000) | (0.000) | (0.000) | (0.000) |
| $\beta_3 + \beta_4$ | | | 0.162** | 0.055 | 0.012 | -0.002 |
| | | | (0.018) | (0.143) | (0.608) | (0.977) |
| BP test | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| BGSC Test | 0.178 | 0.197 | 0.231 | 0.256 | 0.104 | 0.082 |
| Adj $R^2$ | 0.42 | 0.42 | 0.42 | 0.43 | 0.43 | 0.43 |

Noted: Significant levels indicated as: * p<0.1; ** p<0.05; *** p<0.01. Robust standard errors reported in the parentheses. P-values reported for the Wald Test of joint 'significance, Breusch-Pagan test, and Breusch-Godfrey SC Test. Standard errors reported in brackets are computed using the Newey-West (1987) construction of the covariance matrix with three lags

To summarize, in this Section, we extended the sample period from 5 years to 13 years, after adapting Equation (3) first introduced in Section 4. For this longer period, we added dummies in Equation (4) to control for the high level of hedge ratio in corn and soybeans markets in 2007-2008 amid a commodity super-cycle and for the financial crisis during 2009-2011. We also examined the relationship between the VIX and commodity IVols, and introduced an interaction term to capture the apparent decoupling between VIX and IVols from fall 2008 to summer 2009, and from summer to fall 2012, iresented in Equation 5.

The results from Table 6 to Table 11 provide evidence that the theoretical model proposed by Jacobs *et al*. (*AJAE* 2018), with adjusted proxies for market fundamentals, is robust to the longer sample period (13-year period *vs*. 5), with the role of futures prices on hedging decisions always statistically significant, across all base cases and in both the corn and soybeans markets. Interestingly, over the longer time period, we find some statistical evidence that the VIX affects hedging behavior—as theory would predict.

# SECTION 6: THE STRUCTURAL VAR MODEL

In the previous Sections, we provide evidence that the 2018 *AJAE* "optimal hedging" model, estimated by OLS regression after some practical improvements, can be generalized to a longer period and to other commodities. In this section, we use structural vector autoregression (SVAR) model to account for possible endogeneity issues in the analysis of the effects of futures prices on commercial positioning in grains and oilseeds markets.

Precisely, we propose a 3-variable ordered SVAR model to jointly explain and quantify the roles of global macroeconomic uncertainty using the VIX (specifically, the weekly change DVIX) and commodity price levels (precisely, the weekly futures prices changes DFP) in explaining changes in producers' hedge ratio (DHR) for corn and soybeans futures markets during the pre-harvest period. The pre-harvest period is from January to August for corn, and from January to July for soybeans. It is determined based on the level of hedge ratio, which drops dramatically in September for corn and in August for soybeans (*Appendix 1, Figure 1.1 and Figure 1.2*). Also, two seasonal dummies are included in the SVAR model as exogenous variables to capture planting time and crop insurance seasons. Our sample runs from 2007 to 2019.

**Choice of Variables**

*Hedging behavior.* Commercial traders' behavior is reflected by their activities of selling or buying a commodity in the futures market. Because producers must short their futures positions to offset a price drop in the physical market, producers' aggregated net short position captures producers' hedging activities. In the ordered SVAR model, a change in hedge ratio, in which the hedge ratio is calculated by using producers' short positions for new crops in the futures markets scaled by the total futures open interest, is used for estimating commercial hedging decisions in the futures market.

*Futures Prices.* The main question in this paper is whether commodity price levels drive hedging decisions in grains and oilseeds futures markets. We use the change in the "benchmark" futures prices (DFP) as one of the endogenous variable in the ordered SVAR model. The benchmark is commodity-dependent. In the corn market, the December contract is the benchmark. In the soybeans market, the November contract plays the same role.

*Market Uncertainty*. As explained in prior sections, we use the change in VIX (DVIX) as a measure for price uncertainty in our ordered SVAR model.

**Ordering of Variables**

For each commodity futures market, we propose a 3-variable SVAR to investigate the respective contributions of the weekly change in macroeconomic uncertainty and sentiment (DVIX), and of the futures prices return (DFP), to the weekly change in hedgers' net short positions (DHR). The reduced form of SVAR model for each commodity is presented by the vector $y_t$ as

$$A(L)y_t = \theta z_t + \varepsilon_t \tag{6}$$

where A(L) is a matrix of polynomials in the lag operator L, $\{I\text{-}A_1L^1\text{-}A_2L^2\text{-}\ldots A_pL^p\}$, $y_t$ is a (nx1) data vector, $z_t$ is the exogenous variables, and the prediction errors $\varepsilon_t$ are related to the structural shocks $u_t$ by

$$A\varepsilon_t = Bu_t \tag{7}$$

As in Büyüksahin, Bruno, and Robe (*AJAE* 2017), we "impose the standard conditions that A = I and that B is lower-triangular, so that a Cholesky decomposition of the variance-covariance matrix fits a recursively just-identified model." These structural restrictions help preserve the implication that VIX is not contemporaneously affected by futures prices (DFP) and hedgers' short positions (DHR). In turn, futures prices (DFP) should be contemporaneously affected by the VIX, but not by hedgers' positions (DHR). This ordering of prices and hedgers' positions in effect assumes that changes in producers' net short positions "generate signals that are not immediately incorporated into prices." By ordering the hedge ratio last, we can ask whether the intensity of hedging is determined by demand-side macroeconomic uncertainty and/or by prices in corn and soybeans futures markets.

Therefore, equation 7 is specified as

$$\begin{pmatrix} \varepsilon_t^{DVIX} \\ \varepsilon_t^{DFP} \\ \varepsilon_t^{DHR} \end{pmatrix} = \begin{bmatrix} b_{11} & 0 & 0 \\ b_{12} & b_{22} & 0 \\ b_{13} & b_{23} & b_{33} \end{bmatrix} \begin{pmatrix} u_t^{DVIX} \\ u_t^{DFP} \\ u_t^{DHR} \end{pmatrix} \tag{8}$$

Finally, we include seasonal dummies as exogenous variables in our ordered SVAR model. As before, *dummy 1* covers the January to February period when the planting has not started yet, and the crop insurance price has not been established yet. Therefore, *dummy 1* has value of 1 when it is January and February, and 0 otherwise. The *dummy 2* variable covers the planting time, which has a value of 1 from March to May, and 0 otherwise.

# SECTION 7: RESULTS

We first estimate the reduced form SVAR of Equation (6) using ordinary least squares with two lags. Next, we summarize the impulse response functions (IRFs). Finally, we discuss the results' robustness to alternative specification of the SVAR variables.

**Reduced form of SVAR Estimates**

In both commodity markets, we estimate the reduced-form SVAR using ordinary least squares with two lags. The number of lags is determined to help eliminate serial correlation in the residuals. We include two seasonal dummies which capture the planning period and the crop insurance schedule as exogenous variables in this SVAR specification. The two reduced-form SVAR models satisfy stability condition. The parameter estimates and their standard errors are presented in the Table 12 for corn and Table 13 for soybeans below

**Table 12. Reduced-form SVAR Regression Estimates, Corn, Pre-Harvest Period, 2007-2019**

| | Equation | | |
|---|---|---|---|
| | **DVIX** | **DFP** | **DHR** |
| Intercept | 0.003<br>(0.003) | -0.004<br>(0.004) | 0.011***<br>(0.001) |
| DVIX{1} | -0.269***<br>(0.051) | 0.058<br>(0.069) | -0.010<br>(0.020) |
| DFP{1} | -0.010<br>(0.038) | 0.034<br>(0.051) | 0.060***<br>(0.015) |
| DHR{1} | 0.191<br>(0.135) | 0.104<br>(0.182) | 0.325***<br>(0.054) |
| DVIX{2} | -0.094*<br>(0.051) | 0.041<br>(0.069) | 0.010<br>(0.020) |
| DFP{2} | 0.073*<br>(3.801) | 0.045<br>(0.051) | 0.036**<br>(0.015) |
| DHR{2} | -0.192<br>(0.133) | -0.123<br>(0.180) | 0.081<br>(0.053) |

Note: Heteroskedasticity-robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels. Coefficient estimates for seasonal dummies are not reported. AIC: -14.32, HQIC: -14.21, SBIC:-14.051

**Table 13. Reduced-form SVAR Regression Estimates, Soybeans, Pre-Harvest Period, 2007-2019**

| | Equation | | |
|---|---|---|---|
| | **DVIX** | **DFP** | **DHR** |
| Intercept | 0.0001<br>(0.004) | 0.0004<br>(0.004) | 0.022***<br>(0.002) |
| DVIX{1} | -0.301***<br>(0.051) | -0.014<br>(0.059) | -0.029<br>(0.030) |
| DFP{1} | 0.001<br>(0.048) | 0.028<br>(0.056) | 0.040<br>(0.029) |
| DHR{1} | 0.026<br>(0.094) | -0.011<br>(0.109) | 0.317***<br>(0.056) |
| DVIX{2} | -0.136***<br>(0.051) | -0.063<br>(0.060) | 0.069**<br>(0.031) |
| DFP{2} | 0.053<br>(0.048) | 0.007<br>(0.056) | 0.066**<br>(0.028) |
| DHR{2} | -0.094<br>(0.093) | -0.003<br>(0.108) | -0.048<br>(0.055) |

Note: Heteroskedasticity-robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels. Coefficient estimates for seasonal dummies are not reported. AIC: -14.311, HQIC: -14.193, SBIC: -14.016

**Drivers of Hedging Behavior: IRF Analyses**

We estimate impulse response functions for all model variables with respect to each structural shock, and generate confidence interval using the wild bootstrap procedure of Goncalves and Kilian (*JE*, 2004). We use 1,000 replications and report the results with 95% confidence intervals.

Figures 6 and Figure 7 show the IRFs from the 3-variable SVAR with 95% confidence interval bands for, respectively, corn (Figure 6) and soybeans (Figure 7) based on the following ordering: DVIX, DFP, and DHR. As in Büyüksahin *et al*. (AJAE 2017), each chart within these two Figures presents "the impulse responses over 10 weeks of the variable after the arrow to a one-standard deviation shock to the variable before the arrow. For instance," the first row in Figure 8, from left to right, displays the impulses responses over 10 weeks of DVIX, DFP, and DHR to a one-standard deviation shock to DVIX.

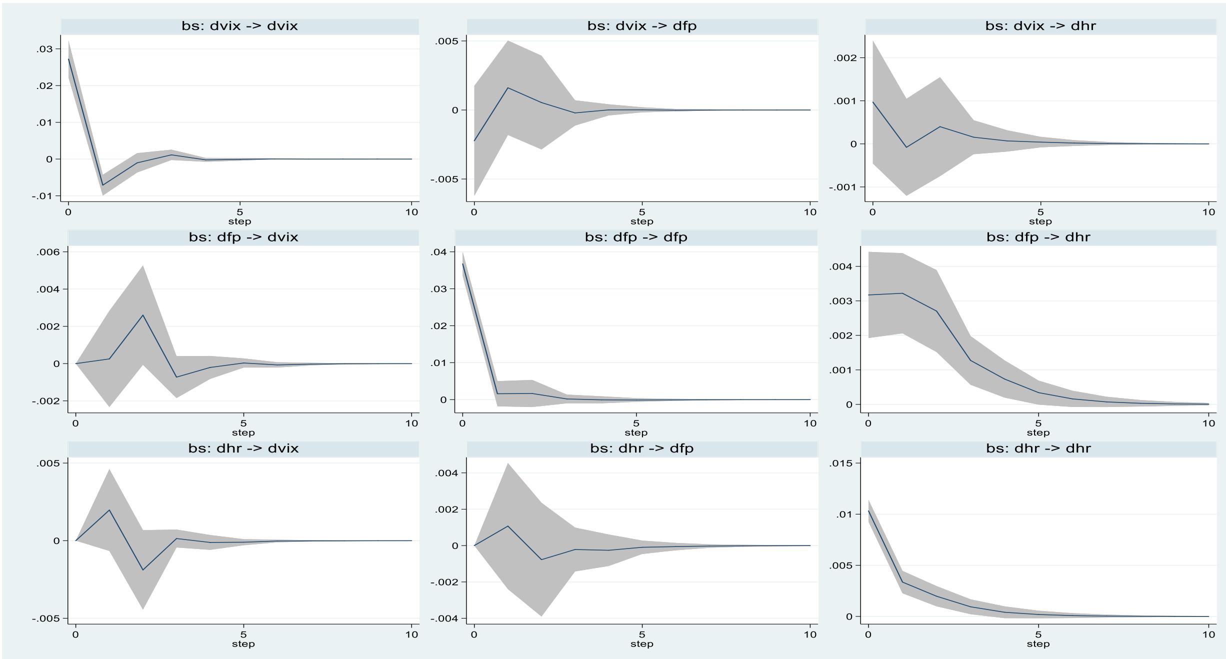


**Figure 6. Impulse Response Functions for corn- Structural VAR in first differences, 2007-2019**

Note: Figure 6 plots 10-week impulse responses of the SVAR model including the change in S&P 500 option-implied volatility representing for macroeconomic uncertainty, VIX; the change in corn futures prices, DFP; and the change in corn producers' net short position, DHR. Confidence bands are plotted at 95% level of statistical significance level. The SVAR model is estimated using the change in weekly data during pre-harvest time period (from January to August) from 2007-2019 with variables ordered as follows: VIX, corn futures prices, and Hedge Ratio which is calculated by using open interest as a denominator


**Figure 7. Impulse Response Functions for soybeans- Structural VAR in first differences, 2007-2019**

Note: Figure 7 plots 10-week impulse responses of the SVAR model including the change in S&P 500 option-implied volatility representing for macroeconomic uncertainty, VIX; the change in soybeans futures prices, DFP; and the change in soybeans producers' net short position, DHR. Confidence bands are plotted at 95% level of statistical significance level. The SVAR model is estimated using the change in weekly data during pre-harvest time period (from January to July) from 2007-2019 with variables ordered as follows: VIX, soybeans futures prices, and Hedge Ratio which is calculated by using open interest as a denominator

*Futures Prices*

The question of whether prices drive commercial traders' aggregated net short positions is answered by the IRFs in Figure 6 and Figure 7. These figures show that a key driver of commercial traders' hedging decisions is the commodity price. Particularly, a one-standard-deviation positive shock to corn/soybeans prices leads to an increase in a change of commercial traders' aggregated net short positions. The impact of a futures price shock remains statistically significant (i.e., lasts) 4 weeks in the corn market, and 3 weeks in the soybeans market.

During pre-harvest months from 2007-2019, in the corn market, the impact of DFP on DHR is immediate and strongest in week 1 at +0.0032. This magnitude is very substantial as it accounts for 31.37% of the 0.0102 average DHR value. Meanwhile, in the soybeans market, the point estimates of the DHR response to a DFP shock are largest at the current time (week 0): +0.0042, accounting for 28.77% of the 0.0146 average DHR value in magnitude.

In sum, the effects of futures prices on hedging decisions are statistically significant, and the responses of DHR to a one standard deviation shock to DFP are immediate, and strong with a large magnitude in both corn and soybeans markets. The effects of futures prices on hedging decisions in the corn market last longer than those in the soybeans market (4 weeks for corn *vs*. 3 weeks for soybeans) and are stronger (with greater relative magnitude of 31.37% *vs*. 28.77%). The positive responses in the two markets show the positive correlations between futures prices and commercial traders' short positions: the higher the futures prices are, the more hedging.

*Global macroeconomic uncertainty (captured by the VIX).*

The OLS regression using Jacobs *et al*.'s (*AJAE* 2018) model shows that, during the pre-harvest periods from 2007-2019, the VIX's effects on commercial traders' short positions are statistically significant at the 10% level for most model variations in the corn market, and for 30-

day moving average price reference case in the soybean market. Using the ordered SVAR, we re-estimate the effects of VIX on producers' short positions at the 95 percent significance level. Intuitively, the higher the market uncertainty, the more hedging should take place, and the lower agricultural commodity prices should be. Therefore, we expect to see the positive effects of the VIX on commercial traders' short positions, and negative effects of the VIX on futures prices in both markets.

Figure 6 and Figure 7 show that a VIX increase immediately boosts producers' net short positions, which is consistent with the findings when employing the 2018 *AJAE* optimal hedging model. However, the VIX changes are not statistically significant in either the corn or the soybean market—at least at the 95 percent confidence level. The results are slightly different from the OLS regression findings in Table 6 and Table 7, in which the VIX coefficient was statistically significant at low level in corn and soybeans markets with some base cases.

We see a negative response of futures prices changes to a one-standard deviation shock to the VIX's change. However, the statistical significance of the VIX's impact is mixed among the two markets. In the corn market, the impact of the change in VIX on the price levels is not statistically significant. Meanwhile, we find a statistically significantly negative impact of the VIX change on the futures return in the soybeans market. The impact is immediate but becomes statistically insignificant after week 1.

In general, the results summarized in the Figure 8 and 9 establish a positive relationship between a change in futures prices and a change in commercial traders' aggregated short positions. This sheds a new light on speculating purpose of commercial traders because, when commercial traders' aggregate positions react to price changes, that empirical fact is consistent with the notion that they are somehow speculating. The VIX, a global macroeconomic uncertainty, does not appear to significantly impact commercial traders' aggregate net short positions in either corn or soybeans markets, but the VIX change has a short-lived impact on the futures prices changes in soybeans market (which, in turn, impact hedging).

***Robustness***

In this section, the effects of DVIX and DFP on the change in commercial traders' short positions are investigated using three different ordered SVAR models (given the ordering of variables are kept unchanged).

The first SVAR model replaces DHR by DHRN. Particularly, the change in hedge ratio using annual crop as a scaling factor suggested by Jacobs *et al*. (*AJAE* 2018) is examined. Therefore, the first SVAR model has 3 endogenous variables: DVIX, DFP, DHRN and two exogenous variables (our seasonal dummies).

The second SVAR model controls for the outliers in hedge ratios in 2007-2008 and amid the financial crisis period in 2009-2011. Particularly, one added year dummy is to cover the outliers in hedge ratio in 2007-2008 with the value of 1 when it's 2007 and 2008, and 0 otherwise; another added year dummy is to cover the financial crisis period with the value of 1 when it is 2009-2011, and 0 otherwise. Therefore, the second SVAR model has 3 endogenous variables: DVIX, DFP, and DHR, and 4 exogenous variables: two seasonal dummies, and two year-dummies.

The third SVAR model controls for the decoupling between the VIX and the corn/soybeans IVols during financial crisis. Particularly, the financial crisis dummy, which has value of 1 when the VIX is bigger than 30, and 0 otherwise, is added to the model. Therefore, the third SVAR model has 3 endogenous variables: DVIX, DFP, and DHR, and 3 exogenous variables: two seasonal dummies and one financial crisis dummy.

The robustness is evaluated based on the parameter estimates and IRFs between each of the three newly proposed SVAR model with the original model (the SVAR with DVIX, DFP, DHR, and two seasonal dummies as exogenous variables). In short: our results are qualitatively robust to using an alternative for measuring commercial hedging behavior, adding year dummies, and adding financial crisis dummy.

First, the results for parameter estimates (*Appendix 2, Table 2.1 to Table 2.6*) show that there is no big difference in the significance level among parameters and their coefficients in the three new models compared to those in the original results. Using the AIC, HQIC, and SBIC criterion in comparing the goodness of fit, we see that the model using DHRN performs better than the original model, while the model adding year dummies and the model adding financial crisis dummy perform worse than the original models in corn and soybeans markets.

Second, the IRF results from the SVAR model with DHRN (*Appendix 1, Figure 4.1 and Figure 4.2*) show that: the statistically significant impact of DFP on DHRN lasts for 6 weeks compared to 4 weeks in the SVAR using DHR; and has the same duration in the soybeans market: lasting for 3 weeks in both SVAR with DHRN and SVAR with DHR. Specifically, during pre-harvest time from 2007-2019, in the corn market, the impact of DFP on DHRN (*Appendix 1, Figure 4.1)* is immediate and strongest in week 1 at +0.0020, accounting for 40.82% of the 0.0049 average DHRN value (vs. 31.37% of the hedge ration in the SVAR with DHR). In the soybeans market, the point estimates of the DHRN response to a DFP shock are largest at the current time (week 0): +0.0058, amounting to 47.93% of the 0.0121 average DHRN value in magnitude (*Appendix 1, Figure 4.2)*. This magnitude is material, 1.67 times larger than that in SVAR model using DHN. In this SVAR model, we also do not find the statistically significant impact of the DVIX on DHRN. The sign of the VIX impact on DHRN turns negative in the corn market while it remains positive in the soybeans market. As discussed in the previous section, the higher the price volatility, the greater should be the hedging. Therefore, the negative impact of DVIX on the DHRN in the corn market does not follow the intuition, however, it is not statistically significant.

Lastly, the model with added year dummies and the model with added financial crisis dummy do not change the impulse responses of DHR to a one-standard deviation shock to the DFP regarding to the time length that the statistically significant impact lasts, and its magnitude (*Appendix 1, Figure 5.1, Figure 5.2, Figure 6.1, and Figure 6.2)* compared to that in the model without adding them (Figure 8 and Figure 9).

In conclusion, the IRFs from the ordered SVAR model with (i) using an alternative for hedge ratio calculation, (ii) added year dummies, (iii) added financial crisis dummy are qualitatively robust. Comparing the goodness of fit among those models, the model using DHRN has the lowest AIC, HQIC, and SBIC, showing that it has the best performance: the statistically significant impact of DFP on DHRN lasts longer in the corn market, stronger in both corn and soybeans markets compared to the model with DHR. This result leads to the suggestion of using annual crop as a scaling factor for hedge ratio in agricultural commodity markets and using open interest as a denominator in calculating hedge ratio in non-agricultural markets. The dummies for capturing the outliers in hedge ratio during 2007-2008 and financial crisis period are not necessary as those events are captured in the prices and hedge ratios already.

## SECTION 8: CONCLUSIONS

In this paper, we examine the role of futures price changes on commercial traders' aggregated net positioning in grains and oilseeds markets via two different approaches: OLS regression inspired by an optimal hedging models (Jacobs et al., 2018), and a structural VAR.

Both the IRFs retrieved from the SVAR and the OLS regressions show similar results. First, market uncertainty (proxied by the VIX) has seldom significant effects on commercial hedging decisions—a puzzling result that needs to be further investigated. Second, the price level is a key driver of commercial traders' behavior in grains and oilseeds markets, shedding a light on possibly speculative behavior by commercial traders. Both market participants and policy makers can benefit from our paper's findings.

## REFERENCES

Adjemian, Michael K. & Bruno, Valentina & Robe, Michel A. 2017. "What Drives Volatility Expectations in Grain and Oilseed Markets?" *2017 Annual Meeting of the Agricultural and Applied Economics Association, July 30-August 1, Chicago, Illinois 258452.*

Basu, Devraj & Miffre, Joëlle, 2013. "Capturing the Risk Premium of Commodity Futures: The role of Hedging Pressure." *Journal of Banking & Finance, Elsevier, vol. 37(7): 2652-2664.*

Bekaert, G., M. Hoerova, and M. Lo Duca, 2013. "Risk, Uncertainty and Monetary Policy." *Journal of Monetary Economics 60(7): 771–788.*

Bessec, Le Pen, Sevi, 2016. “The Hedger’s Response to Price Changes in Energy Futures Markets.” *Energy: Expectations and Uncertainty, 39th International Association for Energy Economics*

Cao, An N.Q.  & Robe, Michel A., 2020. “Market Uncertainty and Sentiment around USDA Announcements.” *Selected paper prepared for presentation at the 202 Agricultural & Applied Economics Association Annual Meeting, Kansas City, MO*

Cheng, Ing-Haw & Wei Xiong, 2014. “Why Do Hedgers Trade So Much?” *The Journal of Legal Studies, University of Chicago Press, vol. 43(S2): 183-207.*

Chen, Kirilenko, and Wei Xiong, 2015.  "Convective Risk Flows in Commodity Futures Markets," *Review of Finance, European Finance Association, vol. 19(5): 1733-1781*

Engle, R. and S. Figlewski. 2015. “Modeling the Dynamics of Correlations among Implied Volatilities.” *Review of Finance 19 (3): 991–1018*

Fishe, Janzen, and Smith, 2014. “Hedging and Speculative Trading in Agricultural Futures Markets,” *American Journal of Agricultural Economics, vol. 96 (2): 542-556*

Fishe, Raymond P.H., Robe, Michel A., and Smith, Aaron D., 2016. “Foreign Central Bank Activities in U.S. Futures Markets.” *Journal of Futures Markets, Vol. 36(1): 3-29.*

Goncalves, S., and L. Kilian. 2004. “Bootstrapping autoregressions with conditional heteroscedasticity of unknown form.” *Journal of Econometrics 123:89 – 120.*

Hambur, Jonathan & Nick Stenner, 2016. “The Term Structure of Commodity Risk Premiums and the Role of Hedging.” *RBA Bulletin (Print copy discontinued), Reserve Bank of Australia, pages 57-66, March.*

Harris, Jeffrey H. and Büyüksahin, Bahattin. 2009. “The Role of Speculators in the Crude Oil Futures Market.” *http://dx.doi.org/10.2139/ssrn.1435042.*

Hicks, Charles (1939). “Value and Capital”. *Oxford University Press, Cambridge.*

Hirshleifer, David (1988). “Residual Risk, Trading Costs, and Commodity Futures Risk Premia”. *Review of Financial Studies 1, 173-193.*

Hirshleifer, David (1990). “Hedging pressure and futures price movements in a general equilibrium model.” *Econometrica 58, 411-428.*

Jacobs, Keri & Li, Ziran and Hayes, Dermot, 2016. “Price Responses in Forward Contracting: Do We Limit the Upside and Expose the Downside?” *2016 Annual Meeting of the Agricultural and Applied Economics Association, July 31-August 2, Boston, Massachusetts 235539.*

Jacobs, Keri & Li, Ziran and Hayes, Dermot, 2018. “Reference-Dependent Hedging: Theory and Evidence from Iowa Corn Producers”. *American Journal of Agricultural Economics, Volume 100, Issue 5, October 2018, Pages 1450–1468.*

Janzen, J., C. Carter, A. Smith, and M. Adjemian, 2014. “Deconstructing Wheat Price Spikes: A Model of Supply and Demand, Financial Speculation, and Commodity Price Comovement.” *USDA-ERS Economic Research Report Number 165.*

JP Janzen, A Smith, CA Carter, 2018. “Commodity price comovement and financial speculation: the case of cotton.”, *American Journal of Agricultural Economics 100 (1), 264-285.*

Jonathan Hambur & Nick Stenner, 2016. “The Term Structure of Commodity Risk Premiums and the Role of Hedging.” *RBA Bulletin (Print copy discontinued), Reserve Bank of Australia, pages 57-66, March.*

Kang, Wenjin and Rouwenhorst, K. Geert and Tang, Ke, 2019. “A Tale of Two Premiums: The Role of Hedgers and Speculators in Commodity Futures Markets”. *Journal of Finance, Forthcoming. http://dx.doi.org/10.2139/ssrn.2449315*

Keynes, John Maynard (1923). “Some Aspects of Commodity Markets”. *Manchester Guardian Commercial, European Reconstruction Series, Section 13, 784-786.*

Mindy L. Mallory & Wenjiao Zhao & Scott H. Irwin, 2015. "The Cost of Post-Harvest Forward Contracting in Corn and Soybeans," *Agribusiness* 31(1): 47-62.

McPhail, L., Du, X., & Muhammad, A., 2012. “Disentangling Corn Price Volatility: The Role of Global Demand, Speculation, and Energy,” *Journal of Agricultural and Applied Economics, 44(3), 401-410*

Newey, W.K., and K.D. West, 1987. “A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix.” *Econometrica, 55(3), 703-708.*

Raman, Vikas and Fernando, Chitru S. and Hoelscher, Seth, 2020. “Dynamic Risk Management and Private Corporate Information: Evidence from Hedging Announcements”. *Journal of Banking and Finance, Forthcoming. https://ssrn.com/abstract=2671878*

Robe, Michel A. and Roberts, John Spencer, 2019. “Who Holds Positions in Agricultural Futures Markets?” CFTC working paper. *https://ssrn.com/abstract=3438627.*

Sherrick, B., 2015. “Understanding the Implied Volatility (IV) Factor in Crop Insurance”. *Farmdoc Daily, 5.*

Valentina G. Bruno, Bahattin Büyüksahin, and Michel A. Robe, 2017. “The Financialization of Food?”, *American Journal of Agricultural Economics, Volume 99, Issue 1, January 2017, Pages 243–264*

Wang, Changyun, 2003. "The Behavior and Performance of Major Types of Futures Traders," *Journal of Futures Markets* 23(1): 1-31.

# APPENDIX 1

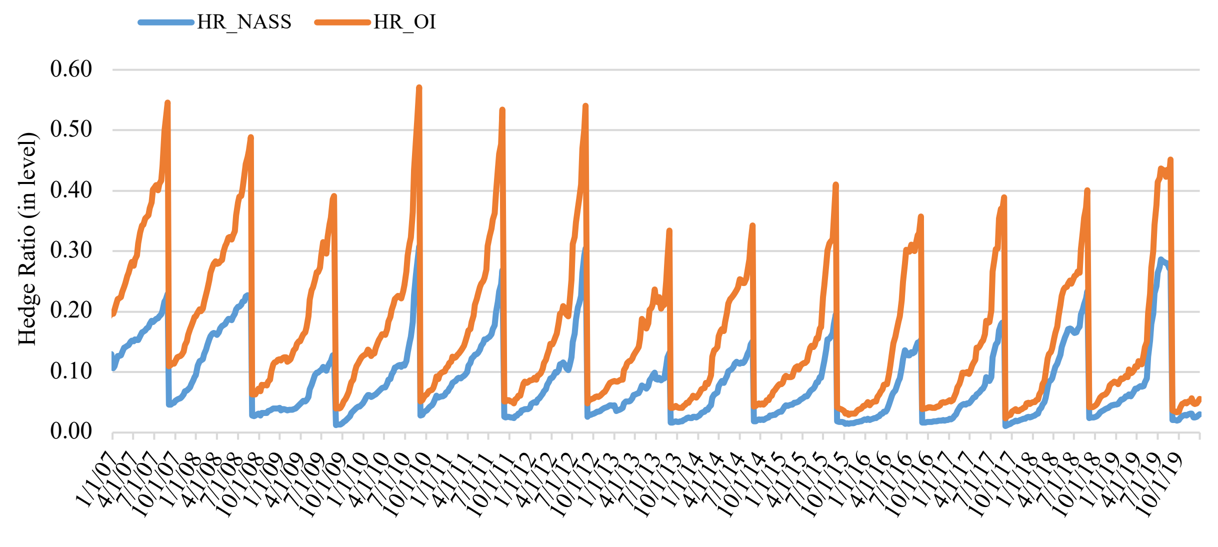


**Figure 1.1. Weekly Hedge Ratio, Corn, 01/2007-12/2019, Hedge Ratio Calculated by Using USDA's Annual Crop (HRN) as a Denominator, and by Using Open Interest (HR) as a Denominator**
*Data source: Bloomberg*

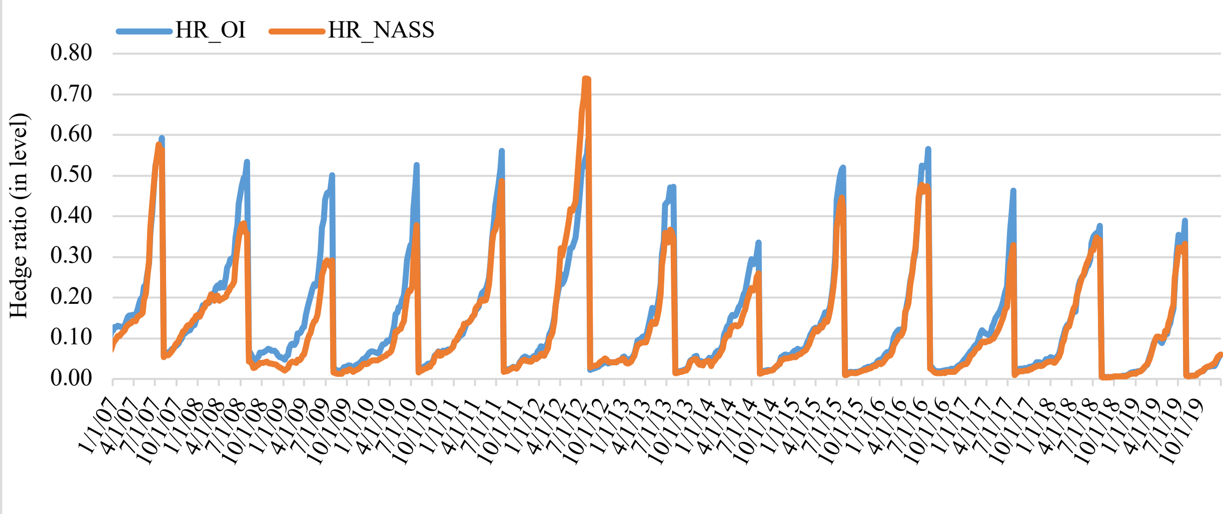


**Figure 1.2. Weekly Hedge Ratio, Soybeans, 01/2007-12/2019, Hedge Ratio Calculated by Using USDA's Annual Crop (HRN) as a Denominator, and by Using Open Interest (HR) as a Denominator**
*Data source: Bloomberg*

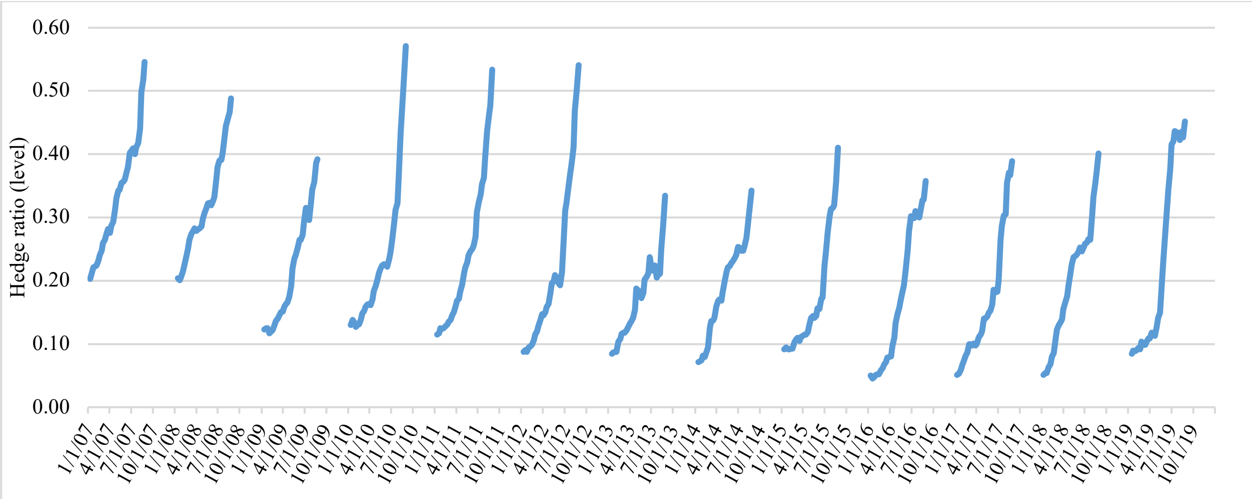


**Figure 2.1. Hedge ratios (in level) of Corn Producers (Hedge Ratio is Calculated by Using Open Interest as a Denominator), Pre-harvest Time from 01/2007-08/2019.** *Data Source: Bloomberg*

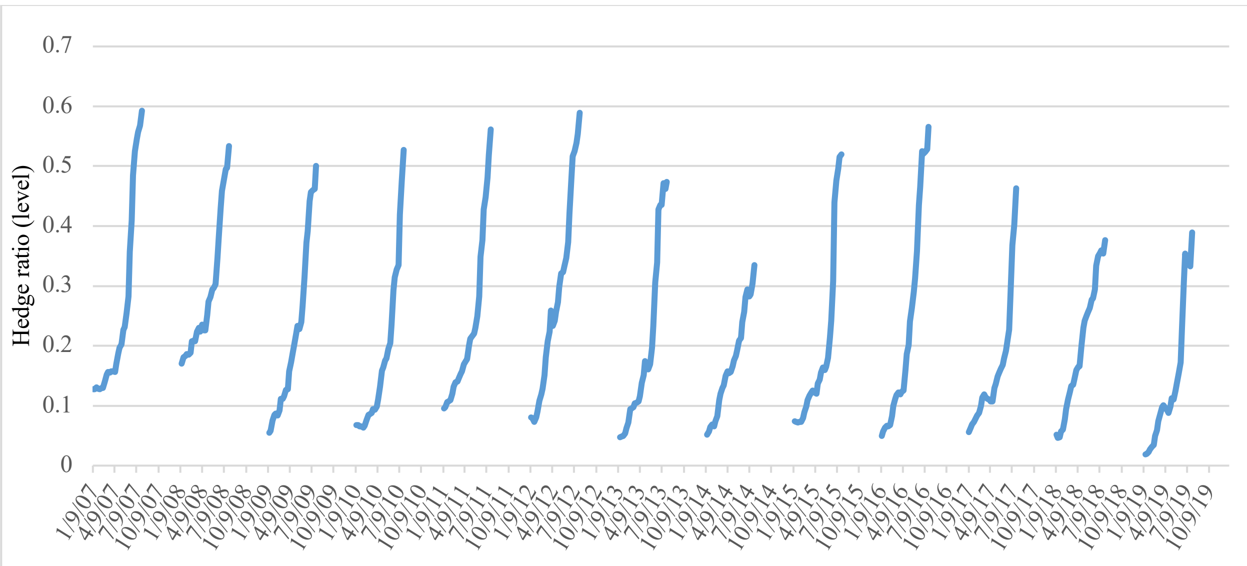


**Figure 2.2. Hedge Ratios (in level) of Soybean Producers (Hedge Ratio is Calculated by Using Open Interest as a Denominator, Pre-harvest Time from 01/2007-07/2019.**
*Data source: Bloomberg*

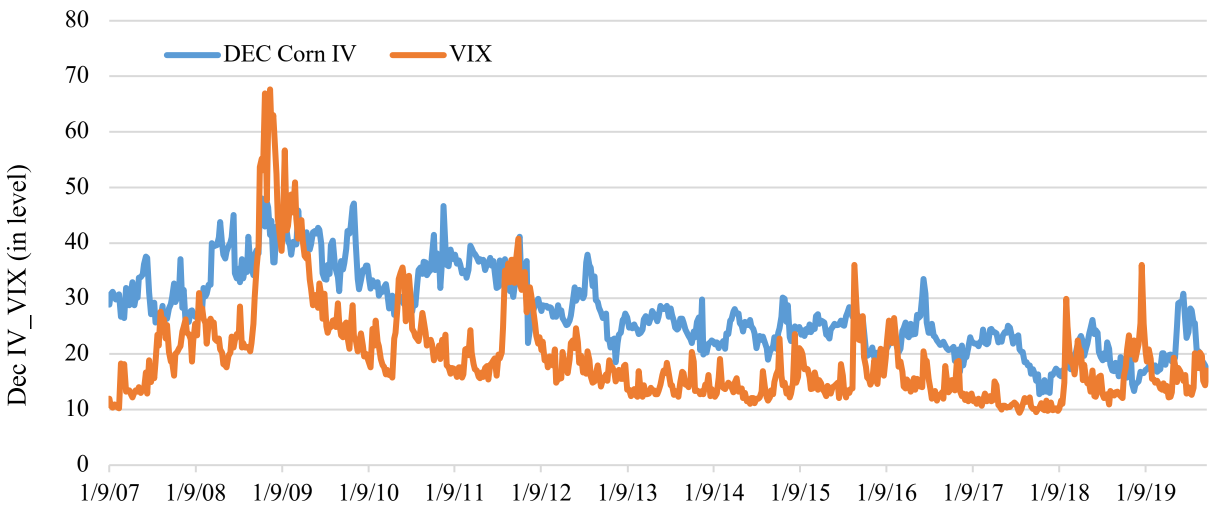


**Figure 3.1. Weekly VIX and December Corn IV, 01/2007-9/2019**
*Data source: Blomberg*

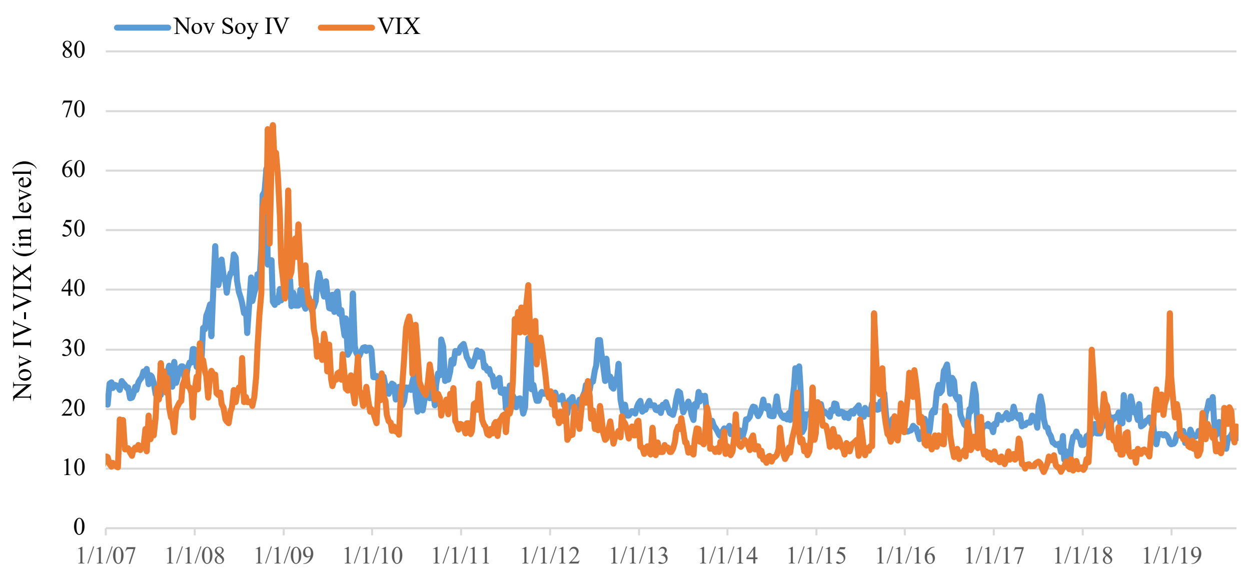


**Figure 3.2. Weekly VIX and November Soy IV, 01/2007- 09/2019.**
*Data source: Bloomberg*

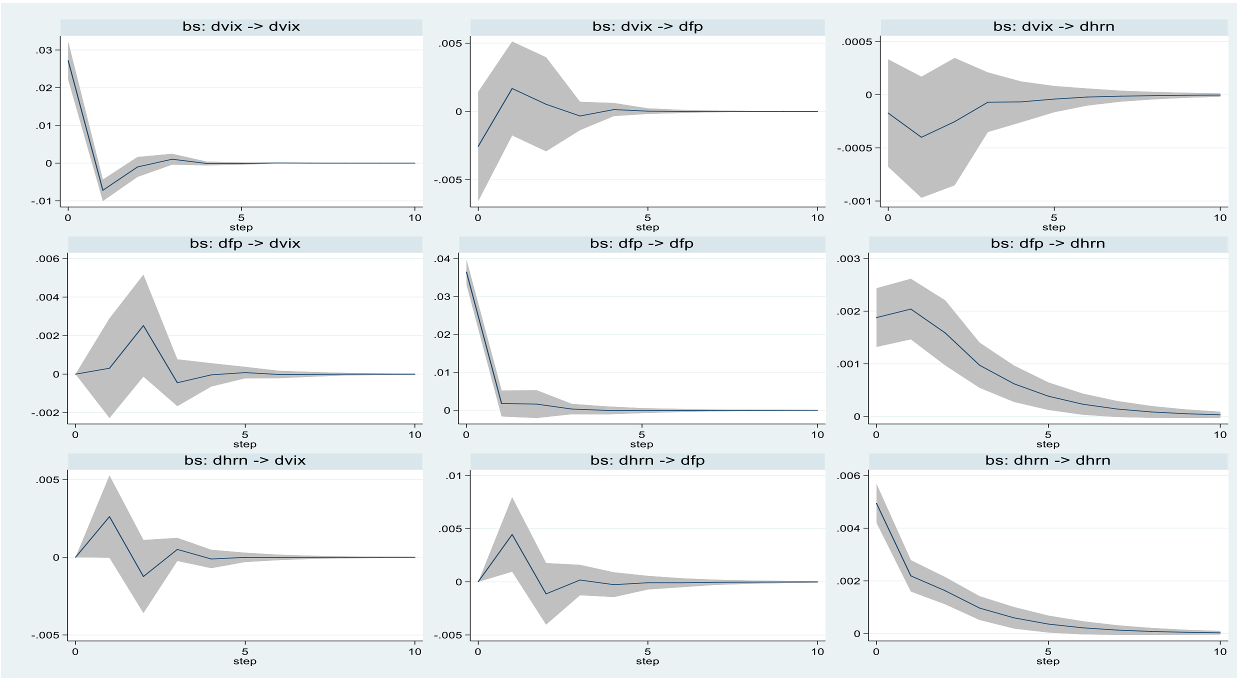


**Figure 4.1. Impulse Response Functions for corn- Structural VAR in first differences with DHRN, 2007-2019**

Note: Figure 4.1 plots 10-week impulse responses of the SVAR model including the change in S&P 500 option-implied volatility representing for macroeconomic uncertainty, VIX; the change in corn futures prices, DFP; the change in corn producers' net short position, DHRN. Confidence bands are plotted at 95% level of statistical significance level. The SVAR model is estimated using the change in weekly data during pre-harvest time period (from January to August) from 2007-2019 with variables ordered as follows: VIX, corn futures prices, and Hedge Ratio which is calculated by using annual crop as a denominator

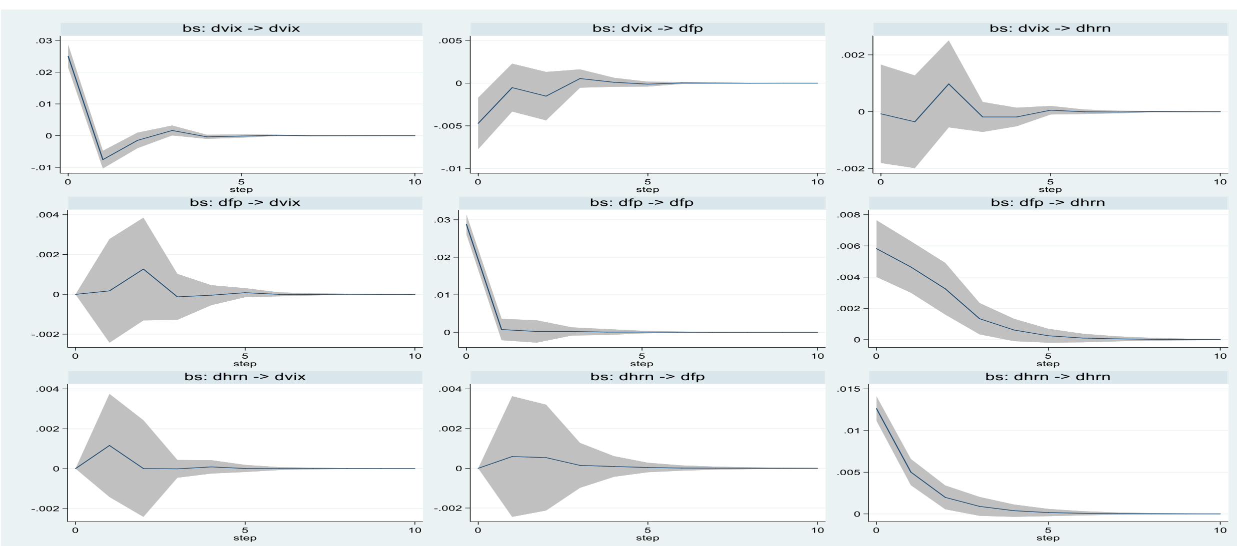


**Figure 4.2. Impulse Response Functions for soybeans- Structural VAR in first differences with DHRN, 2007-2019**

Note: Figure 4.2 plots 10-week impulse responses of the SVAR model including the change in S&P 500 option-implied volatility representing for macroeconomic uncertainty, VIX; the change in soybeans futures prices, DFP; the change in soybeans producers' net short position, DHRN. Confidence bands are plotted at 95% level of statistical significance level. The SVAR model is estimated using the change in weekly data during pre-harvest time period (from January to August) from 2007-2019 with variables ordered as follows: VIX, soybeans futures prices, and Hedge Ratio which is calculated by using annual crop as a denominator

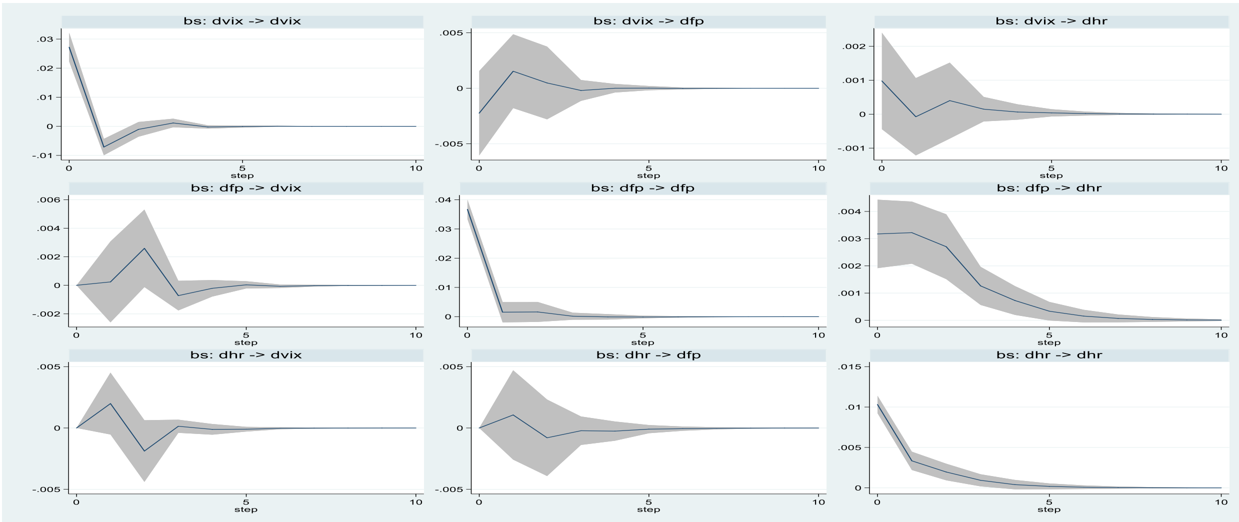


**Figure 5.1. Impulse Response Functions for corn- Structural VAR in First Differences Adding Year Dummies as Exogenous Variables, 2007-2019**

Note: Figure 5.1 plots 10-week impulse responses of the SVAR model including the change in S&P 500 option-implied volatility representing for macroeconomic uncertainty, VIX; the change in corn futures prices, DFP; and the change in corn producers' net short position, DHR. Confidence bands are plotted at 95% level of statistical significance level. The SVAR model is estimated using the change in weekly data during pre-harvest time period (from January to August) from 2007-2019 with variables ordered as follows: VIX, corn futures prices, and Hedge Ratio which is calculated by using open interest as a denominator. This model includes 4 exogenous variables: two seasonal dummies, and two year-dummies

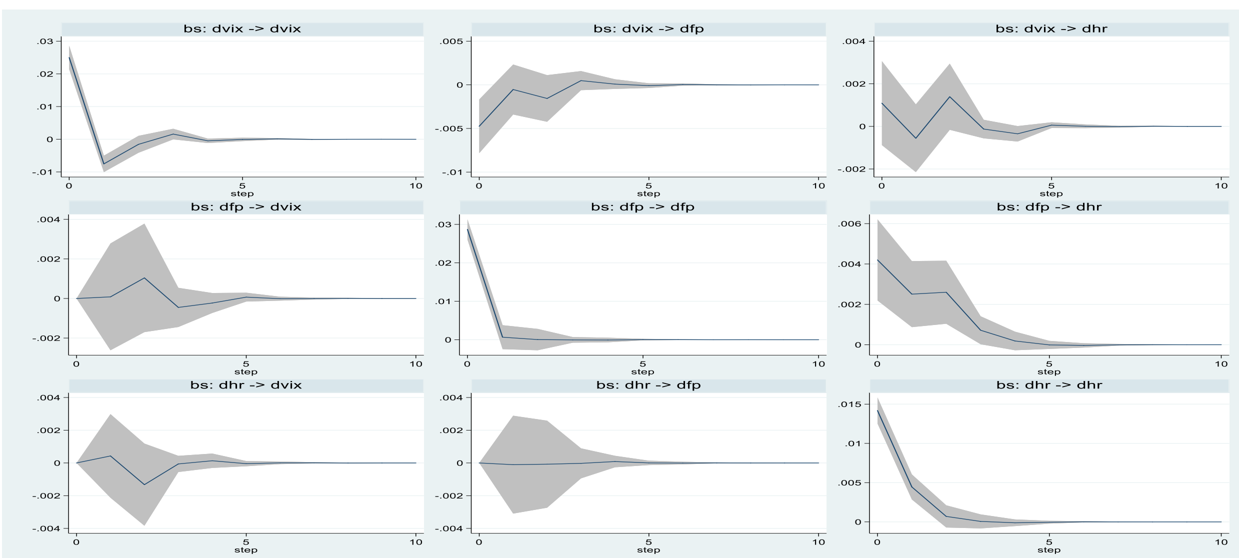


**Figure 5.2. Impulse Response Functions for soybeans- Structural VAR in First Differences Adding Year Dummies as Exogenous Variables, 2007-2019**

Note: Figure 5.2 plots 10-week impulse responses of the SVAR model including the change in S&P 500 option-implied volatility representing for macroeconomic uncertainty, VIX; the change in soybeans futures prices, DFP; and the change in soybeans producers' net short position, DHR. Confidence bands are plotted at 95% level of statistical significance level. The SVAR model is estimated using the change in weekly data during pre-harvest time period (from January to August) from 2007-2019 with variables ordered as follows: VIX, soybeans futures prices, and Hedge Ratio which is calculated by using open interest as a denominator. This model includes 4 exogenous variables: two seasonal dummies, and two year-dummies

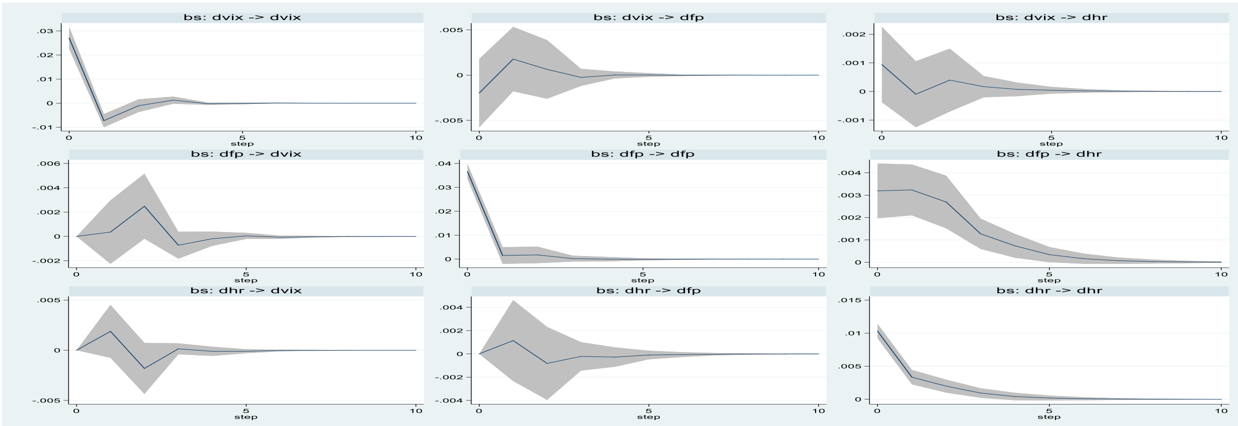


**Figure 6.1. Impulse Response Functions for corn- Structural VAR in First Differences Adding Financial Crisis Dummy as Exogenous Variable, 2007-2019**

Note: Figure 6.1 plots 10-week impulse responses of the SVAR model including the change in S&P 500 option-implied volatility representing for macroeconomic uncertainty, VIX; the change in corn futures prices, DFP; and the change in corn producers' net short position, DHR. Confidence bands are plotted at 95% level of statistical significance level. The SVAR model is estimated using the change in weekly data during pre-harvest time period (from January to August) from 2007-2019 with variables ordered as follows: VIX, corn futures prices, and Hedge Ratio which is calculated by using open interest as a denominator. This model includes 3 exogenous variables: two seasonal dummies, and financial crisis dummy

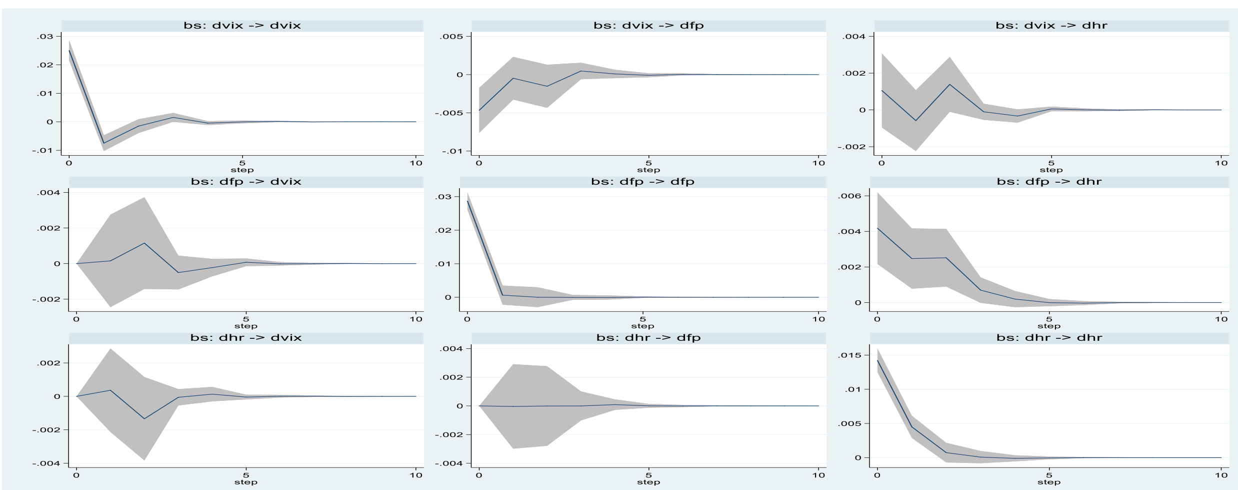


**Figure 6.2. Impulse Response Functions for soybeans- Structural VAR in First Differences Adding Financial Crisis Dummy as Exogenous Variable, 2007-2019**

Note: Figure 6.2 plots 10-week impulse responses of the SVAR model including the change in S&P 500 option-implied volatility representing for macroeconomic uncertainty, VIX; the change in soybeans futures prices, DFP; and the change in soybeans producers' net short position, DHR. Confidence bands are plotted at 95% level of statistical significance level. The SVAR model is estimated using the change in weekly data during pre-harvest time period (from January to August) from 2007-2019 with variables ordered as follows: VIX, soybeans futures prices, and Hedge Ratio which is calculated by using open interest as a denominator. This model includes 3 exogenous variables: two seasonal dummies, and a financial crisis dummy

# APPENDIX 2

**Table 2.1. Reduced-form VAR Regression Estimates, Corn, Pre-Harvest Period, 2007-2019, Using DHRN**

| | Equation | | |
|---|---|---|---|
| | **DVIX** | **DFP** | **DHRN** |
| Intercept | 0.001<br>(0.003) | -0.006*<br>(0.004) | 0.004***<br>(0.001) |
| DVIX{1} | -0.263***<br>(0.051) | 0.068<br>(0.068) | -0.009<br>(0.010) |
| DFP{1} | -0.019<br>(0.039) | 0.003<br>(0.052) | 0.033***<br>(0.008) |
| DHRN{1} | 0.529*<br>(0.272) | 0.901**<br>(0.366) | 0.443***<br>(0.053) |
| DVIX{2} | -0.094*<br>(0.051) | 0.049<br>(0.068) | -0.005<br>(0.010) |
| DFP{2} | 0.060<br>(0.039) | 0.027<br>(0.052) | 0.012<br>(0.008) |
| DHRN{2} | -0.329<br>(0.268) | -0.666*<br>(0.360) | 0.107**<br>(0.052) |

Note: Heteroscedasticity-robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels. Coefficient estimates for seasonal dummies are not reported. AIC: -15.81, HQIC: -15.70, SBIC: -15.54

**Table 2.2. Reduced-form VAR Regression Estimates, Soybeans, Pre-Harvest Period, 2007-2019, Using DHRN**

| | Equation | | |
|---|---|---|---|
| | **DVIX** | **DFP** | **DHRN** |
| Intercept | -0.004<br>(0.004) | -0.002<br>(0.004) | 0.013***<br>(0.002) |
| DVIX{1} | -0.304***<br>(0.051) | -0.018<br>(0.059) | 0.002<br>(0.028) |
| DFP{1} | -0.013<br>(0.051) | 0.016<br>(0.059) | 0.081***<br>(0.028) |
| DHRN{1} | 0.092<br>(0.107) | 0.047<br>(0.125) | 0.397***<br>(0.060) |
| DVIX{2} | -0.144***<br>(0.051) | -0.066<br>(0.060 | 0.056**<br>(0.029) |
| DFP{2} | 0.033<br>(0.050) | -0.005<br>(0.058) | 0.048*<br>(0.028) |
| DHRN{2} | -0.008<br>(0.107) | 0.025<br>(0.124) | -0.004<br>(0.059) |

Note: Heteroscedasticity-robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels. Coefficient estimates for seasonal dummies are not reported. AIC: -14.55, HQIC: -14.43, SBIC: -14.25

**Table 2.3. Reduced-form VAR Regression Estimates, Corn, Pre-Harvest Period, 2007-2019, Adding Year Dummies as Exogenous Variables**

| | Equation | | |
|---|---|---|---|
| | **DVIX** | **DFP** | **DHR** |
| Intercept | 0.002<br>(0.003) | -0.005<br>(0.004) | 0.011***<br>(0.001) |
| DVIX{1} | -0.269***<br>(0.051) | 0.055<br>(0.069) | -0.009<br>(0.020) |
| DFP{1} | -0.010<br>(0.038) | 0.033<br>(0.051) | 0.060***<br>(0.015) |
| DHR{1} | 0.193<br>(0.135) | 0.103<br>(0.182) | 0.324***<br>(0.054) |
| DVIX{2} | -0.095*<br>(0.051) | 0.039<br>(0.069) | 0.010<br>(0.020) |
| DFP{2} | 0.072*<br>(0.038) | 0.044<br>(0.051) | 0.036**<br>(0.015) |
| DHR{2} | -0.192<br>(0.133) | -0.125<br>(0.180) | 0.081<br>(0.053) |

Note: Heteroskedasticity-robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels. Coefficient estimates for seasonal dummies and year dummies are not reported. AIC: -14.29, HQIC: -14.16, SBIC:-13.97

**Table 2.4. Reduced-form VAR Regression Estimates, Soybeans, Pre-Harvest Period, 2007-2019, Adding Year Dummies as Exogenous Variables**

| | Equation | | |
|---|---|---|---|
| | **DVIX** | **DFP** | **DHR** |
| Intercept | -0.0002<br>(0.004) | -0.0004<br>(0.004) | 0.022***<br>(0.002) |
| DVIX{1} | -0.303***<br>(0.051) | -0.017<br>(0.059) | -0.028<br>(0.030) |
| DFP{1} | -0.002<br>(0.048) | 0.024<br>(0.056) | 0.041<br>(0.029) |
| DHR{1} | 0.030<br>(0.094) | -0.007<br>(0.109) | 0.314***<br>(0.056) |
| DVIX{2} | -0.139***<br>(0.051) | -0.067<br>(0.060) | 0.070**<br>(0.031) |
| DFP{2} | 0.048<br>(0.048) | 0.002<br>(0.056) | 0.069**<br>(0.028) |
| DHR{2} | -0.094<br>(0.093) | -0.002<br>(0.108) | -0.048<br>(0.055) |

Note: Heteroskedasticity-robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels. Coefficient estimates for seasonal dummies and year dummies are not reported. AIC: -14.29, HQIC: -14.15, SBIC: -13.93

**Table 2.5. Reduced-form VAR Regression Estimates, Corn, Pre-Harvest Period, 2007-2019, Adding Financial Crisis Dummy as an Exogenous Variable**

| | Equation | | |
|---|---|---|---|
| | **DVIX** | **DFP** | **DHR** |
| Intercept | 0.002<br>(0.003) | -0.004<br>(0.004) | 0.011***<br>(0.001) |
| DVIX{1} | -0.275***<br>(0.051) | 0.064<br>(0.069) | -0.010<br>(0.020) |
| DFP{1} | -0.006<br>(0.038) | 0.031<br>(0.051) | 0.060***<br>(0.015) |
| DHR{1} | 0.183<br>(0.134) | 0.111<br>(0.182) | 0.324***<br>(0.054) |
| DVIX{2} | -0.101**<br>(0.051) | 0.047<br>(0.069) | 0.009<br>(0.020) |
| DFP{2} | 0.071*<br>(0.038) | 0.047<br>(0.051) | 0.035**<br>(0.015) |
| DHR{2} | -0.184<br>(0.133) | -0.130<br>(0.180) | 0.082<br>(0.053) |

Note: Heteroskedasticity-robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels. Coefficient estimates for seasonal dummies financial crisis dummy are not reported. AIC: -14.32, HQIC: -14.21, SBIC: -14.02

**Table 2.6. Reduced-form VAR Regression Estimates, Soybeans, Pre-Harvest Period, 2007-2019, Adding Financial Crisis Dummy as an Exogenous Variable**

| | Equation | | |
|---|---|---|---|
| | **DVIX** | **DFP** | **DHR** |
| Intercept | 0.0001<br>(0.004) | 0.0005<br>(0.004) | 0.022***<br>(0.002) |
| DVIX{1} | -0.301***<br>(0.051) | -0.015<br>(0.059) | -0.029<br>(0.030) |
| DFP{1} | 0.002<br>(0.048) | 0.023<br>(0.056) | 0.040<br>(0.029) |
| DHR{1} | 0.026<br>(0.094) | -0.003<br>(0.109) | 0.316***<br>(0.056) |
| DVIX{2} | -0.136***<br>(0.051) | -0.065<br>(0.060) | 0.069**<br>(0.031) |
| DFP{2} | 0.053<br>(0.048) | 0.0004<br>(0.056) | 0.067**<br>(0.028) |
| DHR{2} | -0.095<br>(0.093) | 0.001<br>(0.108) | -0.048<br>(0.055) |

Note: Heteroskedasticity-robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels. Coefficient estimates for seasonal dummies are not reported. AIC: -14.30, HQIC: -14.17, SBIC: -13.97