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DO PRICES DRIVE COMMERCIAL TRADER POSITIONS IN GRAINS AND OILSEEDS MARKETS?

BY

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THESIS

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ABSTRACT

We examine the impacts of futures price changes on commercial traders' aggregate net positioning in grains and oilseeds markets during the pre-harvest period from 2007-2019. We proceed in two steps. First, we modify and extend the analysis of optimal hedging proposed by Jacobs, Li, and Hayes (*AJAE* 2018) to: (i) confirm its applicability for the two largest agricultural markets (soybeans and corn) over a longer period of time than previously tested (13-year period vs. 5); (ii) provide evidence regarding the relevance of the Chicago Board Options Exchange (CBOE) Volatility Index-VIX in determining commercial hedging decisions; (iii) provide evidence that the Disaggregated Commitment of Traders Reports (DCOT) data can be used as a benchmark for examining hedging behavior. Second, we develop a Structural Vector Auto-Regressive Model (SVAR) to account for endogeneity issues in the analysis of the effects of futures prices and of the VIX on commercial positioning in grains and oilseeds markets. The results from Impulse Response Functions (IRFs) retrieved from the SVAR confirm the role of futures price changes in driving position changes, shedding new light on whether commercial traders hedge or instead speculate.

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CHAPTER 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 the agricultural futures markets. In particular, commodity producers will go short more often when the 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). Noticeably, in a 2018 *American Journal of Agricultural Economics* article ("the 2018 *AJAE* paper"), Jacobs, Li and Hayes for the first time introduced a theoretical model to explore the role of price history ("reference-dependence") in Iowan farmers' pre-harvest hedging of corn crops. Their empirical results show that, during pre-harvest time in the examined period of 2009-2013, Iowan corn producers sell more forward when the current futures prices are trending above the reference prices, and that the changes in futures prices have statistically significant impacts on the change in producers' hedge ratios.

Being interested in further investigating whether commodity prices drive commercial trades' aggregated net short positions in grains and oilseeds markets, and inspired by the optimal hedging model proposed by Jacobs, Li, and Hayes (*AJAE* 2018), we modify and extend their study for the following purposes. First, we extend the empirical analysis to a longer period of time, and to other commodities. Because Jacobs et al. (2018) examine the 5-year period of 2009-2013 in the corn market alone, which covers the financial crisis during 2009-2011, and then the 2011-2012 drought, it is not obvious that the results remain valid once generalized to a longer period and to other commodities. By applying the model not only for corn, but also for soybeans over a much longer testing window with better proxies for market fundamentals, our results show that the theoretical model of optimal hedging does survive.

Second, we provide evidence that the VIX index can be a good alternative to the commodity option-implied volatility in analyzing the effects of forward-looking market uncertainty on commercial hedging decisions. There are two reasons why we change the price uncertainty measure used in Jacobs et al. First, because volatility expectations should matter to hedging decisions, the statistical insignificance of the corn implied volatility in the 2018 *AJAE* paper is puzzling. Second, because the near-dated commodity implied volatility is influenced by seasonality and USDA announcements (Cao and Robe, *AAEA* 2020), it may not be the best choice for an uncertainty indicator. For those reasons, we investigate the VIX as a possibly better proxy for 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 USDA news events; (iii) it has a close relationship with commodity option-implied volatilities (Adjemian et al., *AAEA* 2017). The empirical analysis in this thesis shows mixed results for the VIX: in the OLS regression inspired by the 2018 *AJAE* model, while the VIX does not show any significant effect on commercial traders' aggregated net short positions during the sample period of 2009-2013, it is significant during a longer period of 2007-2019; however, the impulse response functions (IRF) from the SVAR suggest that the VIX changes do not have significantly affect hedging decisions in 2007-2019, except indirectly through short-term impacts on soybeans futures prices.

Third, we confirm the usefulness of the U.S. Commodity Futures Trading Commission's (CFTC) disaggregated Commitments of Traders Reports (DCOT) data as a benchmark for hedging behavior after (i) using DCOT data to replicate Jacobs et al. (2018) results, and (ii) extending the investigation with longer DCOT data series and with other commodities. Jacobs et al. (2018) use proprietary over-the-counter (OTC) farm level data to calculate a "producers' hedge ratio" for their empirical analysis. However, they also suggest calculating "commercials' hedge ratio" instead using producers' aggregate short position in new-crop futures contracts from the DCOT as a numerator, and the annual expected crop production from the USDA as denominator. They show graphically that "producers' hedge ratio" and "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 verify their conclusion by using "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. The results show that DCOT data can be used as a benchmark for examining commercial traders' hedging behavior in the agricultural futures market. Furthermore, we propose an alternative measure of hedging intensity. Particularly, 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 DCOT data as a scaling factor. The results from the newly proposed hedge ratio calculation method are qualitatively the same with those estimated by using the "old" hedge ratio calculation method, suggesting the ability of using this measure for all commodities for which DCOT data exist but expected production figures do not—not just grains and oilseeds.

Our final contribution to the literature is the methodological improvement by using the structural VAR to account for possible endogeneity issues in the analysis of the effects of futures prices and of the VIX on commercial positioning in grains and oilseeds markets. 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 relation is not statistically significant at the 95% confidence level. The changes in futures prices, in contrast, have highly statistically significant impacts on the changes in commercial traders' aggregated short positions in grains and oilseeds 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 thesis proceeds as follows. Chapter 2 reviews the literature and covers the most recent and the most related-to-our-research papers. Chapter 3 shows a quasi-replication study of Jacobs et al.'s 2018 *AJAE* paper. Chapter 4 provides the details of our replication modifications, followed by a replication-extension study in Chapter 5. Chapter 6 describes the SVAR model. Chapter 7 summarizes the results of our SVAR analysis from the impulse-response functions, and results from robustness tests. Chapter 8 concludes. Appendix A and Appendix B include figures and tables, respectively, for the replication modifications and extensions, as well as the robustness analyses.

CHAPTER 2: LITERATURE REVIEW

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 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 DCOT 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) get DCOT data from June 2006 until February 2015 for weekly change 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) to study the explanatory power of prices to model positions. Most recently, Jacobs, Li and Haynes (*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 short 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 the energy market, 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[1]. On the other hand, in the report of Farm Services of American in 2017, most producers view themselves as being risk tolerant 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 risks or they also speculate (Cheng and Xiong, *JLS* 2014). Cheng and Xiong (*JLS* 2014) claim some form of speculating from commercial producers in the wheat, corn, soybeans, and cotton as 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 thesis further supports the notion that commercial traders also speculate.

Another factor that should matter to hedging decisions is the expectation of volatility. Jacobs, Li, and Hayes (*AJAE* 2018) use option-implied volatility (IV) for corn as a measure for 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, Robe, and Wallen, *AAEA* 2016)and by USDA scheduled releases (Cao and Robe, *AAEA* 2020), which might hide the effects of price uncertainty on commercial positioning.

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

A good candidate for the replacement of IV is the 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 the option-implied volatility is documented in many papers.[4] Regarding the 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 and commercial hedgers' positions in grains, livestock, and softs markets. *Post*-financial crisis (September 2009 to June 2011), however, its effects on prices is statistically significant. In addition, its effects on commercial hedgers' positions are statistically significant in some futures markets (but not corn, lean hogs, and cocoa futures markets). In our thesis, we use two statistical methods to examine the role of the VIX on commercial positioning in grains and oilseeds markets: (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 markets. 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 key drivers on wheat prices. Kilian and Murphy (*IER* 2014) and Kilian and Lee (*EnJ* 2014) employ SVAR to examine the impacts of speculative on crude oil prices. Janzen, Smith, and Carter (*AJAE* 2018) use SVAR to identify main factors that affect cotton prices. Bruno,

[4] 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, *RF* 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, Robe, and Wallen (*AAEA* 2016) 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) contribute to the literature the statistically and economically significant impacts of the VIX on the IV in sugar and coffee markets.

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. SVAR is employed to explore the impacts of the VIX on implied volatility in grain and oilseeds markets (Adjemian et al., *AAEA* 2017). Our thesis also employs SVAR to deal with endogeneity issues in the analysis of the effects of futures prices and of the VIX on commercial positioning in grains and oilseeds markets..

CHAPTER 3: QUASI-REPLICATION STUDY

In a 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:

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

where: Δh_t is the proportion of total harvest hedged in week t. The variable *time* measures the number of weeks left till harvest. ΔVol_t is the weekly change in the annualized implied volatility in the December corn futures contract. The price change, ΔF_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 β_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[5], in which the numerator is total bushels contracted from January through week *t* for delivery in the period September 1 to August 31 of the following year, and the denominator is the total annual receipts of corn (in bushels)[6]. Some of their findings relating to this thesis are that (i) uncertainty does not matter to the hedging decisions due to statistically insignificant coefficients of corn option-

[5] The weekly hedge ratio is constructed on every Tuesday, which is the CFTC's COT report day.
[6] Corn receipts are the bushels hauled to the firm from producers during the marketing year, which is used as a proxy for new grain production that producers intend to market.

implied volatility, and suggestion of using another price volatility measure; (ii) corn futures prices are key drivers of commercial hedging behavior because corn producers sell more forward when prices increase, especially when the current futures price is higher than the reference price; (iii) suggestion of using the CFTC's "DCOT data" as an alternative measure for commercial hedging behavior.

Being inspired by the optimal hedging model of Jacobs et al. (*AJAE* 2018), we employ that model to replicate the results[8] in exploring possible references prices to (i) confirm the value of DCOT data for analyzing commercial hedging behavior; (ii) examine the impacts of futures prices and implied volatility on commercial traders' decisions in the 2009-2013 period.

Jacobs et al. use their confidential database to calculate hedge ratios, which we are not able to obtain. Hence, we use the alternative candidates suggested by Jacobs et al. (*AJAE* 2018) to calculate hedge ratios. Specifically, short producers' open positions for new crops obtained from DCOT report 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) replace the annual total corn received to be the denominator

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

The replication period follows the same period as Jacobs et al. (*AJAE* 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 A, Figure 8a*). The pre-harvest period for corn is confirmed as the hedge ratio, as calculated above,

[8] Particularly, results from Table 2, which uses equation 10 in the 2018 *AJAE* paper are replicated

drops tremendously in September each year (because of the start of a new crop cycle in futures data).

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

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

In which, 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 zero otherwise. The exogenous variable *time* again 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[9], 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' belief.

The intercept α_0 estimates the proportion of crop hedged each week when the current December futures price is above the reference price, and α_1 is the difference in the proportion of crop hedged per week when the current December futures price is below the reference price. One

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

autoregressive lag for dependence variable is recommended by BIC criterion for eliminating serial correlation[10].

The error term ε_t is typically assumed to be an identically, independently, and normally distributed (i.i.d.) shock, with mean zero and variance, σ^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% significant level for all candidate references. A general Breusch-Godfrey LM test is used to check for serial correlation in residuals[11]. 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, α_0 is statistically significant with positive side, and α_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

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[10] Jacobs et al. (*AJAE* 2018) do not discuss the number of lags in their OLS regression. Without including 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 BIC criterion.

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

	No Reference Price	Nonlinear Price Response	Last Year's Avg Price	RMA Forecast Price	30-day Moving Average (1)	30-day Moving Average (2)	30-day Moving Average (3)	30-day Moving Average (4)
α_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)
α_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)
μ	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)
β_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)
β_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)
β_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)
β_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)
β_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.

CHAPTER 4: REPLICATION MODIFICATIONS

In this section, we modify the model of Jacobs et al. (*AJAE* 2018) to enhance its practical application to a larger market (e.g. soybeans, non-agricultural commodity markets).

The first modification is the replacement of time variable. In the *AJAE* paper, the *time* variable measures the number of weeks left to harvest. However, that variable is not ideal because the crop progress differs from year to year, as shown in Figures 1.1 to 1.5).

Figure 1a to 1d 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[13] (*USDA Surveys/Crop Progress and Condition).* Clearly, the percentage planted varies substantially from year to year, making the *time* variable unsuitable[14].

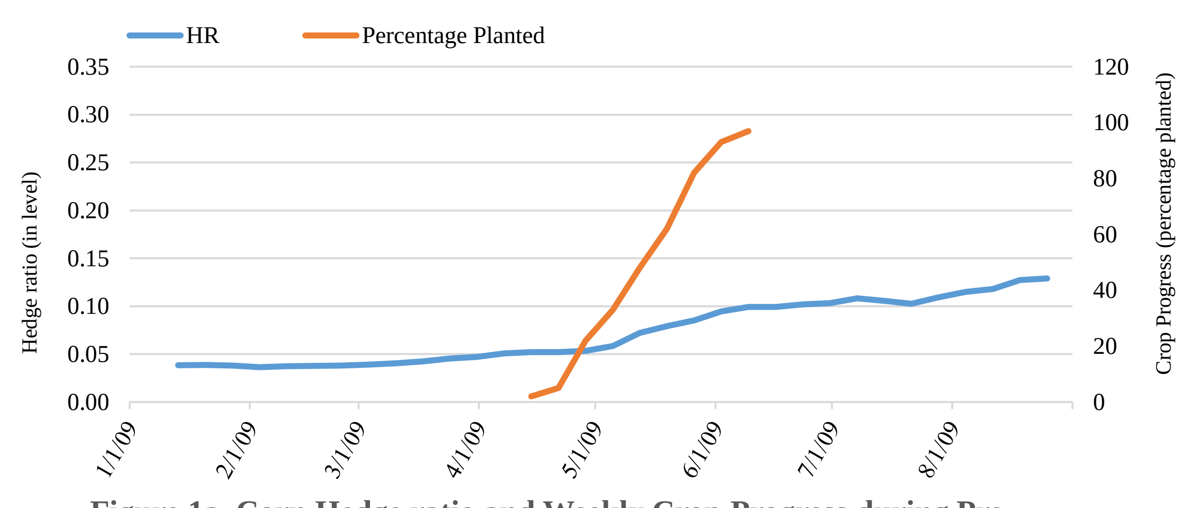

Figure 1a. Corn Hedge ratio and Weekly Crop Progress during Pre-Harvest Time in 2009. *Data Source: Bloomberg*

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

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

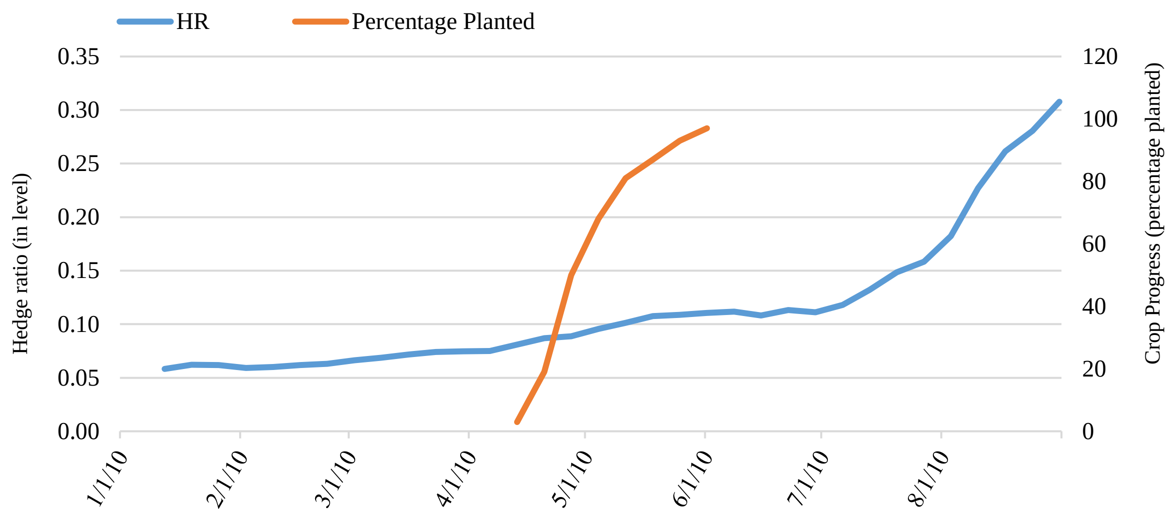

Figure 1b. Corn Hedge ratio and Weekly Crop Progress during Pre-Harvest Time in 2010. *Data Source: Bloomberg*

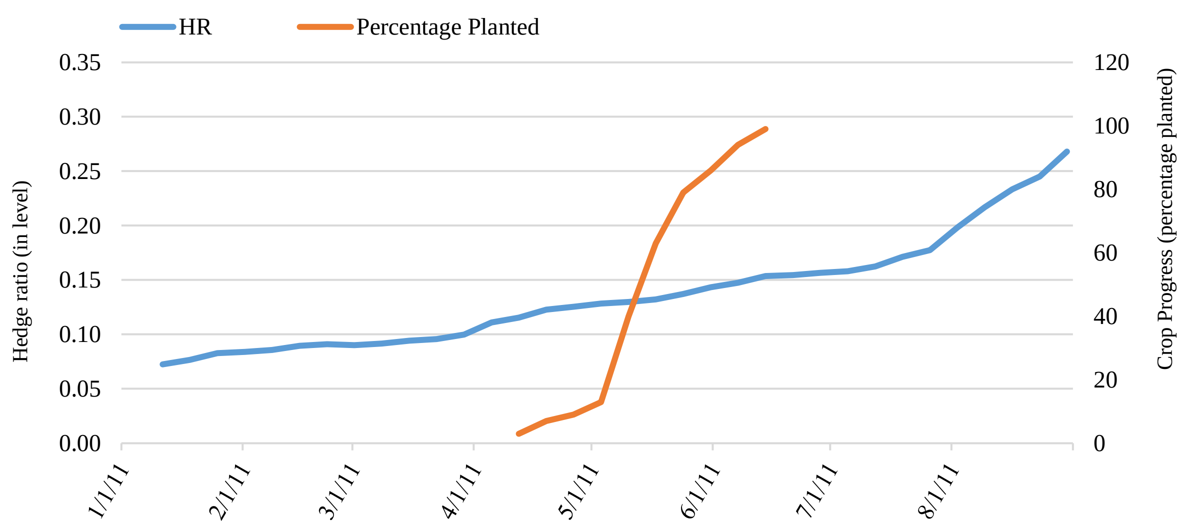

Figure 1c. Corn Hedge ratio and Weekly Crop Progress during Pre-Harvest Time in 2011. *Data Source: Bloomberg*

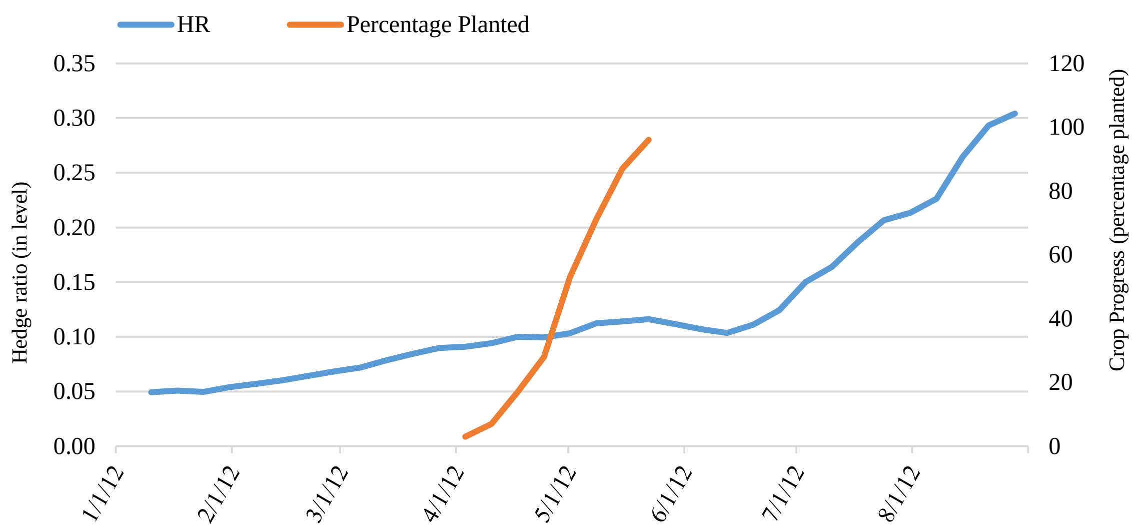

Figure 1d. Corn Hedge ratio and Weekly Crop Progress during Pre-Harvest Time in 2012. *Data Source: Bloomberg*

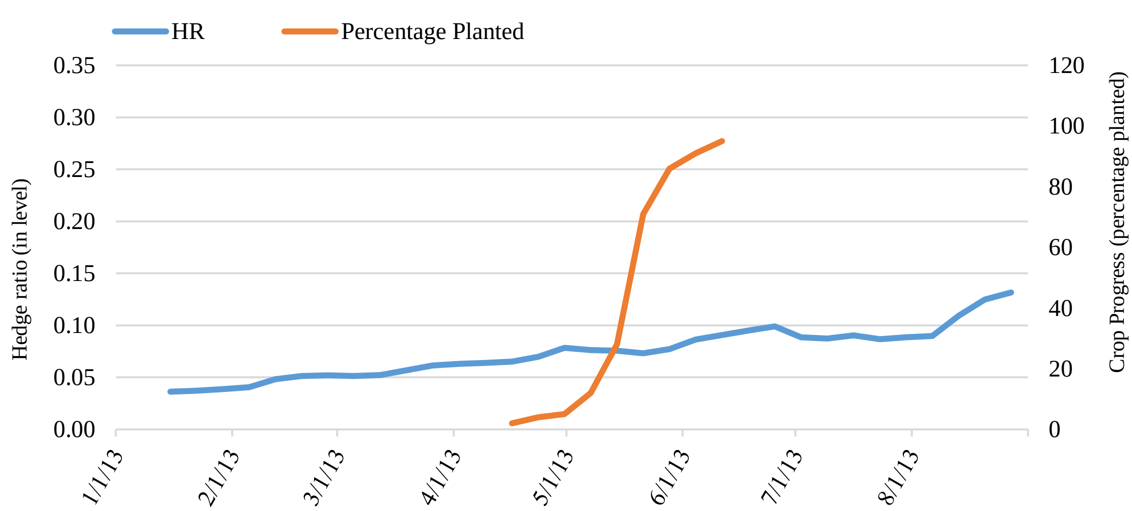

Figure 1e. Corn Hedge ratio and Weekly Crop Progress during Pre-Harvest Time in 2013. *Data Source: Bloomberg*

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: dummy 1 is for the first period, and dummy 2 is 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.

β_0 and $\beta_{1,}$ coefficients of seasonal dummy 1 and seasonal dummy2, respectively, are expected to be statistically significant with negative signs because producers will increase their hedge ratio as yield uncertainty diminishes towards harvest.

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)
α_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)
α_1			-0.002**	-0.001	-0.001	-0.001
			(0.001)	(0.001)	(0.001)	(0.001)
μ	0.622***	0.619***	0.564***	0.590***	0.607***	0.592***
	(0.059)	(0.058)	(0.061)	(0.057)	(0.059)	(0.060)
β_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)
β_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)
β_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)
β_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)
β_4			-0.012	-0.027	-0.019	-0.097***
			(0.022)	(0.018)	(0.023)	(0.033)
β_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

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.

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 other (non-agricultural) commodities. We propose replacing annual crop production by the Open Interest from the CFTC's DCOT (HR) so that the scaling factor would be 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 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[15].

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

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.

[15] 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.

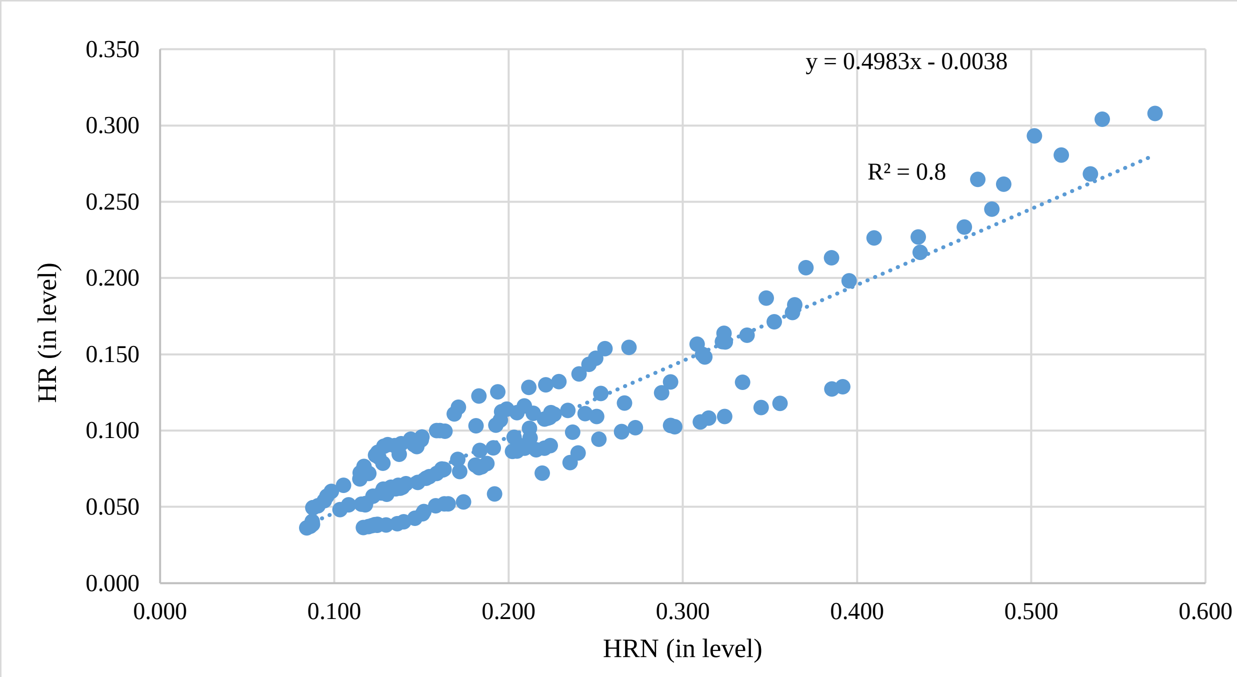

Figure 2. Coefficient Correlations of Hedge Ratios Calculated by Using Annual Crop Production as Denominator (HRN) and by Using Open Interest as Denominator (HR), Corn, Pre-harvest period 2009-2013

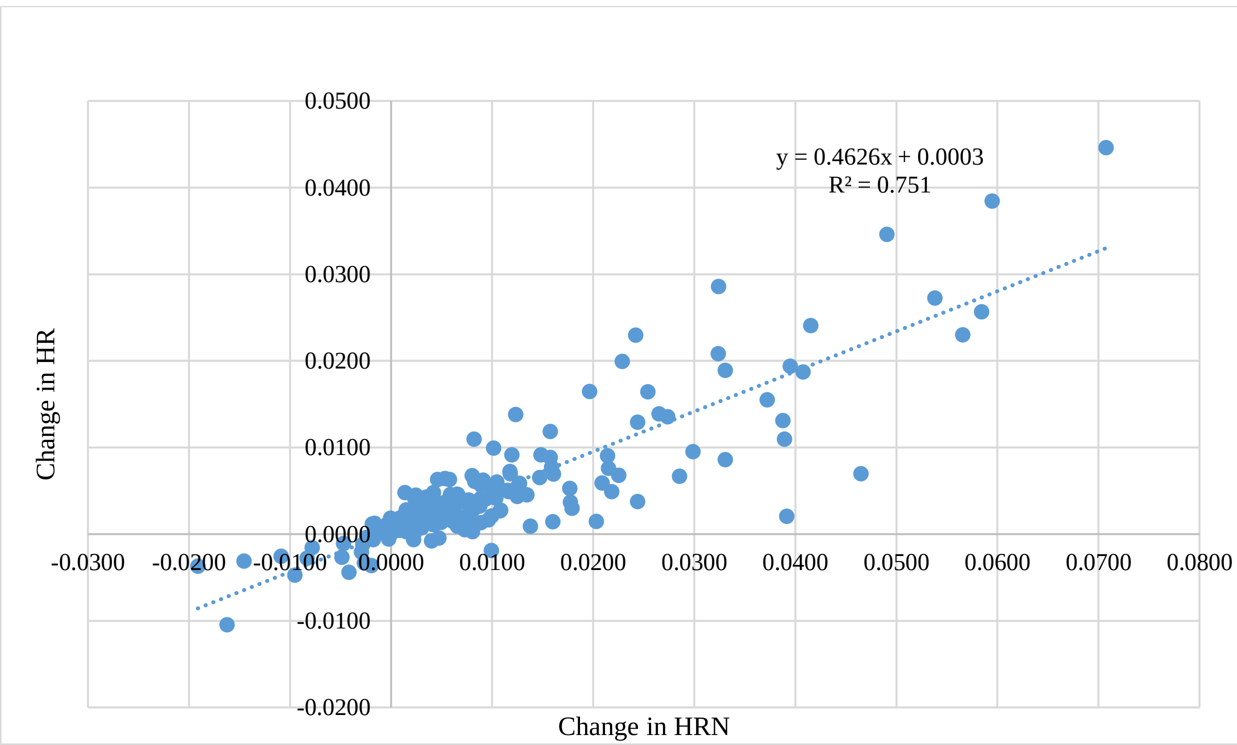

Figure 3. Coefficient Correlations of the Change in Hedge Ratio, in which Hedge Ratio is Calculated by Using Annual Crop Production as Denominator (HRN) and by Using Open Interest as Denominator (HR), Corn, Pre-harvest period 2009-2013

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

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

	No reference Price	Nonlinear Price Response	Last Year's Avg Price	RMA Forecast Price	30-day Moving Average	
					(1)	(2)
α_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)
α_1			-0.005***	-0.003	-0.002	-0.002
			(0.002)	(0.002)	(0.002)	(0.002)
μ	0.466***	0.467***	0.420***	0.442***	0.448***	0.445***
	(0.081)	(0.081)	(0.079)	(0.078)	(0.083)	(0.082)
β_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)
β_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)
β_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)
β_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)
β_4			0.087**	0.017	-0.020	-0.080
			(0.041)	(0.049)	(0.051)	(0.078)
β_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 corn implied volatility remains statistically insignificant (though it is now negative). The futures prices' coefficient is positive and 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 implied volatility by the CBOE Volatility Index, the VIX, as a proxy for market uncertainty and sentiment. As noted earlier, the commodity option-implied volatility 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* 2016; Covindassamy et al., *JFutM* 2017), because it reflects of the market sentiment and macro-economic uncertainty that simultaneously permeate both equity (Bekaert *et al.*, *JME* 2013) and commodity markets.

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

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

The coefficient of the VIX, β_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).

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)
α_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)
α_1			-0.005**	-0.003	-0.002	-0.002
			(0.002)	(0.002)	(0.002)	(0.002)
μ	0.457***	0.459***	0.412***	0.431***	0.438***	0.434***
	(0.081)	(0.081)	(0.079)	(0.079)	(0.083)	(0.082)
β_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)
β_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)
β_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)
β_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)
β_4			0.084**	0.022	-0.023	-0.097
			(0.041)	(0.051)	(0.051)	(0.074)
β_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

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 ratio drops like a stone in August for soybeans (*See Appendix A, Figure 8b),* rather than September for corn, its pre-harvest period is determined from January to July.

Table 5 presents our OLS estimates for the soybeans market during a sample period of 2009-2013, in which the implied volatility is replaced by the VIX instrument, the time variable is replaced by 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 expected negative sides. Futures prices are statistically significant with positive signs. And, while the VIX coefficient has an unexpected negative sign, it is not statistically significant.

In this section, the theoretical model proposed by Jacobs et al. (*AJAE* 2018) is generalized to a broader set of commodities with the following modifications.

First, the time variable (weeks to harvest) was replaced by two seasonal dummies that capture planting periods and the crop insurance schedule. This replacement did not change the performance of each base case as the adjusted R^2 in the new equation is only one percentage point lower than that in the equation using time variable. Other than that, the coefficients of two seasonal dummies are statistically significant with the expected negative signs; the coefficient of futures prices is statistically significant with the expected positive side, and the coefficient of corn implied volatility is statistically insignificant with the expected positive sign.

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)
α_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)
α_1			-0.002	-0.006**	-0.008***	-0.008***
			(0.003)	(0.002)	(0.003)	(0.003)
μ	0.421***	0.425***	0.400***	0.381***	0.356***	0.353***
	(0.101)	(0.100)	(0.106)	(0.110)	(0.101)	(0.100)
β_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)
β_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)
β_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)
β_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)
β_4			-0.098	-0.151*	-0.168*	-0.238**
			(0.120)	(0.078)	(0.094)	(0.113)
β_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

Second, a different method of calculating hedge ratio (using open interest from DCOT data as a denominator, and scaling the numerator accordingly) provides results that are qualitatively similar to those estimated using the original hedge ratio calculation method (based on harvest-size expectations). Particularly, the coefficients of two seasonal dummies retain their statistical significance. The coefficient of the corn implied volatility remains statistically insignificant. And, the coefficient on futures prices is statistically significant with the expected positive sign in most base cases.. Although the value of adjusted R^2 in this model is smaller than that in the previous model, we propose that it be used due to its benefits of having potentially broader uses (in that it can be applied for both agricultural and non-agricultural commodity markets).

Lastly, we submit that the commodity implied volatility may usefully be replaced by the VIX. Jacobs et al. (*AJAE* 2018) suggest using another price volatility measure because they find that corn implied volatility does not have a statistically significant impact on hedging decision. We argue that a possible reason is that, in agricultural markets, the commodity implied volatility is affected by seasonality and USDA releases. Due to the close relation with implied volatility, and the reflection of financial sentiment and macro uncertainty, we propose to use the VIX instead. Comparing to a corn model which uses implied volatility, the VIX plays a better role with the expected positive side in its coefficient, and the improvement in the goodness of fit measure.

CHAPTER 5: REPLICATION EXTENSION STUDY

In this section, we extend the examined from 2009-2013 to 2007-2019 using 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 in the corn, and soybeans markets, respectively.

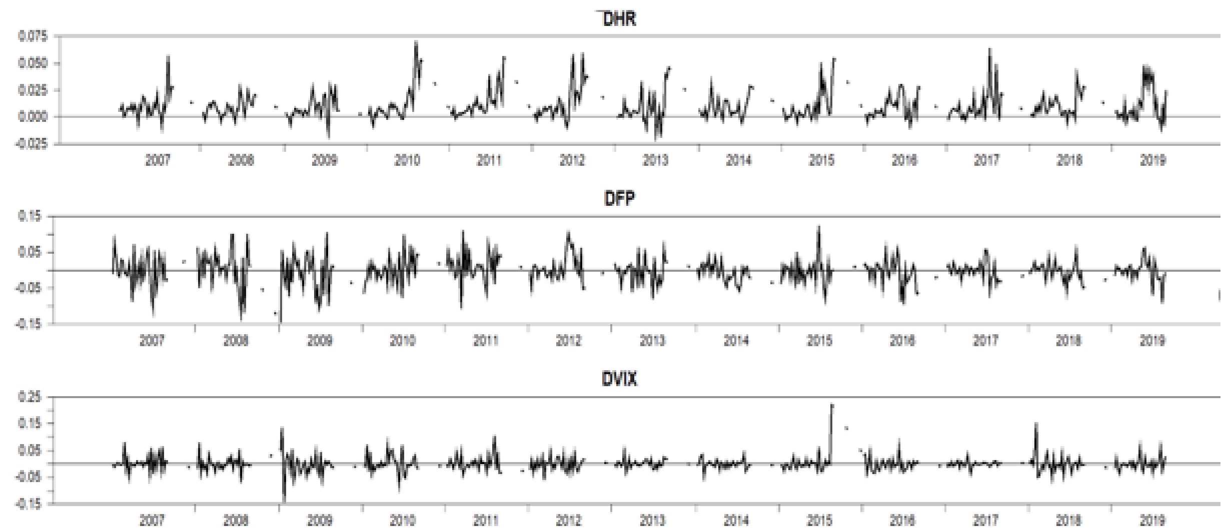

Figure 4. Weekly Changes in Hedge Ratio, Futures Prices, and VIX in Corn Futures Market, Pre-harvest period from 01/2007-08/2019

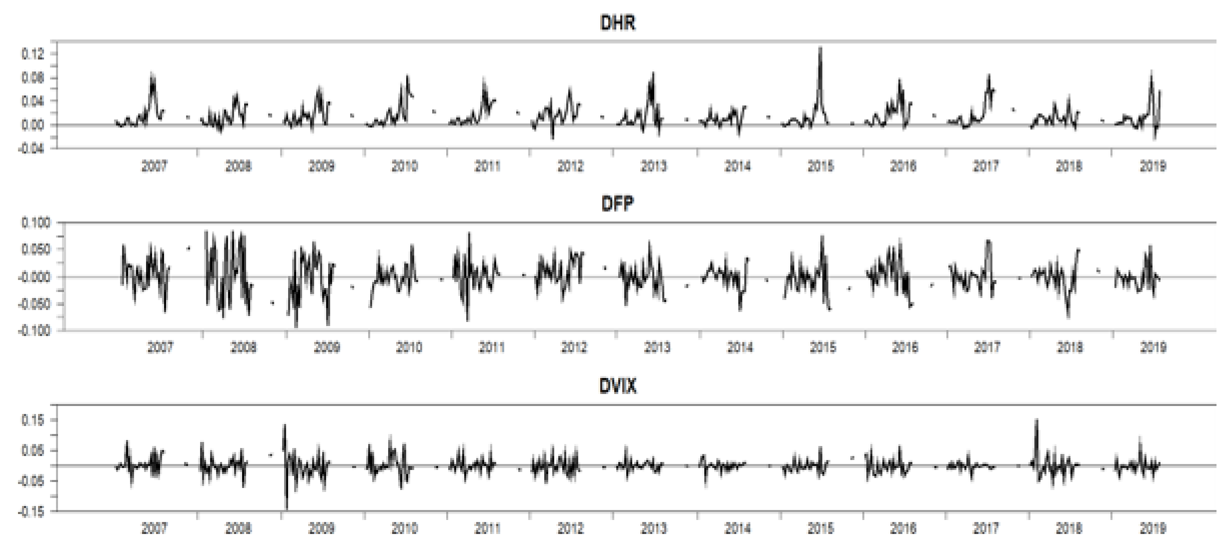

Figure 5. Weekly Changes in Hedge Ratio, Futures Prices, and VIX in Soybeans Futures Market, Pre-harvest period from 01/2007-07/2019

The year 2007 is chosen as the starting point because the data used for calculating hedge ratio is from the DCOT data, which is 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 open interest as a scaling factor to compute the hedge ratio; two seasonal dummies are used; the VIX acts as a proxy for demand-side uncertainty and market sentiment.

Tables 4 and 5 show that prolonging the examined period does not change the OLS estimates qualitatively. The two seasonal dummies are statistically significant with expected negative signs; and the futures prices' coefficient maintains its statistically significant with positive side 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 5 base cases, except for the model using last year's average price as reference. 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.

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

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

	No reference Price	**Nonlinear Price Response**	**Last Year's Avg Price**	**RMA Forecast Price**	**30-day Moving Average**	
					(1)	(2)
α_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)
α_1			-0.002**	-0.003**	-0.003***	-0.003***
			(0.001)	(0.001)	(0.001)	(0.001)
μ	0.417***	0.416***	0.397***	0.390***	0.385***	0.385***
	(0.054)	(0.054)	(0.055)	(0.054)	(0.055)	(0.055)
β_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)
β_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)
β_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)
β_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)
β_4		0.232	0.055*	0.003	-0.037	-0.025
		(0.270)	(0.032)	(0.035)	(0.038)	(0.052)
β_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: $DHR_t= \alpha_0+ \alpha_1 1\{Ft-Rt<0\} + \mu DHR\{1\}+ \beta_0 dummy_1+ \beta_1 dummy_2+ \beta_2 DVIX_t + \beta_3 DFP_t + \beta_4 DFP_t * 1\{Ft-Rt<0\} + \beta_5 DFP_t^2 + \varepsilon_t$

	No reference Price	Nonlinear Price Response	Last Year's Avg Price	RMA Forecast Price	30-day Moving Average	
					(1)	(2)
α_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)
α_1			-0.002	-0.003**	-0.004**	-0.004**
			(0.002)	(0.001)	(0.002)	(0.002)
μ	0.331***	0.327***	0.325***	0.317***	0.311***	0.317***
	(0.050)	(0.049)	(0.053)	(0.051)	(0.053)	(0.053)
β_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)
β_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)
β_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)
β_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)
β_4			0.065	-0.136**	-0.140*	-0.185***
			(0.081)	(0.059)	(0.072)	(0.067)
β_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 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 A, Figure 9a, and Figure 9b*). 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. In the meanwhile, two seasonal dummies, the VIX and futures prices maintained their significant level compared to those in the 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)
α_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)
α_1			-0.003**	-0.003**	-0.003***	-0.003***
			(0.001)	(0.001)	(0.001)	(0.001)
μ	0.416***	0.415***	0.384***	0.389***	0.383***	0.383***
	(0.053)	(0.053)	(0.053)	(0.053)	(0.054)	(0.054)
β_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)
β_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)
β_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)
β_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)
β_4			0.059*	0.005	-0.039	-0.018
			(0.031)	(0.035)	(0.039)	(0.052)
β_5		0.261				0.172
		(0.284)				(0.389)
β_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)
β_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)
α_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)
α_1			-0.004**	-0.003**	-0.004***	-0.004**
			(0.002)	(0.001)	(0.002)	(0.002)
μ	0.330***	0.326***	0.318***	0.317***	0.309***	0.313***
	(0.051)	(0.050)	(0.055)	(0.051)	(0.054)	(0.054)
β_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)
β_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)
β_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)
β_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)
β_4			0.067	-0.135**	-0.145*	-0.180***
			(0.080)	(0.059)	(0.074)	(0.068)
β_5		0.615				-0.459
		(0.731)				(0.725)
β_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)
β_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 IV during financial crisis. Particularly, when looking at the movements of VIX and option-implied volatility during 2007-2019 period (*Appendix A, Figure 10a, and Figure 10b*), we note that (i) the VIX has two big jumps: one is in fall 2008 to summer 2009, and the other one is during summer and fall 2012; (ii) although commodity implied volatilities also show concomitant 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 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 β_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 β_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's 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)
α_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)
α_1			-0.002**	-0.003**	-0.003**	-0.003**
			(0.001)	(0.001)	(0.001)	(0.001)
μ	0.416***	0.414***	0.395***	0.388***	0.383***	0.383***
	(0.054)	(0.054)	(0.054)	(0.053)	(0.055)	(0.054)
β_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)
β_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)
β_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)
β_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)
β_4			0.055*	0.003	-0.038	-0.031
			(0.032)	(0.035)	(0.039)	(0.055)
β_5		0.226				0.063
		(0.272)				(0.398)
β_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)
α_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)
α_1			-0.002	-0.003**	-0.004***	-0.004***
			(0.002)	(0.001)	(0.002)	(0.002)
μ	0.332***	0.328***	0.326***	0.319***	0.312***	0.317***
	(0.050)	(0.049)	(0.053)	(0.052)	(0.053)	(0.053)
β_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)
β_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)
β_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)
β_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)
β_4			0.059	-0.139**	-0.145**	-0.182***
			(0.080)	(0.059)	(0.073)	(0.070)
β_5		0.611				-0.461
		(0.652)				(0.624)
β_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

In this Chapter, we extended the examined period from 5 years to 13 years, after adapting the same Equation 3 introduced in the previous Chapter (4). For this longer period, the high level of hedge ratio in corn and soybeans markets (perhaps due to the commodity price spike during 2007-2008 period) and the financial crisis during 2009-2011 are controlled by the dummies in Equation 4. We also examine the relationship between the VIX and option-implied volatilities, and introduce an interaction term to capture the decoupling between those two series during two large jumps in the value of VIX (one is in fall 2008 to summer 2009, and the other one is during summer and fall 2012) presented in Equation 5.

The results from Table 6 to Table 11 provide evidence that (i) the theoretical model proposed by Jacobs et al. (*AJAE* 2018), with adjusted proxies for market fundamentals, remains valid over the long run (13-year period vs. 5); (ii) the role of futures prices on hedging decisions is always statistically significant, across all base cases and in both the corn and soybeans markets; (iii) there is mixed statistical evidence that the VIX statistically significantly affects hedging behavior; (iv) the two seasonal dummies continue are statistically significant, showing that hedging picks up in the summer months.[16]

[16] We also extended the model by introducing year dummies and interaction term of the VIX*DummyVIX. Neither change improved the model performance as judged by the adjusted R^2 compared to that in the model without having those proposed dummies. The extra variables do not show statistically significant impacts – cue the statistically insignificant level of year dummies' coefficients (Equation 4) and the interaction term's coefficient (Equation 5).

CHAPTER 6: THE STRUCTURAL VAR MODEL

In the previous Chapters, we provide evidences that the 2018 *AJAE* optimal model with some modifications estimated by OLS regression can be generalized to a longer period and to other commodities. In this section, we use structural vector autoregression (SVAR) 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 A, Figure 8a and Figure 8b*). 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 thesis 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 variables in the ordered SVAR model. In the corn market, a change in December futures prices is the price measure because the December contract is the benchmark. In the meanwhile, in the soybeans market, the November contract plays the same role, so a change in November futures prices is used as the price variable.

Price Uncertainty. The 2018 *AJAE* paper uses the weekly change in December corn implied volatility as a price volatility measure. However, the coefficient of implied volatility is found to be statistically insignificant. In addition, agricultural implied volatilities are affected by seasonality and by USDA releases (Cao and Robe, *AAEA* 2020). Due to the close relationship of the VIX – the CBOE Volatility Index and commodity implied volatilities (Robe and Wallen, *JFutM* 2016; Adjemian et al., *AAEA* 2016; Covindassamy et al., *JFutM* 2017), and its reflection of financial sentiment and demand-side uncertainty (Bekaert *et al.*, *JME* 2013), 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

$$A(L)y_t = \theta z_t + \varepsilon_t \qquad (6)$$

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

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

As in Bu̲yüksahin, 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 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, the dummy 1 has value of 1 when it is January and February, and 0 otherwise. The dummy 2 covers the planting time, which has a value of 1 when it is from March to May, and 0 otherwise.

CHAPTER 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 (0.003)	-0.004 (0.004)	0.011*** (0.001)
DVIX{1}	-0.269*** (0.051)	0.058 (0.069)	-0.010 (0.020)
DFP{1}	-0.010 (0.038)	0.034 (0.051)	0.060*** (0.015)
DHR{1}	0.191 (0.135)	0.104 (0.182)	0.325*** (0.054)
DVIX{2}	-0.094* (0.051)	0.041 (0.069)	0.010 (0.020)
DFP{2}	0.073* (3.801)	0.045 (0.051)	0.036** (0.015)
DHR{2}	-0.192 (0.133)	-0.123 (0.180)	0.081 (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 (0.004)	0.0004 (0.004)	0.022*** (0.002)
DVIX{1}	-0.301*** (0.051)	-0.014 (0.059)	-0.029 (0.030)
DFP{1}	0.001 (0.048)	0.028 (0.056)	0.040 (0.029)
DHR{1}	0.026 (0.094)	-0.011 (0.109)	0.317*** (0.056)
DVIX{2}	-0.136*** (0.051)	-0.063 (0.060)	0.069** (0.031)
DFP{2}	0.053 (0.048)	0.007 (0.056)	0.066** (0.028)
DHR{2}	-0.094 (0.093)	-0.003 (0.108)	-0.048 (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

Impulse response functions are estimated 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.

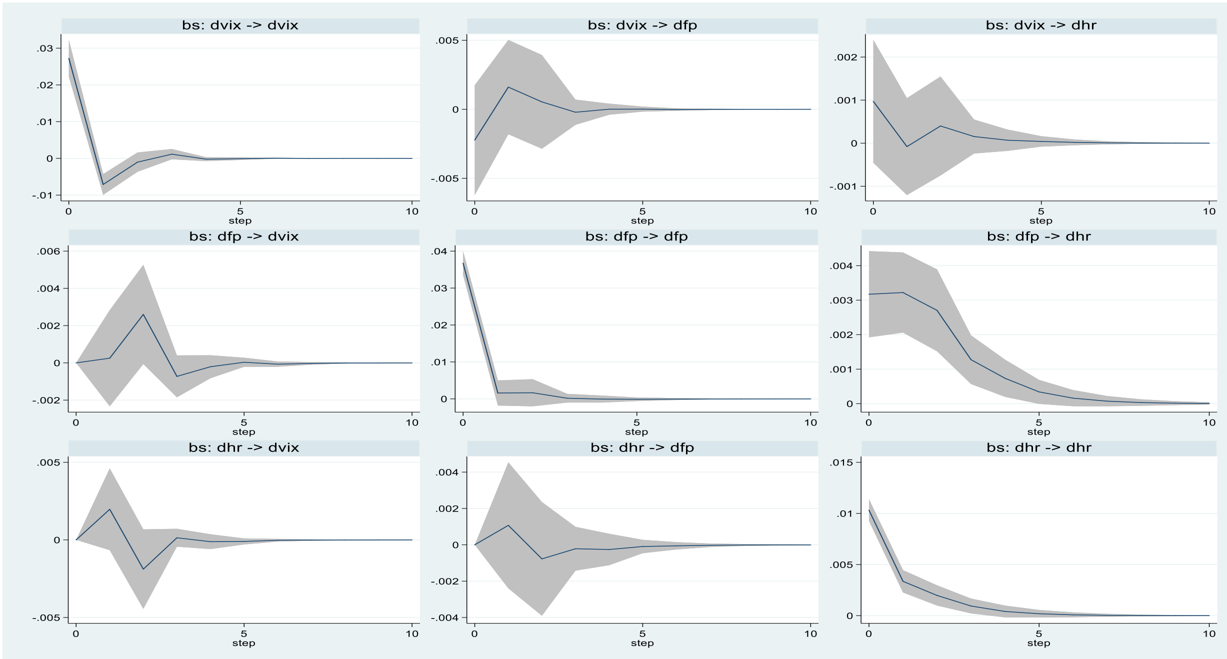

Figure 6. Impulse Response Functions for corn- Structural VAR in first differences, 2007-2019

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

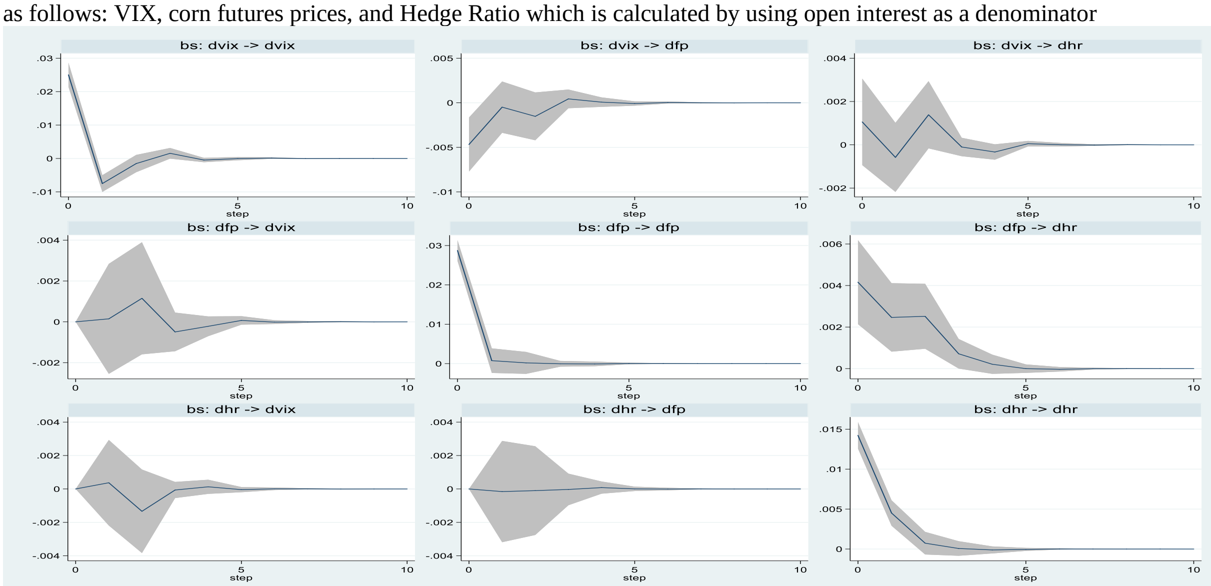

Figure 7. Impulse Response Functions for soybeans- Structural VAR in first differences, 2007-2019

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 results in Figure 6 and Figure 7. These figures show that a key driver of commercial traders' hedging decisions is the commodity price. Particularly, the standard deviation of weekly returns (precisely, log price changes) is 3.76% in the corn space, and 2.96% in the soybeans space. A one-standard deviation positive shock to corn/soybeans prices leads to a statistically significant increase in the magnitude of commercial traders' aggregated net short positions. The impact of a such futures price shock remains statistically significant 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 lasts 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 95% significant level. Intuitively, the higher the price volatility is, 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 both corn and soybeans markets at 95% confidence level. The results are slightly different from the OLS regression findings in Table 6 and Table 7, in which the VIX's coefficient is found to be 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.

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: 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 IV 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 B*, *Table 16 to Table 21*) 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 A, Figure 11a and Figure 11b*) 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 A, Figure 11a)* 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 A, Figure 11b)*. 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 A, Figure 12a, Figure 12b, Figure 13a, and Figure 13b)* compared to that in the model without adding them (Figure 6 and Figure 7).

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.

CHAPTER 8: CONCLUSIONS

In this thesis, 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.

By employing the optimal hedging model to analyze the impact of futures price on commercial traders' aggregated net positioning, we contribute to the literature by assessing the usefulness of the DCOT data as a benchmark when examining hedging behavior. In addition, we improve the practical application of the theoretical model of optimal hedging to a longer period and to a larger commodity market by introducing better proxies for market fundamentals, and an alternative for calculating hedge ratio. Particularly, the modified optimal hedging model which uses the VIX as measure of price uncertainty eliminates possible issues due to the effects of seasonality and USDA announcements on commodity option-implied volatilities. In addition, two seasonal dummies that capture seasonalities in the yearly planting and crop insurance schedule enhance the timing measure in the model. Furthermore, the newly proposed hedge ratio using open interest from DCOT data as a scaling factor has a potential for broader use beyond agricultural markets. The SVAR model helps deal with endogeneity issue in investigating the effects of futures prices and of the VIX on commercial traders' aggregate net short positions.

Both the IRFs retrieved from the SVAR and the OLS regressions show similar results. First, The VIX's effects on commercial hedging decisions need to be further investigated as it is seldom significant. 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 thesis' findings.

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APPENDIX A: FIGURES

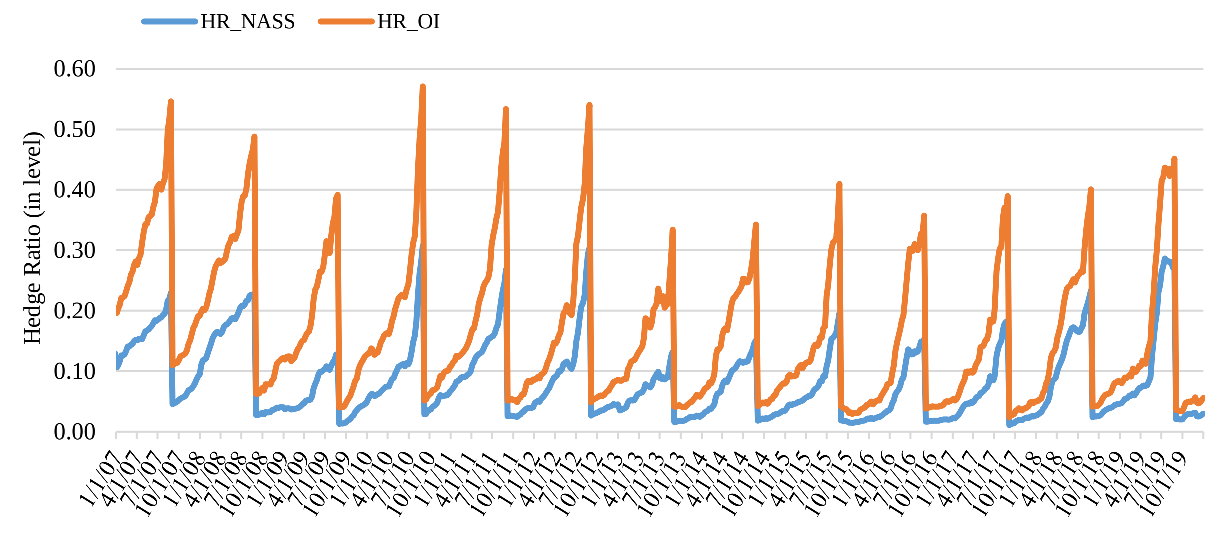

Figure 8a. Weekly Hedge Ratio, Corn, 01/2007-12/2019, Hedge Ratio Calculated by Using USDA's Annual Crop (HRN) as a Denominator, and by Using Open Interest (HR) as a Denominator
Data source: Bloomberg

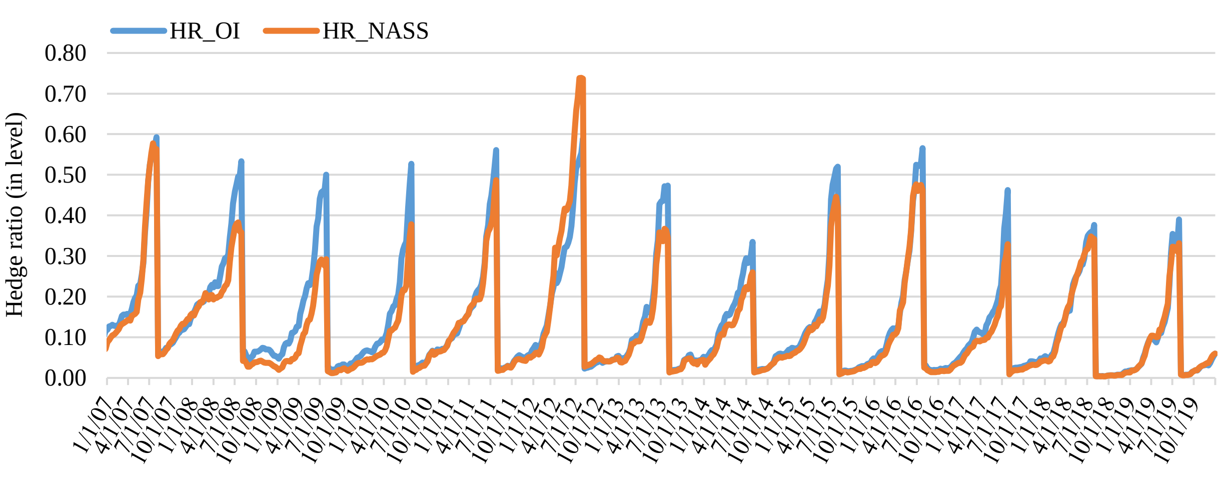

Figure 8b. Weekly Hedge Ratio, Soybeans, 01/2007-12/2019, Hedge Ratio Calculated by Using USDA's Annual Crop (HRN) as a Denominator, and by Using Open Interest (HR) as a Denominator
Data source: Bloomberg

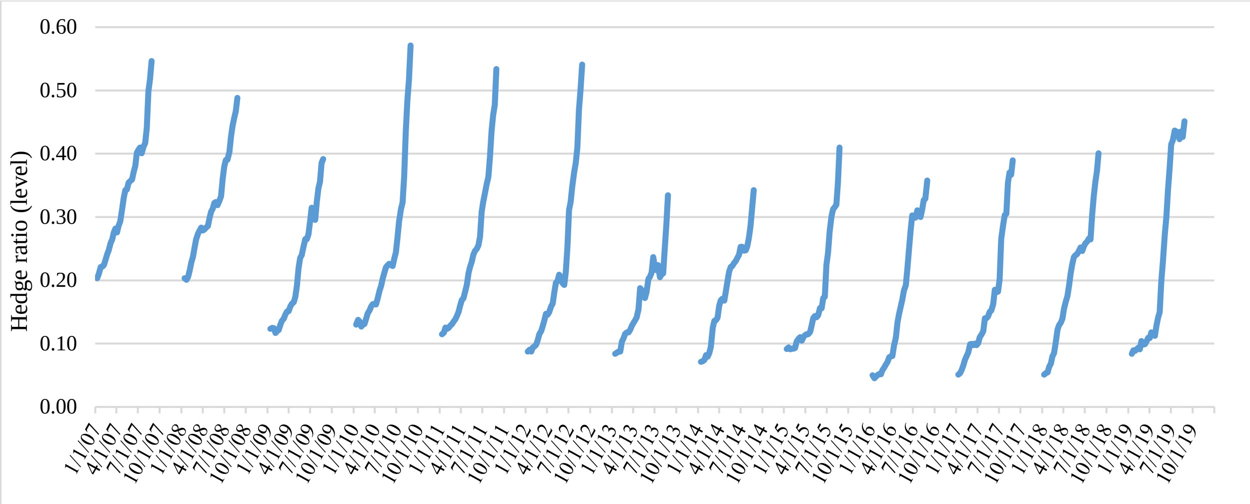

Figure 9a. Hedge ratios (in level) of Corn Producers (Hedge Ratio is Calculated by Using Open Interest as a Denominator), Pre-harvest Time from 01/2007-08/2019.
Data Source: Bloomberg

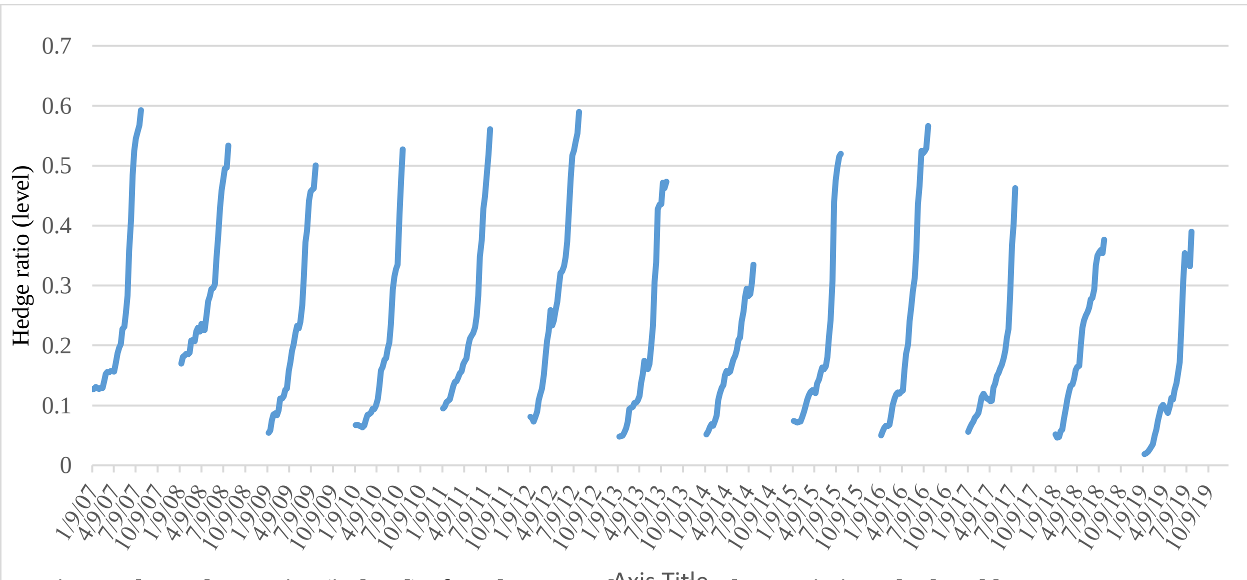

Figure 9b. Hedge Ratios (in level) of Soybean Producers (Hedge Ratio is Calculated by Using Open Interest as a Denominator, Pre-harvest Time from 01/2007-07/2019.
Data source: Bloomberg

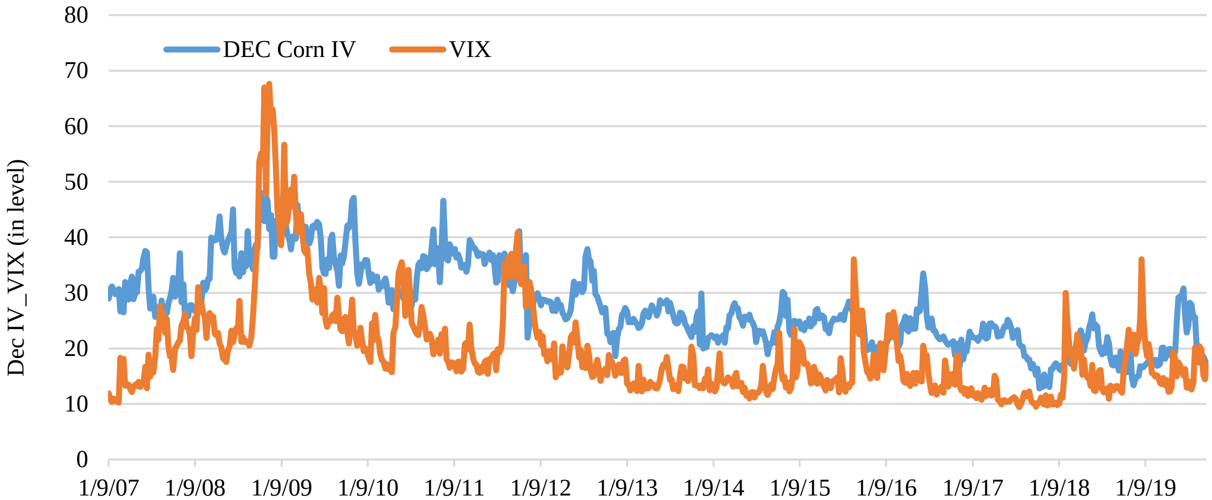

Figure 10a. Weekly VIX and December Corn IV, 01/2007-9/2019
Data source: Blomberg

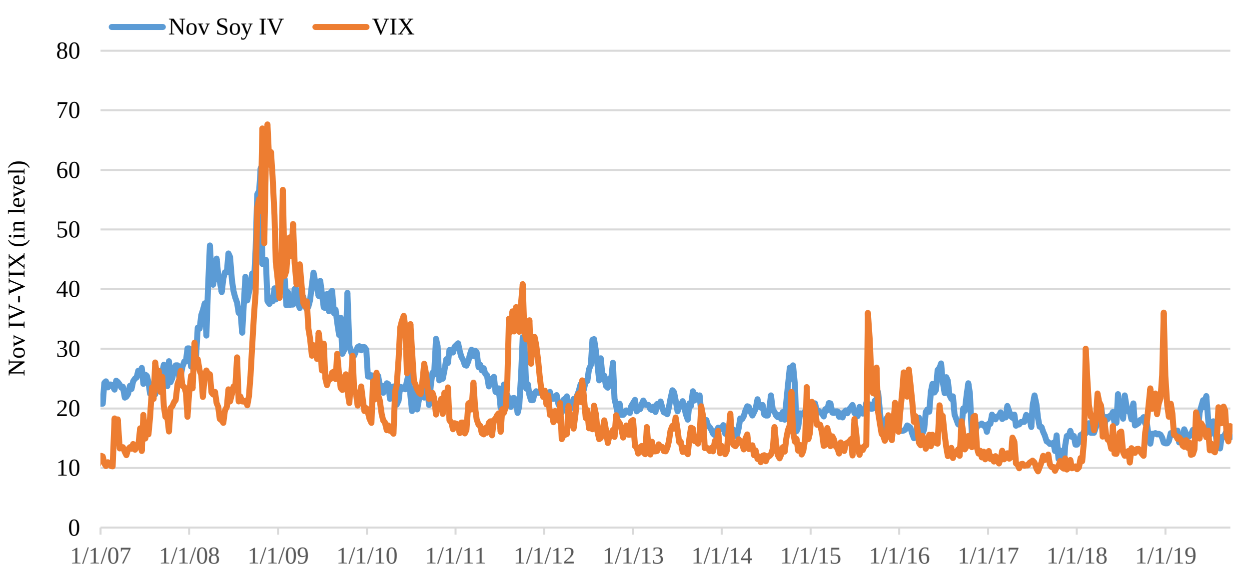

Figure 10b. Weekly VIX and November Soy IV, 01/2007- 09/2019.
Data source: Bloomberg

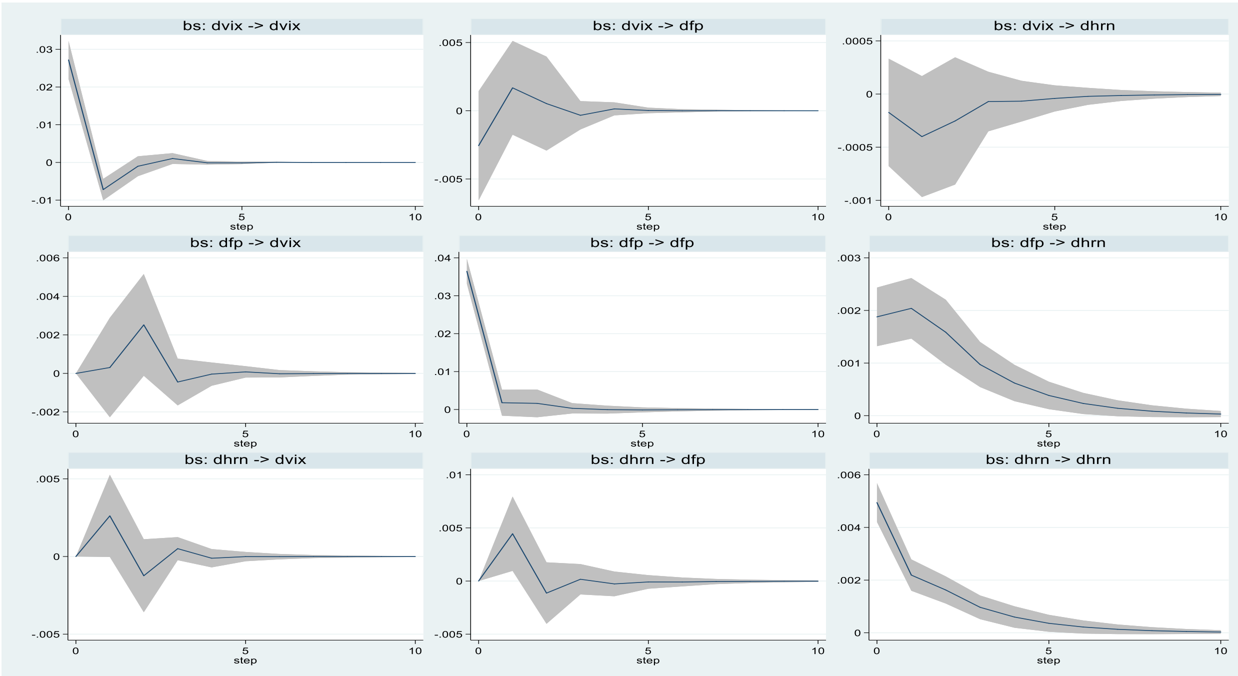

Figure 11a. Impulse Response Functions for corn- Structural VAR in first differences with DHRN, 2007-2019
Note: Figure 11.1 plots 10-week impulse responses of the SVAR model including the change in S&P 500 option-implied volatility representing for macroeconomic uncertainty, VIX; the change in corn futures 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

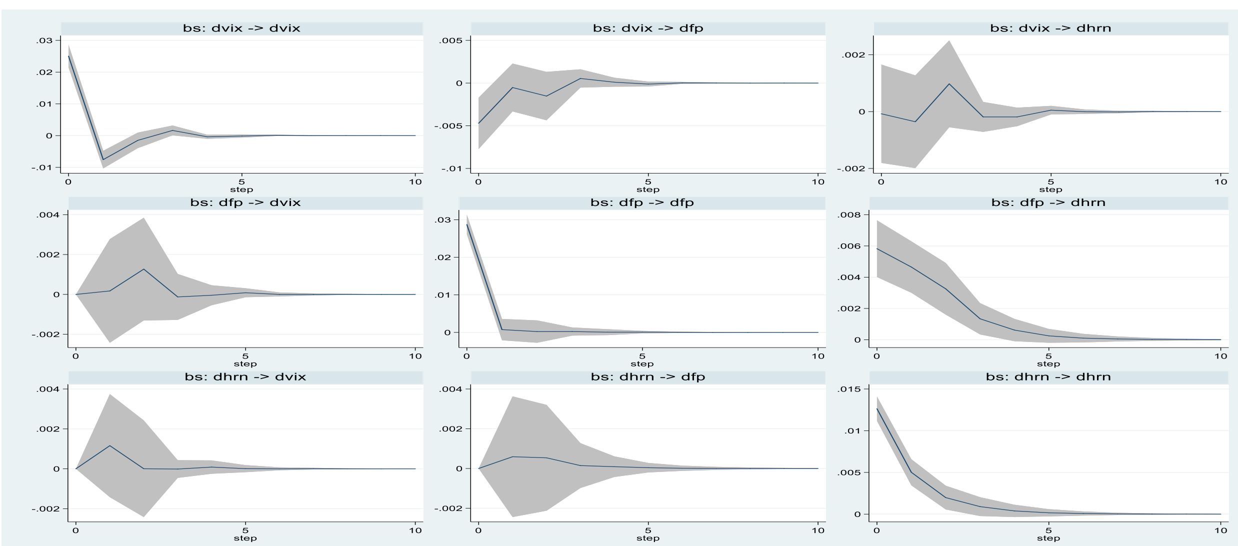

Figure 11b. Impulse Response Functions for soybeans- Structural VAR in first differences with DHRN, 2007-2019
Note: Figure 11.2 plots 10-week impulse responses of the SVAR model including the change in S&P 500 option-implied volatility representing for macroeconomic uncertainty, VIX; the change in soybeans 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

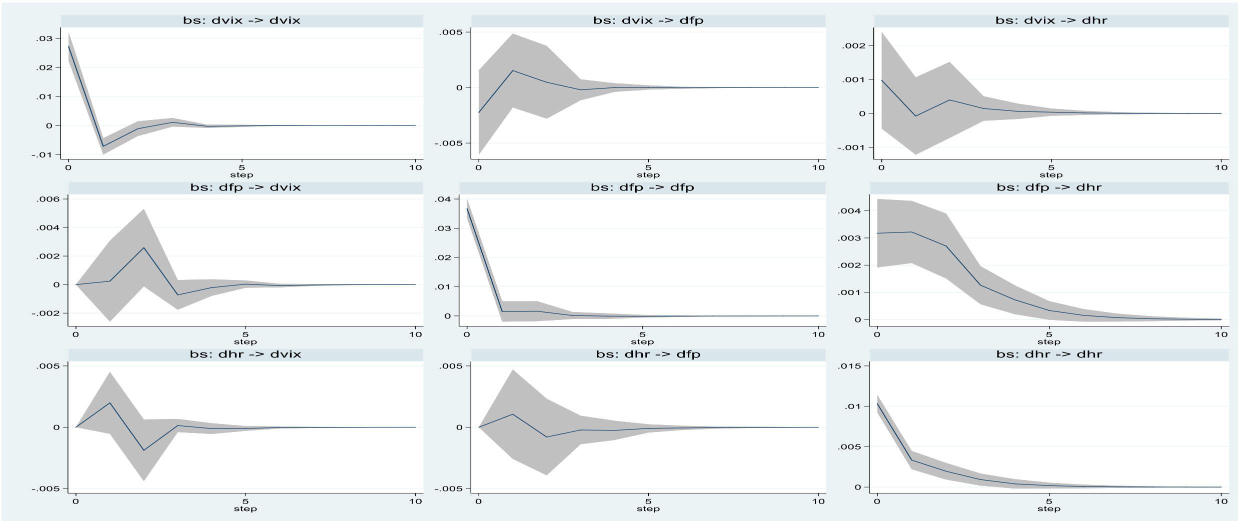

Figure 12a. Impulse Response Functions for corn- Structural VAR in First Differences Adding Year Dummies as Exogenous Variables, 2007-2019

Note: Figure 12.1 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

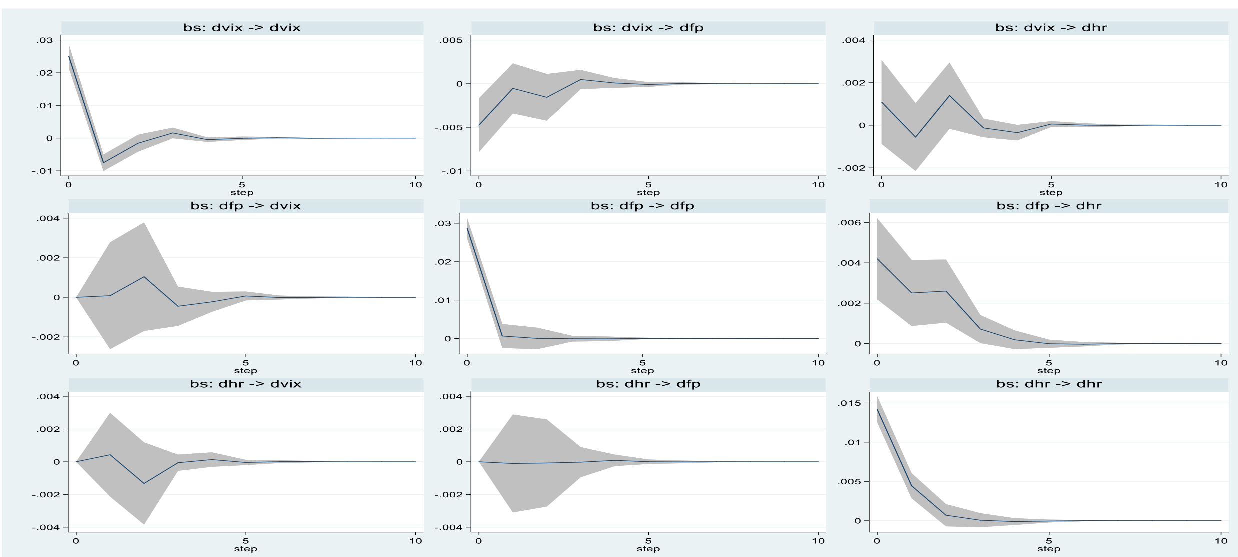

Figure 12b. Impulse Response Functions for soybeans- Structural VAR in First Differences Adding Year Dummies as Exogenous Variables, 2007-2019

Note: Figure 12.2 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

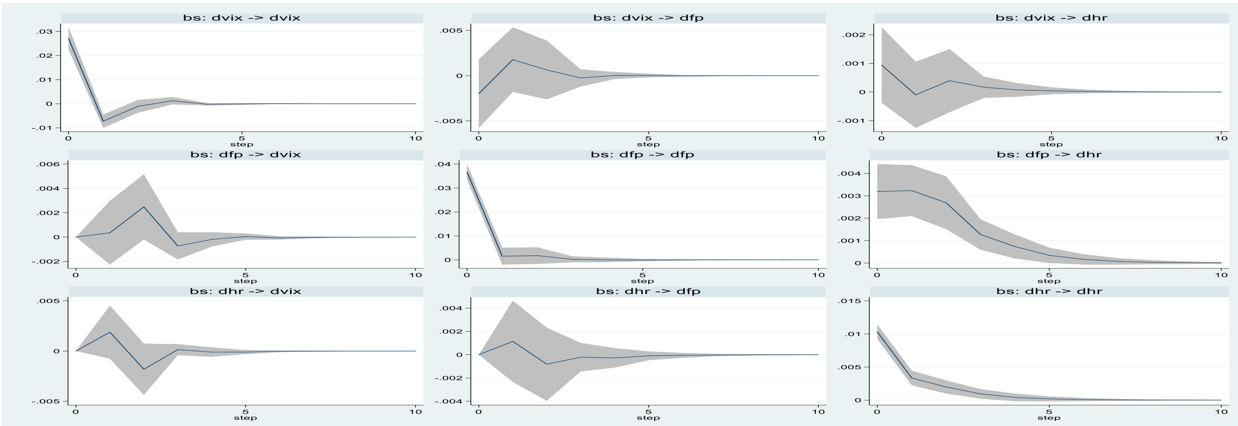

Figure 13a. Impulse Response Functions for corn- Structural VAR in First Differences Adding Financial Crisis Dummy as Exogenous Variable, 2007-2019

Note: Figure 13.1 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

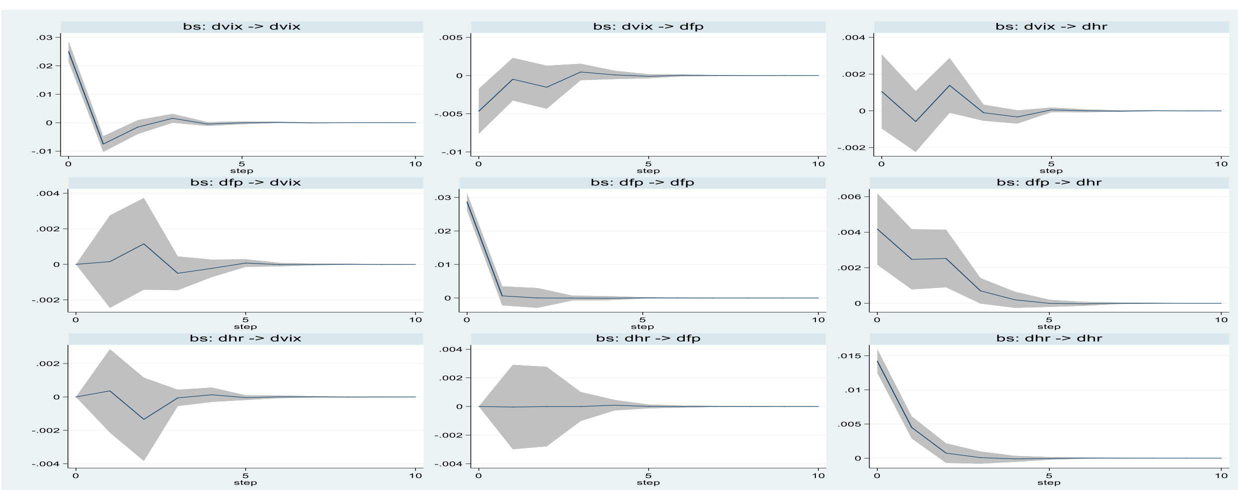

Figure 13b. Impulse Response Functions for soybeans- Structural VAR in First Differences Adding Financial Crisis Dummy as Exogenous Variable, 2007-2019

Note: Figure 13.2 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 B: TABLES

Table 14. Summary Statistics, Corn, Pre-Harvest Period, 2007-2019

SUMMARY STATISTICS_CORN						
	HR	**DHR**	**HRN**	**DHRN**	**DVIX**	**DFP**
Median	0.2041	0.0068	0.1011	0.0033	-0.0019	-0.0004
Mean	0.2203	0.0102	0.1131	0.0049	0.0005	-0.0013
Standard deviation	0.1139	0.0130	0.0626	0.0068	0.0289	0.0376
Variance	0.0130	0.0002	0.0039	0.00005	0.0008	0.0014
Min	0.0453	-0.0191	0.0208	-0.0104	-0.1440	-0.1466
Max	0.5710	0.0707	0.3078	0.0446	0.2223	0.1238

Table 15. Summary Statistics, Soybeans, Pre-Harvest Period, 2007-2019

SUMMARY STATISTICS_SOYBEANS						
	HR	**DHR**	**HRN**	**DHRN**	**DVIX**	**DFP**
Median	0.1690	0.0095	0.1429	0.0079	-0.0022	0.0012
Mean	0.2134	0.0146	0.1897	0.0121	-0.0006	0.0009
Standard deviation	0.1405	0.0186	0.1387	0.0168	0.0272	0.0296
Variance	0.0197	0.0003	0.0192	0.0003	0.0007	0.0009
Min	0.0188	-0.0255	0.0181	-0.0263	-0.1440	-0.0961
Max	0.5927	0.1314	0.7387	0.0975	0.1519	0.0852

Table 16. Reduced-form VAR Regression Estimates, Corn, Pre-Harvest Period, 2007-2019, Using DHRN

	Equation		
	DVIX	**DFP**	**DHRN**
Intercept	0.001 (0.003)	-0.006* (0.004)	0.004*** (0.001)
DVIX{1}	-0.263*** (0.051)	0.068 (0.068)	-0.009 (0.010)
DFP{1}	-0.019 (0.039)	0.003 (0.052)	0.033*** (0.008)
DHRN{1}	0.529* (0.272)	0.901** (0.366)	0.443*** (0.053)
DVIX{2}	-0.094* (0.051)	0.049 (0.068)	-0.005 (0.010)
DFP{2}	0.060 (0.039)	0.027 (0.052)	0.012 (0.008)
DHRN{2}	-0.329 (0.268)	-0.666* (0.360)	0.107** (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 17. Reduced-form VAR Regression Estimates, Soybeans, Pre-Harvest Period, 2007-2019, Using DHRN

	Equation		
	DVIX	**DFP**	**DHRN**
Intercept	-0.004 (0.004)	-0.002 (0.004)	0.013*** (0.002)
DVIX{1}	-0.304*** (0.051)	-0.018 (0.059)	0.002 (0.028)
DFP{1}	-0.013 (0.051)	0.016 (0.059)	0.081*** (0.028)
DHRN{1}	0.092 (0.107)	0.047 (0.125)	0.397*** (0.060)
DVIX{2}	-0.144*** (0.051)	-0.066 (0.060	0.056** (0.029)
DFP{2}	0.033 (0.050)	-0.005 (0.058)	0.048* (0.028)
DHRN{2}	-0.008 (0.107)	0.025 (0.124)	-0.004 (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 18. Reduced-form VAR Regression Estimates, Corn, Pre-Harvest Period, 2007-2019, Adding Year Dummies as Exogenous Variables

	Equation		
	DVIX	**DFP**	**DHR**
Intercept	0.002 (0.003)	-0.005 (0.004)	0.011*** (0.001)
DVIX{1}	-0.269*** (0.051)	0.055 (0.069)	-0.009 (0.020)
DFP{1}	-0.010 (0.038)	0.033 (0.051)	0.060*** (0.015)
DHR{1}	0.193 (0.135)	0.103 (0.182)	0.324*** (0.054)
DVIX{2}	-0.095* (0.051)	0.039 (0.069)	0.010 (0.020)
DFP{2}	0.072* (0.038)	0.044 (0.051)	0.036** (0.015)
DHR{2}	-0.192 (0.133)	-0.125 (0.180)	0.081 (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 19. Reduced-form VAR Regression Estimates, Soybeans, Pre-Harvest Period, 2007-2019, Adding Year Dummies as Exogenous Variables

	Equation		
	DVIX	**DFP**	**DHR**
Intercept	-0.0002 (0.004)	-0.0004 (0.004)	0.022*** (0.002)
DVIX{1}	-0.303*** (0.051)	-0.017 (0.059)	-0.028 (0.030)
DFP{1}	-0.002 (0.048)	0.024 (0.056)	0.041 (0.029)
DHR{1}	0.030 (0.094)	-0.007 (0.109)	0.314*** (0.056)
DVIX{2}	-0.139*** (0.051)	-0.067 (0.060)	0.070** (0.031)
DFP{2}	0.048 (0.048)	0.002 (0.056)	0.069** (0.028)
DHR{2}	-0.094 (0.093)	-0.002 (0.108)	-0.048 (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 20. 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 (0.003)	-0.004 (0.004)	0.011*** (0.001)
DVIX{1}	-0.275*** (0.051)	0.064 (0.069)	-0.010 (0.020)
DFP{1}	-0.006 (0.038)	0.031 (0.051)	0.060*** (0.015)
DHR{1}	0.183 (0.134)	0.111 (0.182)	0.324*** (0.054)
DVIX{2}	-0.101** (0.051)	0.047 (0.069)	0.009 (0.020)
DFP{2}	0.071* (0.038)	0.047 (0.051)	0.035** (0.015)
DHR{2}	-0.184 (0.133)	-0.130 (0.180)	0.082 (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 21. 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 (0.004)	0.0005 (0.004)	0.022*** (0.002)
DVIX{1}	-0.301*** (0.051)	-0.015 (0.059)	-0.029 (0.030)
DFP{1}	0.002 (0.048)	0.023 (0.056)	0.040 (0.029)
DHR{1}	0.026 (0.094)	-0.003 (0.109)	0.316*** (0.056)
DVIX{2}	-0.136*** (0.051)	-0.065 (0.060)	0.069** (0.031)
DFP{2}	0.053 (0.048)	0.0004 (0.056)	0.067** (0.028)
DHR{2}	-0.095 (0.093)	0.001 (0.108)	-0.048 (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