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# What Drives Volatility Expectations in Grain and Oilseed Markets?

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# **What Drives Volatility Expectations in Grain and Oilseed Markets?**

## **Abstract**

We analyze empirically the drivers of option-implied volatilities (IVs) for major agricultural commodities. We document that forward-looking uncertainty and risk aversion in equity market (jointly captured by the VIX) as well as the state of grain or oilseed inventories (proxied by the net cost of carry for each commodity) have significant impacts on forward-looking volatility in the three largest U.S. agricultural markets: corn, soybeans, and wheat. We also find some evidence that financial speculation has an immediate, but short-lived and negative, impact on IVs. The relative importance of macroeconomic *vs.* commodity-specific drivers varies across commodities and over time, with VIX shocks having a greater effect on commodity IVs during recessions. The impact of inventory shocks is asymmetrical: (near-)stockouts boost IVs to a greater extent than plentiful stocks moderate IVs.

## 1. Introduction

Since the mid-2000's, field crop prices have experienced considerable spikes and falls. While not unusual in historical terms (Wright, 2000), recent episodes of elevated grain and oilseed price volatility have hurt consumers and attracted the attention of market regulators and researchers worried about their sources and implications. For commodity merchandisers, farmers, and other market participants, knowing what drives this volatility is important for both short-run hedging decisions and—over the longer run—“effective commodity marketing and efficient derivative pricing” (Egelkraut, Garcia, and Sherrick, 2007 p.1). That is, a better understanding of market volatility and uncertainty is bound to increase the efficiency of decision making in the agricultural sector. The same need applies to managers of, and participants in, the Federal Crop Insurance Program (FCIP, i.e., the “primary means through which the United States government subsidizes domestic agriculture”), given that the FCIP relies on “market implied volatilities to price around \$80 billion in liabilities annually (and is) the largest direct agricultural subsidy program” (Woodard and Sproul, 2016 pp. 2-3).

The extant empirical literature has been principally concerned with realized (i.e., *past*) commodity market volatility—see, e.g., Karali, Power, and Ishdorj (2011), McPhail, Du, and Muhammad (2012), Karali and Power (2013), Etienne, Irwin, and Garcia (2015), and Brunetti, Büyüksahin, and Harris (2016). Matching market participants' forward-looking perspective, we seek instead to understand what drives their expectations of *future* volatility.

Egelkraut, Garcia, and Sherrick show that the volatility expectations embedded in the prices of options on field crop futures “anticipate realized volatilities and their (seasonal) patterns well” (2007, p.2). We build on their results and carry out the first empirical analysis of the extent

to which option-implied volatilities (IVs) themselves are driven by uncertainty and risk aversion in the broad economy *vs.* by developments specific to the agricultural space.

To that effect, we use a newly constructed weekly dataset of financial and fundamental variables. To promote domestic production, the U.S. Department of Agriculture (USDA) collects, and publishes weekly, administrative data on the progress and condition of key crops. Linking these USDA figures with other weekly data between 1995 and 2015 yields a 20-year dataset of fundamental factors in physical grain and oilseed markets, which we augment with weekly proxies for the intensity of financialization in individual agricultural futures markets and for global macroeconomic conditions—including proxies for uncertainty and risk aversion in financial markets.

The first explanatory variable we consider is the level of the Chicago Board Options Exchange (CBOE) Volatility Index or VIX, which is constructed using the implied volatilities of a wide range of options on Standard and Poor's S&P 500 equity index. Bekaert, Hoerova, and Lo Duca (2013) link the VIX to uncertainty about world macroeconomic conditions and to global risk aversion. Intuitively, both of those factors should significantly impact uncertainty regarding future levels of crop demand. Our other explanatory variables are specific to grain and oilseed markets.

The first of those other variables is the precautionary and speculative demand for field crops that is reflected in the state of inventories. Consistent with the forward-looking nature of our IV analysis, we use market participants' expectations of future storage levels that are embedded in the slope of the term structures of agricultural commodity futures prices. Bruno, Büyükşahin, and Robe (2017) show that this price-based proxy is closely related to the USDA's monthly forecasts of end-of-crop-cycle ("ending") stock levels.

We capture weather's impact on agricultural commodity-market supply through progress and condition indices for different crops. Intuitively, exceptional weather conditions (especially,

poor weather) should intensify forward-looking price volatility. As well, we take into account a number of one-off shocks' possible impacts on crop market uncertainty (including the 2005 biofuel mandate and the mad cow and swine flu epidemics). Finally, we include weekly estimates of the intensity of financial speculation in each futures market.

We use all these variables in the context of a structural vector autoregression model (SVAR)—allowing us to identify what drives option-implied volatilities (IVs), i.e., the market's consensus expectation of future price volatility that are embedded in agricultural option prices.<sup>1</sup>

We document, *via* innovation accounting, that option-implied forward-looking uncertainty and risk aversion in equity markets (jointly captured by the VIX) and the state of commodity stocks (proxied by the net cost of carry for each commodity) have statistically and economically significant impacts on forward-looking volatility in the three largest U.S. agricultural commodity markets: corn, soybeans, and wheat. This result presents a counterpoint to Engle and Figlewski's (2015) finding that, in equity markets, the VIX index is a “viable measure of *the* (emphasis added) common component of IV fluctuations for individual options and portfolios of options” (*ibid.* p.993). In other words, for equities, a single common factor explains the dynamics of single-stock IVs (and correlations among them)—and the VIX is a good proxy for that factor.

For field crops, in contrast, we show that the factor captured by the VIX is far from the sole driver of IVs. First, inventories matter too, in that they systematically affect traders' volatility expectations. This impact of storage shocks on commodity IVs is asymmetrical: (near-)stockouts heighten IVs to a greater extent than plentiful inventories moderate IVs. Second, impulse-response functions (for corn and winter wheat) and historical decompositions (for all three commodities)

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<sup>1</sup> Robe and Wallen (2016) and Covindassamy, Robe, and Wallen (2017) use different econometric techniques to investigate forward-looking volatility in crude oil and softs markets, respectively. Watugala (2015) finds empirical evidence that “fundamental economic uncertainty” is a strong factor in *realized* commodity futures volatility.

show also that increased financial speculation has an immediate, but short-lived, negative impact on forward-looking volatility. This result complements recent evidence that speculative activity, on average, tends to lower *realized* volatility in U.S. futures markets (Kim, 2015; Brunetti, Büyükşahin, and Harris, 2016).

The relative importance of macroeconomic vs. commodity-specific drivers varies a lot over time, with VIX shocks having a greater effect on commodity IVs during recessions, increasing them for corn and soybeans by about 5 percentage points from 2008-2009; for wheat, that increase was almost twice as high. In terms of economic magnitude, the impact of VIX shocks on commodity IVs is two to three times greater in the case of wheat than in the case of corn or soybeans. After 2012, record-low values of the VIX drive grain and oilseed IVs down by up to two percentage points.

Conversely, inventory shocks have the largest impact on corn IVs and the lowest on wheat IVs. Intuitively, these patterns are consistent with the geographic concentration of each crop. Corn production in the western hemisphere is dominated by the United States (and part of its demand is derived from the relatively more inelastic demand for fuel), so its implied volatility is more sensitive to concerns over tight stocks than a commodity like wheat, whose production is much more diversified geographically.

The paper proceeds as follows. Section 2 provides descriptive evidence on option-implied volatility patterns in agricultural commodities (corn, soybeans, wheat) and equity markets. Section 3 discusses the fundamental and financial variables whose explanatory power we investigate. Section 4 describes our SVAR model. Section 5 summarizes the results of the SVAR analysis by plotting and discussing our impulse-response functions and historical decompositions. Section 6 concludes. A technical Appendix ends the paper.

## 2. Volatility Expectations in Field Crop and Equity Markets, 1995—2015

A key hypothesis in our analysis is that option-implied or forward-looking volatility (IV) in crop markets should be connected to macroeconomic uncertainty and economy-wide risk-aversion levels, as captured by IVs in financial markets. This Section describes how we quantify crop and equity IVs and documents their respective evolutions in the past two decades.

### 2.1. Data

We use data from the U.S. markets where price discovery mostly takes place for corn, soybeans, and wheat (Adjemian and Janzen, 2016). For each commodity, we construct weekly time series for the Tuesday term structures of futures prices and of option-implied volatilities (IVs) based on CME Group (and, formerly, Chicago Mercantile Exchange or Chicago Board of Trade) settlement prices for futures and options on futures contracts.<sup>2,3</sup>

Our sample period spans two decades, running from January 3<sup>rd</sup>, 1995 to September 15<sup>th</sup>, 2015. We obtain from Bloomberg daily futures prices, IVs computed from the prices of European options on futures, and volume and open interest for futures and option contracts. The Bloomberg IV series for a given maturity are based on the daily closing prices of the most actively traded option contracts, i.e., on at-the-money options for that maturity (Cui, 2012).

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<sup>2</sup> If a Tuesday is a market holiday, we use the following Wednesday and adjust the position data accordingly. If that Wednesday is also a holiday, then we select the Monday prior to the Tuesday. In the rare occasions when an IV value (*futures price*) is missing from the Bloomberg dataset for the three first days of a given week even though the relevant options (*futures*) were traded on one or more of those three days, we use interpolation to fill the gap.

<sup>3</sup> We use IVs computed from Tuesday option settlement prices because one of our explanatory variables is a financial speculation index constructed from data on trader positions in commodity futures markets. As explained in the Appendix, the public position data come from the U.S. Commodity Futures Trading Commission's (CFTC) weekly Commitments of Traders Reports (COTs), which are based on Tuesday end-of-day futures and options positions.



We focus on nearby futures and options on futures. We define the “nearby” futures (and corresponding option) for each commodity as the nearest-dated futures listed on Standard and Poor’s S&P GSCI’s investment schedule for that commodity. When that contract approaches expiration, we use the preponderance of the futures open interest (rather than calendar dates) to select roll dates for futures and options on futures. Choosing roll dates based on open interest and focusing on GSCI contracts minimizes the likelihood that our “nearby” commodity IV time series could be spuriously impacted by low-liquidity patterns around prompt-contract expiration dates or due to transitions between contract months with historically very different liquidity levels.

For equities, we use the Chicago Board Options Exchange’s (CBOE) VIX index, i.e., the near-term IVs implied by Standard and Poor’s S&P 500 equity index option prices. We obtain daily VIX values from Bloomberg and, as we do for commodity IVs, sample them on Tuesdays.

## ***2.2. Patterns***

Figure 1 plots, from January 3<sup>rd</sup>, 1995 to September 15<sup>th</sup>, 2015, the nearby option-implied volatilities for corn (Panel A), soybeans (Panel B), and Chicago wheat (Panel C). Superimposing the graphs for major crop IVs with the VIX, Figure 1 shows that IVs in crop and equity markets are all extremely high during the financial crisis that followed the demise of Lehman’s Brothers (between September 2008 and February 2009)—suggesting the existence of a common factor affecting these markets. At the same time, Figure 1 also highlights commodity-specific IV fluctuations that appear unrelated to the behavior of the VIX—indicating that an investigation into crop-specific explanations for those IV patterns should prove quite fruitful.

### **3. Potential Drivers of Price Uncertainty and Cross-market Linkages**

Our premise is that both commodity-market fundamentals and financial-market variables help explain market expectations of future volatility levels in crop markets. This Section introduces the variables that we use to test that hypothesis in our econometric analyses.

#### ***3.1. Macroeconomic Uncertainty and Investor Risk Aversion***

Bekaert, Hoerova, and Lo Duca (2013, p.771) show that the VIX index “can be decomposed into a component that reflects actual expected stock market volatility (uncertainty) and a residual (reflecting) risk aversion and other non-linear pricing effects, perhaps even Knightian uncertainty.” Intuitively, uncertainty levels in financial and field crop markets should be related because both are tied to the uncertainty regarding the future strength of global consumption demand for goods and services—including agricultural commodities. They should also be related insofar as it has been shown (He, Kelly, and Manela, 2016) that an intermediary capital factor prices many classes of assets, including commodities—so that changes in investors’ risk-bearing desire or capacity are likely to permeate all asset markets.<sup>4</sup> Based on those findings, we use the equity VIX as a variable that can capture macroeconomic uncertainty and global risk aversion—both of which we expect to substantially affect crop IVs.<sup>5</sup>

#### ***3.2. Precautionary and Speculative Demand: Inventories***

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<sup>4</sup> As Covindassamy *et al.* (2017, p.12) note, “insofar as commodity markets are not segmented from financial asset markets, higher levels of uncertainty or risk aversion in financial markets are likely to spill over into commodity markets. Spillovers in the opposite direction are unlikely to happen in the case of most commodities—especially (agricultural commodities that) make up but a very small part of the world’s asset markets.”

<sup>5</sup> Han (2008) shows that investor sentiment is an important determinant of the smile or smirk in Standard and Poor’s S&P 500 equity-index option markets. We focus on at-the-money options.

Starting with Gustafson (1958a, 1958b), economic theory has established a link between commodity stocks and price volatility. Vercammen and Doroudian (2014) and Knittel and Pindyck (2016) build (and numerically simulate or test empirically) theoretical models of the interplay between physical storage and financial speculation. Both papers show that inventories should be a key variable for analyses of the impact of speculation on price volatility for storable commodities.<sup>6</sup>

Intuitively, forward-looking crop price uncertainty should be muted if investors expect commodity inventories to be healthy going forward. In contrast, expectations of unusually low stocks should make field crop prices more susceptible to possible supply shocks and, consequently, less predictable—boosting forward-looking IVs. As well, extremely low inventory levels could weaken the intensity of the co-movements between financial and crop markets, thus weakening the link between global uncertainty and IVs.

We consider two possible data sources on expected future storage levels. First, the USDA's World Agricultural Supply and Demand Estimates (WASDE) reports include expert forecasts of next-September commodity storage levels. These reports move markets—see Isengildina-Massa, Irwin, Good, and Gomez (2008) and Adjemian (2012). Unfortunately, they are monthly, whereas our analysis is weekly. They are also backward- (as opposed to forward-) looking.

Absent actual higher-frequency data on physical inventory levels or forecasts, we rely on a price-based proxy for market participants' views regarding the state of inventories in each grain or oilseed market. This proxy (Working, 1933, 1948, 1949; Fama and French, 1987, 1988) is the

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<sup>6</sup> Alquist and Gervais (2010) and Kilian and Murphy (2014) make related points in their investigations of the impact of speculation in the crude oil market. See also Myers, Sexton, Tomek (2010) and Carter, Raussler, and Smith (2017) for other recent work the importance of inventories for commodity price dynamics in the specific context of agricultural markets.

commodity's net cost of carry, computed as the percentage slope of the nearby term structure of futures prices for that commodity, *minus* interest-rate costs.<sup>7,8</sup>

We denote the resulting variable *STORAGE*. We expect a negative relationship between crop IVs and *STORAGE* given that low current inventories are associated with backwardation, i.e., with a negative futures term structure slope.

### **3.3. Output shocks**

As noted by Bruno, Büyükşahin, and Robe (2017), “U.S. grain output is affected mostly by planting decisions (yearly for most crops) and by weather conditions (temperature and rain, which vary daily) ... Intuitively, episodes of extremely bad weather are likely to be associated with sharp but commodity-specific price movements.” *Ceteris paribus*, one should thus expect extreme weather to boost crop IVs—especially when commodity inventories are low.

From a practical perspective, Lehecka (2013) shows that the weather's impact in U.S. agricultural commodity markets is parsimoniously captured by a crop condition index computed from the USDA's weekly “Crop Progress and Condition” reports (CPCR). We adopt a similar approach but adjust it in the manner suggested by Bruno, Büyükşahin, and Robe (2017). First, for each U.S. crop (corn, soybean, or wheat), we construct a weighted-average index that gives more weight to plots listed in “very poor” condition. This weighing scheme is based on the intuition that crop prices should be more sensitive to very bad (*vs.* very good) weather—an insight inspired by Boudoukh, Richardson, Shen, and Whitelaw's (2007) empirical evidence that only extreme

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<sup>7</sup> Joseph, Garcia, and Irwin (2016) provide detailed empirical evidence that this price-based approach remains a valid way of estimating market participants' views of the state of agricultural inventories. Bruno, Büyükşahin, and Robe (2017) show that the price-based proxy we use in the present paper is closely related to the USDA's forecasts of ending-stock levels for major agricultural commodities.

<sup>8</sup> We select the “nearby” contract anchoring the futures term structure so as to match the IV term structure. As for the IV time series, we sample futures prices and interest rates weekly on Tuesdays in order to compute *STORAGE*.

weather materially affects orange production levels and, in turn, has a significant impact on frozen orange juice futures prices. Second, the SVAR analysis requires index values for all weeks in the sample, including during winters—but the USDA only produces CPCRs after a crop has been planted. This problem is solved by centering each crop’s condition index for all weeks when that crop is growing (by subtracting a crop-specific index average in each market) and by setting the condition indices equal to 0 in weeks when no CPCR was published.

### ***3.4. Paper Market Activity***

In addition to macroeconomic and physical market fundamentals, our analysis accounts for the possibility that financial speculation has an impact on forward-looking volatility.

We follow most of the extant literature and use Working’s (1960)  $T$  index to measure speculative intensity in terms of how much the positions of “non-commercial” traders (i.e., traders who neither own nor owe the underlying commodity) exceed the minimum amount that would be required to offset any unbalanced hedging needs at the market-clearing price (i.e., to satisfy “commercial” traders’ net demand for hedging at that price).

Over the course of the past 15 years, the relative importance of financial institutions such as hedge funds increased dramatically in commodity futures markets (Büyüksahin and Robe, 2014; Cheng and Xiong, 2014). Much of that growth took the shape of calendar spread trading. We therefore adjust the  $T$  index so that it accounts for non-commercial spread positions as well as for directional positions. For each commodity, we compute the  $T$  using data from the U.S. Commodity Futures Trading Commission’s (CFTC) weekly reports on aggregate end-of-Tuesday positions for different trader categories. The Appendix provides details of our  $T$  index computations.

Figure 2 plots, from January 3<sup>rd</sup>, 1995 to September 15<sup>th</sup>, 2015, the indices of speculative intensity (Working’s  $T$  index minus 1) in U.S. corn, wheat, and soybean futures markets. In all

cases, the  $T$  index is quite volatile. Still, it is apparent that all series trend upward over the course of the past two decades, with accelerating growth after 2011.

#### 4. The Structural VAR Model

We propose a 4-variable SVAR model to jointly explain and quantify, in the three main U.S. agricultural commodity markets (corn, soybeans, Chicago wheat), the respective roles of macroeconomic uncertainty and investor risk aversion (jointly captured by the equity  $VIX$ ), physical market fundamentals (affecting commodity supply or demand), and financial speculation (Working's  $T$ ) in explaining a fourth variable: commodity price volatility expectations or  $IV$ .<sup>9</sup> For each commodity, these variables are represented by the vector  $y_t$  as

$$(1) \quad A(L)y_t = \mu'x_t + \varepsilon_t$$

where  $L$  is the lag operator,  $x_t$  represents the exogenous variables (including a constant and a time trend), and the prediction errors  $\varepsilon_t$  are related to the structural shocks  $u_t$  by

$$(2) \quad A\varepsilon_t = Bu_t$$

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 imply that the  $VIX$  is not contemporaneously affected by physical

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<sup>9</sup> We do not include seasonality (via dummies) in the deterministic portion of the SVAR whose impulse-response functions we report. For the historical decompositions of the SVAR, we add seasonal dummies in robustness checks and obtain qualitatively similar results. Intuitively, because there is seasonality inherent to crop production, adding seasonal dummies in essence allows the idiosyncratic portion of the  $IV$  to represent any difference in uncertainty (that is not due to exogenous shocks) from the normal crop-specific uncertainty experienced at that point each year. Removing seasonality dummies gives the idiosyncratic shocks for each commodity the flexibility to display seasonal patterns in uncertainty.

inventory forecasts (*STORAGE*), *T*, or *IVs*. In turn, we assume that inventory forecasts (*STORAGE*) are contemporaneously affected by the *VIX*, but not by financial speculation (*T*) or price uncertainty (*IV*) in commodity markets. This ordering assumes that changes in *financial* traders' positions generate signals that are not immediately incorporated into *physical* speculators' choices.

Next, we assume that financial speculation in each commodity market (*T*) is affected contemporaneously by the *VIX* and by inventory forecasts for that commodity (*STORAGE*) but not by that commodity's *IV*. Finally, we assume that each commodity's *IV* is affected by contemporaneous shocks in *VIX*, *STORAGE*, and *T*. By ordering *T* in third position and before *IV*, we assume that financial speculation in a given crop market (*T*) does not have an immediate impact on global uncertainty (the *VIX*) or on expectations of future inventory levels—but has an instantaneous effect on the *IV*. We make this assumption in order to test whether the intensity of financial speculation impacts volatility expectations or uncertainty in commodity markets.

Therefore, we specify (2) as

$$(3) \quad \begin{pmatrix} \varepsilon_t^{VIX} \\ \varepsilon_t^{STORAGE} \\ \varepsilon_t^T \\ \varepsilon_t^{IV} \end{pmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 \\ b_{12} & b_{22} & 0 & 0 \\ b_{13} & b_{23} & b_{33} & 0 \\ b_{14} & b_{24} & b_{34} & b_{44} \end{bmatrix} \begin{pmatrix} u_t^{VIX} \\ u_t^{STORAGE} \\ u_t^T \\ u_t^{IV} \end{pmatrix}$$

In (3), it is trivial to see that for any time *t*, the identification structure of the model permits structural innovations of the *VIX* to affect contemporaneous forecast errors for *STORAGE*, *T*, and *IV*, but not *vice versa*, although the latter are allowed to affect the *VIX* at a lag. Finally, we use our proxy for crop supply as an exogenous variable in our SVAR model. Precisely, we use for each commodity a weekly crop-specific, centered, asymmetrically-weighted average of the percentages of soybean, wheat, or corn plots in “very poor”, “poor”, “good”, or “excellent” condition.

Having estimated the above model, we rearrange its structural vector moving average (VMA) representation to recover the impulse responses generated by each of the structural shocks. We then calculate historical decompositions of the path of each commodity *IV* into the respective contributions of its component structural shocks, plus the deterministic portion of the model, made up of the exogenous variable at each point in time plus the feedback effects given the lag structure of the SVAR.

## 5. Results

In all cases, we run estimations for a two-decade sample period (1995—2015) that includes multiple business cycles—one of them being the Great Recession. We use three lags in the specifications for all three commodities, which eliminates serial correlation in the residuals, and report our results via innovation accounting. With our relatively large number of observations (1,081), we use a standard non-parametric bootstrapping with replacement and 1,000 replications to report 90 percent confidence bands around estimated impulse response functions (IRFs). To highlight time-dependent effects of the factors in the model, we further estimate historical decompositions of the SVAR for each commodity.

Figure 3 shows the IRFs from our four-variable SVAR for, respectively, corn (Panel A), soybeans (Panel B), and wheat (Panel C) based on the following ordering—the *VIX* followed by three commodity-specific variables: expected future inventory conditions (*STORAGE*), financial speculation (*T*), and forward-looking volatility for the relevant commodity (*IV*). Each of the 16 charts in a given Panel of Figure 3 gives the impulse response,s over 20 weeks, of the variable listed after the arrow to a one-standard deviation shock to the variable listed before the arrow. For instance, reading from left to right, the first row in Panel A of Figure 3 gives the impulse responses



to a one standard deviation shock to *VIX* of the *VIX* itself, followed by corn *STORAGE*, corn *T*, and corn *IV*.

Figure 4 shows the graphical representation of the historical decomposition of the SVARs, segregating the stochastic path of *IV* for each commodity (corn, soybeans, and wheat in Panels A, B, and C, respectively) into its uncorrelated, component parts, using the same variables and ordering described above. The series related to each shock is represented by a different color: *VIX* (green), *STORAGE* (purple), speculation *T* (yellow), and idiosyncratic commodity *IV* (blue). In all three graphs, component shocks are stacked; their sum equals the total stochastic innovation (red line) to commodity *IV*s at each point in time.

### **5.1. *VIX***

Figure 3 shows that a key driver of forward-looking volatility in agricultural commodity markets is the *VIX*, i.e., forward-looking volatility in financial markets—which itself captures global economic uncertainty and risk aversion. On average, higher *VIX* levels lead to a statistically significant and long-lasting increase in field crop *IV*s after one (soybean, winter wheat) or two (corn) weeks.

Panels A to C in Figure 4 display those effects over the course of time: uncertainty about commodity prices varies with uncertainty about global macroeconomic conditions transmitted by the *VIX*. Broadly speaking, economic expansions lead to lower levels of implied volatility in commodity markets according to Figure 4 Panels A to C, in particular during the mid-2000's (from early 2004 until the week prior to Lehman Brother's demise, in September 2008) and again starting in 2012. In all three Panels, negative innovations in the *VIX* (the green region) over these timeframes reduce each commodity's *IV* compared to what it would have been, otherwise. Conversely, recessions in the United States and economic crises abroad (in 1998, 2001, or

2008-2009) are associated with higher levels of uncertainty about commodity prices. In particular, all three Panels highlight that positive *VIX* innovations during the Great Recession (especially amid the Lehman crisis) contributed to much higher levels of commodity uncertainty than would have otherwise been observed.

In addition, *VIX* levels that aren't perfectly tied to the world business cycle are also shown to affect commodity IVs. Although the early-2000s recession officially ended in November 2001, Panels A to C in Figure 4 show that elevated *VIX* between the terrorist attacks in New York and Washington, D.C., and the invasion of Iraq in 2003, led to higher levels of gain and oilseed implied volatility compared to the counterfactual.

## ***5.2. Storage Conditions***

Consistent with economic theory, we find that inventory conditions have an economically significant impact on forward-looking price volatility. In all cases, according to our impulse response results, the impact is statistically significant either immediately (corn, soybean) or after just a week (wheat); it is stronger and longer lasting in the case corn (more than three months—see Panel A), followed by soybean (Panel B) and wheat (Panel C in Figure 3). In all three crop field markets, our point estimates of the *IV* response to a *STORAGE* shock are largest in the first one to three weeks.

In the same vein, *STORAGE* shocks in Figure 4 are inversely related to the path of inventory conditions for our three grains or oilseeds and, for the most part, display an asymmetric effect on price uncertainty: (near-)stockouts place upward pressure on implied volatilities to a larger extent than the extent to which plentiful inventories moderate commodity IVs. For example, extremely low inventory levels (as proxied by a steeply negative slope of the term structure of futures prices) for corn are associated with sharp increases in that commodity's implied volatility.

Tight corn stocks following droughts in the mid-1990's and again in the early 2010's noticeably increased uncertainty about corn prices in Panel A. As stocks-to-use ratios fell for corn in these periods due to adverse growing conditions (see Figure 5), corn *IV* increased substantially. Spikes in *IV* due to inventory concerns (reflected in historically large old-crop/new-crop inversions in the futures term structure) amounted to over 10 percentage points during April-June 1996, between 6-8 percentage points in April-June 2012, and ranged from 6-8 percentage points in April-June 2013.

Notably, consistently adequate corn inventory levels between those two periods generated far less noticeable downward pressure on commodity implied volatilities. Changes in government agricultural commodity stockholding policy contained in the 1996 Farm Bill promoted growth in private stocks, but we estimate that the greatest reduction in corn *IV* due to sufficient corn stocks levels reached a maximum of about 2 percentage points in the mid-2000s. This asymmetric impact of storage conditions on corn price uncertainty is economically intuitive, since tight inventory levels can dramatically reduce the slope of the term structure, but the possibility of storage arbitrage prevents that slope from becoming too positive.

Just as in the case of corn, negative soybean and wheat storage shocks occur in Figure 4 when U.S. inventory levels for those commodities fall in relation to their domestic usage, but the magnitude of those effects on commodity option *IV* are lower than we observe for corn (and follow a similar ordering as we found in our impulse responses). Figure 5 shows that, relative to usage, U.S. soybean stocks track at the same level as (or even lower than) corn stocks over much of the period of observation. However, U.S. soybean production is rivaled by Brazil's, itself a major exporter into the world market (the USDA presently forecasts the ratio of Brazilian soybean exports to U.S. use in 2016/17 at 111%). Consequently, poor domestic soybean harvests can more easily be smoothed out with Brazilian imports, reducing the impact of bad U.S. weather on soybean

price uncertainty relative to what might be expected in the corn market. For corn, in contrast, a substantial portion of U.S. demand stems from government fuel requirements, and domestic crop shortfalls cannot as easily be met by a producer in the same hemisphere: even the sum of forecasted Brazilian and Argentinian corn exports in 2016/17 is just a fraction of expected US use, at 18%.

For wheat, smaller storage shocks are easier to explain. Figure 5 shows that, since 1990, US wheat stocks have been (except for a single marketing year) more plentiful—and sometimes far more plentiful—compared to either corn or soybean.

### ***5.3. Discussion***

Putting together the results of Sections 5.1 and 5.2, our *VIX* and *STORAGE* findings present an interesting counterpoint to extant findings for equity markets. Engle and Figlewski (2015) provide empirical evidence that a single common factor explains IV dynamics for individual stocks and that the *VIX* is a good proxy for that factor. In a similar vein, a principal component analysis of options on individual Dow-Jones stocks (Christoffersen, Fournier, and Jacobs, 2016) reveals a strong factor structure: notably, the first principal component explains a full three-fifths of the implied volatility term structure across those equities and has a 92 percent correlation with the *VIX*. For agricultural commodities, in contrast, Figure 3 establishes that the *VIX* matters but is not the sole driver of commodity IVs: inventories significantly affect traders' volatility expectations (*IV*) as well. Figure 4 makes an even stronger case: its Panels A to C make it clear that, while at certain times the *VIX* is the most important factor that explains commodity price uncertainty, at other times, inventories and other market-specific shocks play a much more significant role in shaping the paths of IVs. As surmised in Section 3.2 above, low-inventory shocks do indeed serve to disconnect commodity-specific uncertainty from the *VIX*—that is, from global financial

markets. To wit, tight soybean stock conditions in early-2004 boosted soybean IVs, at a time when uncertainty about equity markets was falling.

#### ***5.4. Financial Speculation in Agricultural Commodity Markets***

Panel B in Figure 3 shows a generally negative, if statistically insignificant, impact of financial speculation ( $T$ ) on near-dated soybean  $IV$ . Panels A and C in Figure 3 show that, on average, a one-standard deviation shock to the  $T$  index for corn and wheat, respectively, decreases  $IV$ s in those two crop markets. For corn and wheat, the impact is immediate, statistically significant and strongest contemporaneously. Compared to the impact of  $STORAGE$  and  $VIX$  on  $IV$ , the impact of  $T$  is smaller in magnitude and much shorter-lived, with the response becoming statistically insignificant in all markets after two weeks at the most.

The historical decompositions in Figure 4 are consistent with those findings: shocks to the  $T$  index are inversely associated with changes in commodity  $IV$ s. Steep increases in the  $T$ -index values towards the end of the sample are shown to reduce uncertainty about commodity prices for all three commodities. On the other hand, reductions in the intensity of financial speculation—such as was observed for every commodity in the 2010-2011 period—lead  $IV$ s higher than they would have otherwise been, according to the SVAR.

In total, the results summarized in Figures 3 and 4 establish that fundamentals matter and suggest that, if anything, financial speculation moderates crop-market specific forward-looking volatility. This result complements evidence that commodity index traders did not drive large bubbles in grain futures markets—see, e.g, Irwin and Sanders (2010, 2011), Wright (2011), Irwin (2013), Etienne, Irwin, and Garcia (2015, 2017), and references cited in those papers.

Insofar as speculative activity appears to dampen the uncertainty that is idiosyncratic to grain and oilseed markets, it may in turn increase the importance of shocks common to all asset

markets. If so, then our findings would help understand Bruno, Büyükşahin, and Robe's (2017) evidence that trading by hedge funds and similar institutions helps explain co-movements between agricultural and financial markets.

## 6. Conclusions

We build a structural econometric model that explains market expectations of future field crop price volatility (IVs) *via* financial and fundamental variables. We provide empirical evidence that elevated forward-looking volatility and risk aversion in equity markets as well as grain and oilseed inventory conditions (namely, expected future stress in the storage space) both boost forward-looking in those markets (captured through option-implied volatilities), whereas financial speculation in the relevant agricultural futures markets dampens forward-looking volatility levels.

Ideally, understanding the respective contributions of these observable factors to IVs should inform and aid market participants in their micro-level decisions, from production and purchasing to marketing and storage choices. In a companion project, Adjemian, Bruno, and Robe (2016) investigate the extent to which the results of the present paper can also provide the basis for analysts to use these factors, along with their own expert judgment, to adjust expected commodity price distributions. Such an approach could be used to enhance public policy. For example, the USDA Risk Management Agency uses IVs to determine crop guarantee levels and premium costs: providing the agency with the tools to improve those forecasts in response to expected market developments could boost producer welfare.

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## Appendix: The Intensity of Financial Speculation in Crop Markets

In Section 5, we test empirically if the intensity of financial speculation in agricultural commodity markets has an impact on market expectations of future price volatility. As a proxy for that intensity, we employ a version of Working’s (1960)  $T$  index.<sup>10</sup> This Appendix explains how we construct  $T$ .

### *Data*

We compute weekly  $T$  values from aggregate trader position data published by the U.S. Commodity Futures Trading Commission (CFTC) for corn, soybean, and Chicago wheat futures markets. Precisely, we use the CFTC “Legacy Commitments of Traders Report” (COT) showing the aggregate long, short, and spread end-of-Tuesday positions of “commercial” and “non-commercial” traders.<sup>11,12</sup> A trading entity generally gets all of its futures and options positions in a given commodity classified by the CFTC as “commercial” if it is commercially “engaged in business activities hedged by the use of the futures or option markets” as defined in CFTC regulations. The “non-commercial” group includes various types of mostly financial traders including floor brokers, hedge funds, and other types of institutional financial traders.

### *Measuring the intensity of financial speculation*

For each commodity market in our sample, we use public COT data to compute Working’s  $T$  every Tuesday in our sample (January 3<sup>rd</sup>, 1995 to September 15<sup>th</sup>, 2015). This  $T$  index covers all contract maturities. Formally, in the  $i^{\text{th}}$  commodity market in week  $t$ :

$$\text{Working's } T_{i,t} \equiv T_{i,t} = \begin{cases} 1 + \frac{SS_{i,t}}{HL_{i,t} + HS_{i,t}} & \text{if } HS_{i,t} \geq HL_{i,t} \\ 1 + \frac{SL_{i,t}}{HL_{i,t} + HS_{i,t}} & \text{if } HL_{i,t} \geq HS_{i,t} \end{cases} \quad (i = \text{corn, wheat, beans}),$$

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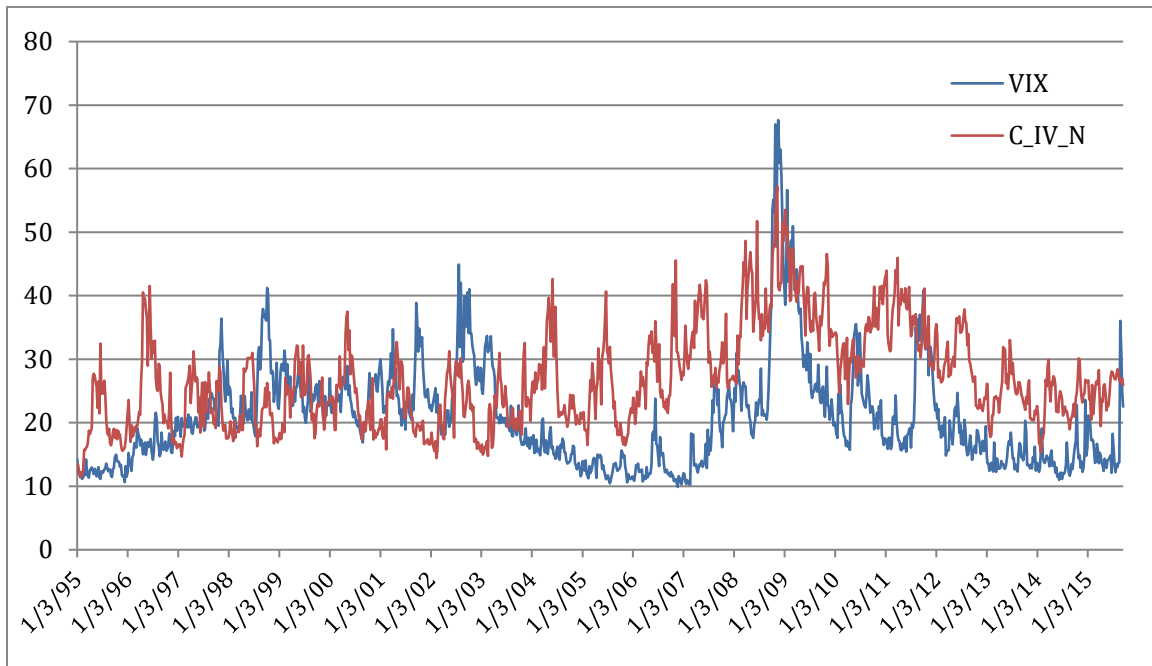
<sup>10</sup> This measure has been widely used in the literature, and Sanders, Irwin, and Merrin (2010) document its continued usefulness in capturing speculation in agricultural futures markets. Büyüksahin and Robe (2014) use non-public CFTC data to document that changes in the  $T$  index (computed using the same public CFTC data as in the present paper) capture changes in hedge fund activity.

<sup>11</sup> The CFTC’s COT reports started differentiating between “managed money traders” (i.e., hedge funds) and “other non-commercial traders with reportable positions” on September 4<sup>th</sup>, 2009. The CFTC only makes these more disaggregated data available back to 2006. We therefore rely on the legacy classification scheme, in order to obtain a sufficient time series of trader positions for our entire sample (1995–2015).

<sup>12</sup> COT reports also provide data on the positions of non-reporting (i.e., small) traders.

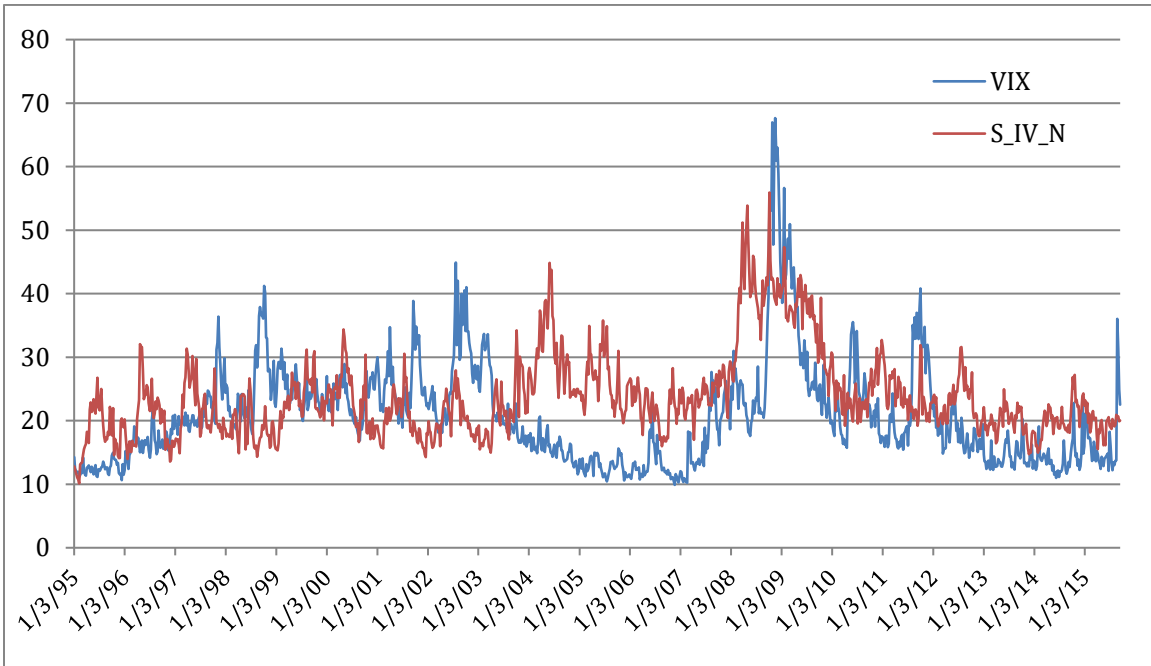
where  $SS_{i,t} \geq 0$  is the (absolute) magnitude of the short and spread positions held in the aggregate by all non-commercial traders (“Speculators Short”);  $SL_{i,t} \geq 0$  is the (absolute) value of all non-commercial long or spread positions;  $HS_{i,t} \geq 0$  stands for all commercial short positions (“Hedge Short”); and  $HL_{i,t} \geq 0$  stands for all long commercial positions. By including non-commercial traders’ spread positions alongside their directional positions in either numerator, this version of the  $T$  index captures changes in the extent of spread trading activity by financial institutions over the course of our sample period.

**Figure 1 – Panel A: Forward-Looking Volatility in Corn and Equity Markets**

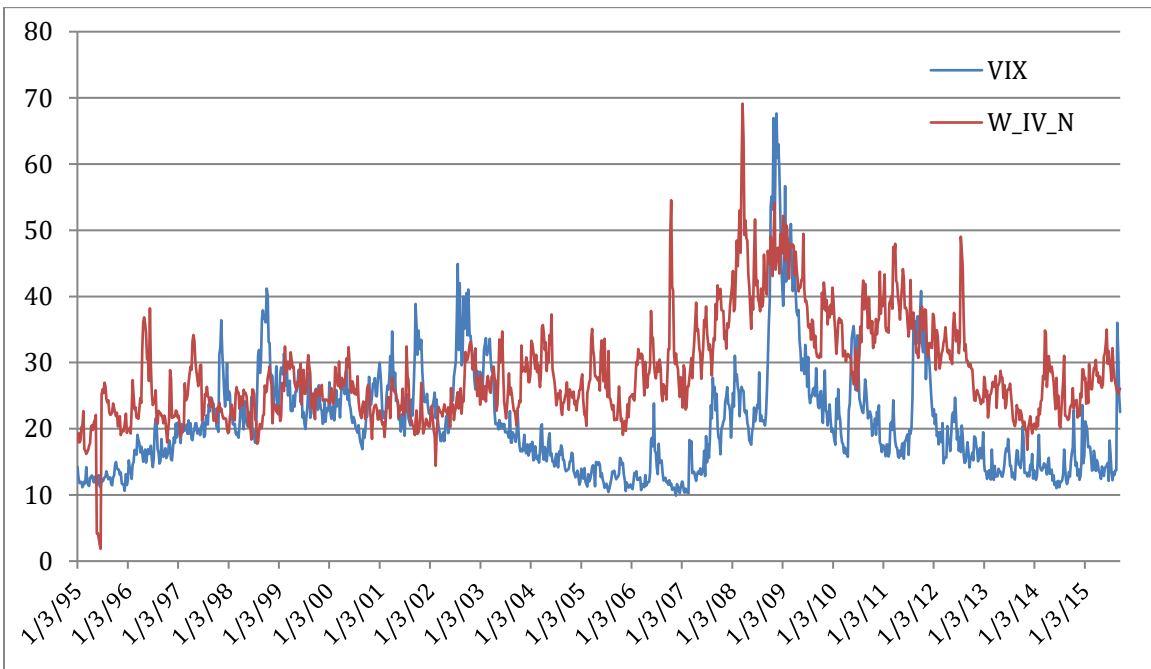


**Figure 1** plots in **red**, from January 3<sup>rd</sup>, 1995 to September 15<sup>th</sup>, 2015, the forward-looking volatilities (IV) implied by prices of nearby at-the-money call options on futures for corn (Panel A), soybeans (Panel B, next page), and Chicago wheat (Panel C, next page) – *Source*: Bloomberg. In all three panels, we superimpose the contemporaneous forward-looking volatility implied by the prices of near-dated options on Standard and Poor’s S&P500 equity index (VIX, in **blue**; *Source*: CBOE – Chicago Board Options Exchange). For all three commodities, near-dated forward-looking volatility is more volatile than longer-dated (6-month out) figures (not displayed). Although all nearby IV time series show concomitant increases from the third quarter of 2008 to the first quarter of 2009 (after the demise of Lehman’s Brothers), the three panels show commodity-specific spikes unrelated to the VIX.

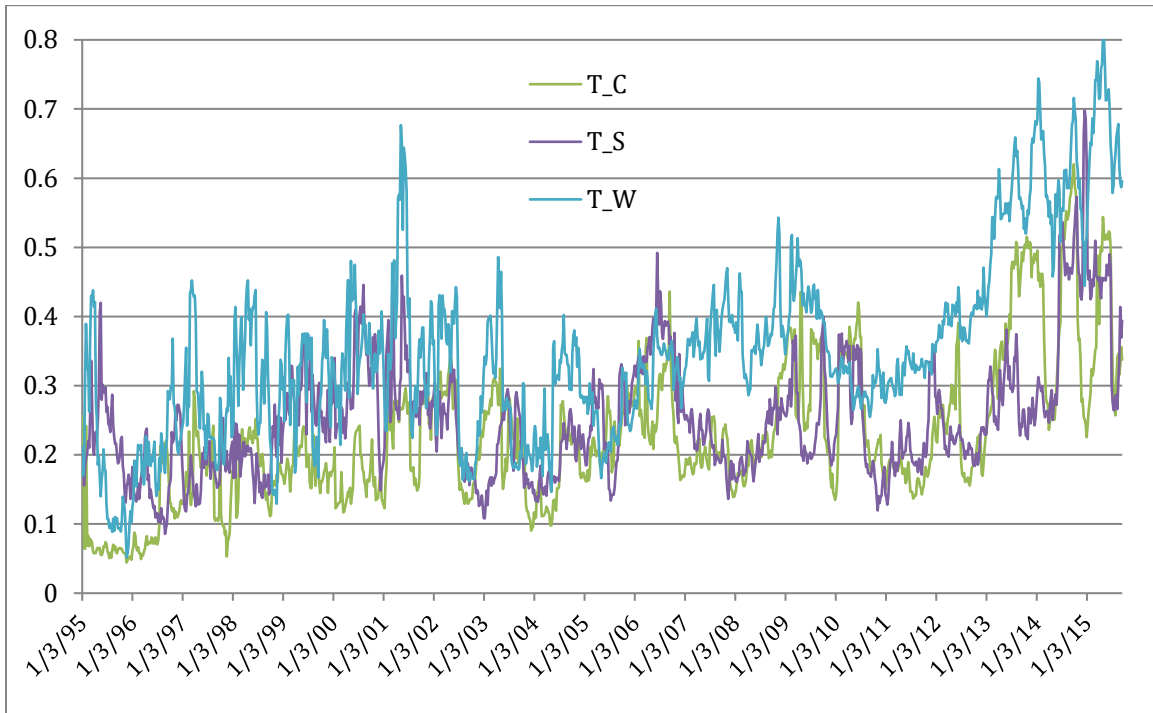
**Figure 1 – Panel B: Forward-Looking Volatility in Soybean and Equity Markets**



**Figure 1 – Panel C: Forward-Looking Volatility in Wheat and Equity Markets**

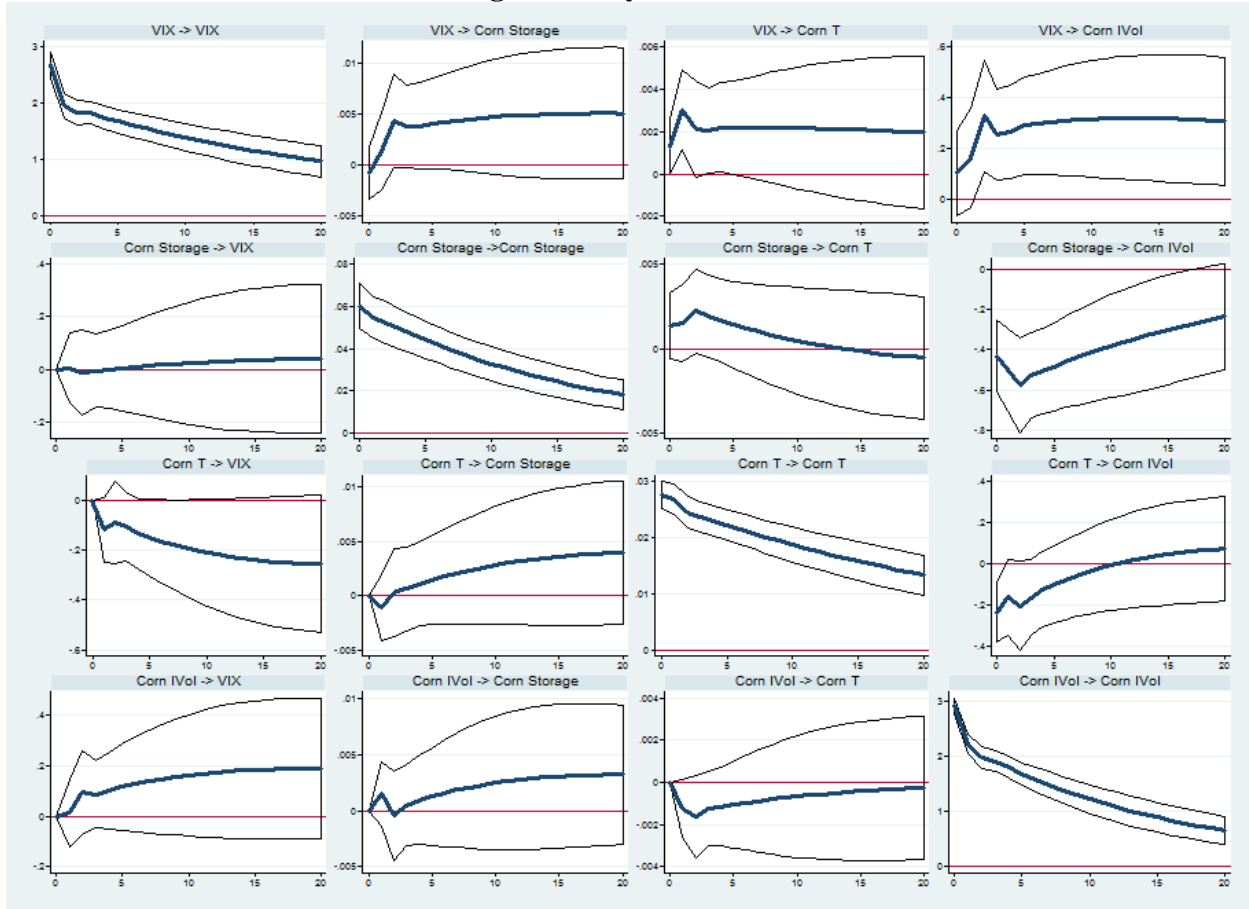


**Figure 2 – Financial speculation in Agricultural Commodity Markets**



**Figure 2** plots, from January 3<sup>rd</sup>, 1995 through September 15<sup>th</sup>, 2015, indices of the intensity (adjusted Working’s (1960)  $T$  index *minus* 1) of financial speculation in the U.S. futures markets for corn (**green** series), Chicago wheat (**blue** series), and soybeans (**purple** series). We use data regarding end-of-Tuesday trader positions, published every Friday during our sample period by the U.S. Commodity Futures Trading Commission (CFTC Commitments of Traders Reports), to compute weekly  $T$  values for each market. All series trend upward in the sample period, with growth especially visible starting in 2011.

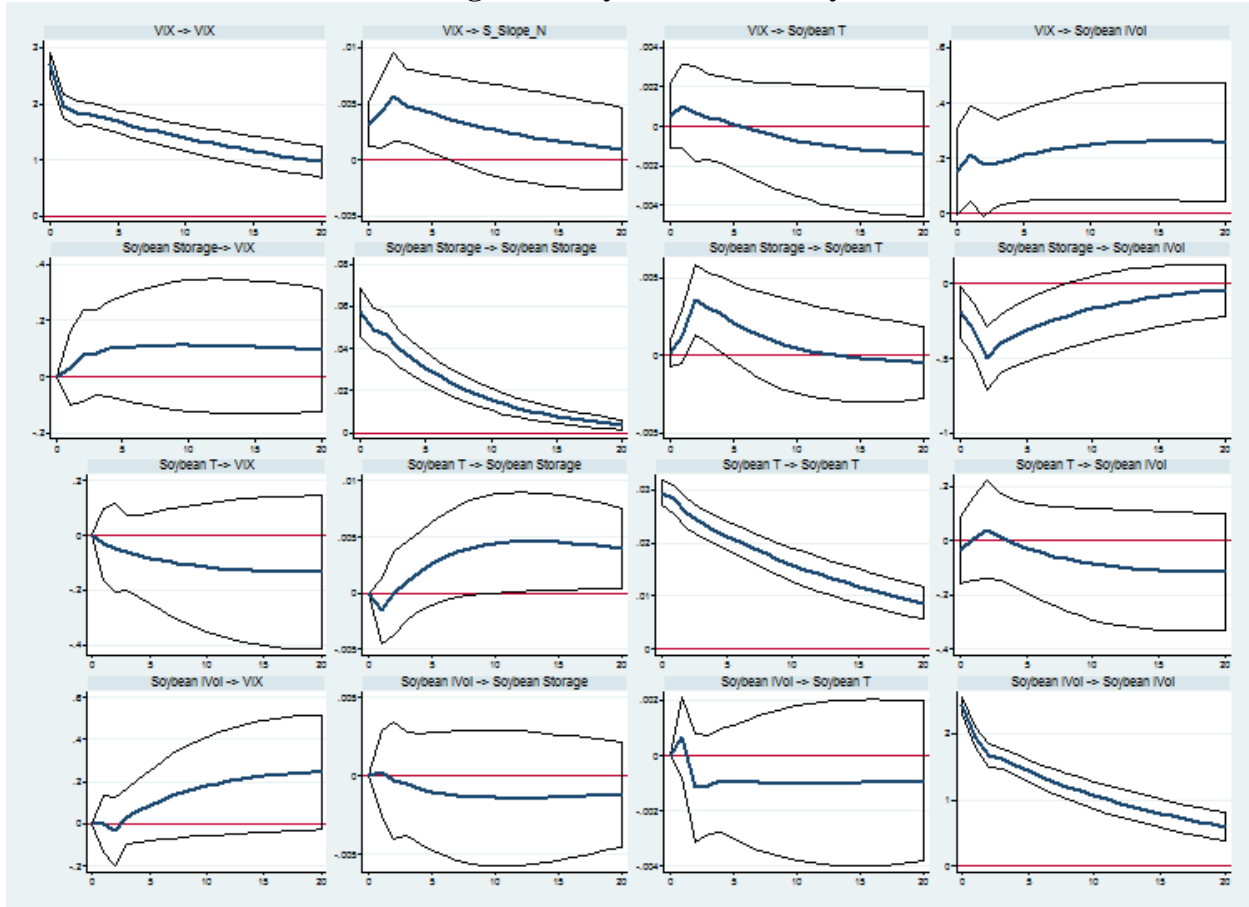
**Figure 3 – Panel A: Impulse Response Functions for Drivers of Forward-Looking Volatility in the CME Corn Market**



**Note:** Each Panel of Figure 3 plots the 20-week impulse responses of our model variables (S&P 500 option-implied volatility, *VIX*; Storage conditions; financial speculation in crop futures markets, *T*; and option-on-futures-implied volatility, *IVol*). Confidence bands are plotted at the 90 percent level of statistical significance. The SVAR model is estimated using weekly data between January 3<sup>rd</sup>, 1995 and September 15<sup>th</sup>, 2015, with variables ordered as follows: *VIX*, *Corn Storage*, *Corn T*, and *Corn IV*. The U.S. commodities covered are corn (Panel A), soybeans (Panel B), and winter wheat (Panel C). Equities are those included in Standard and Poor’s S&P 500 index.

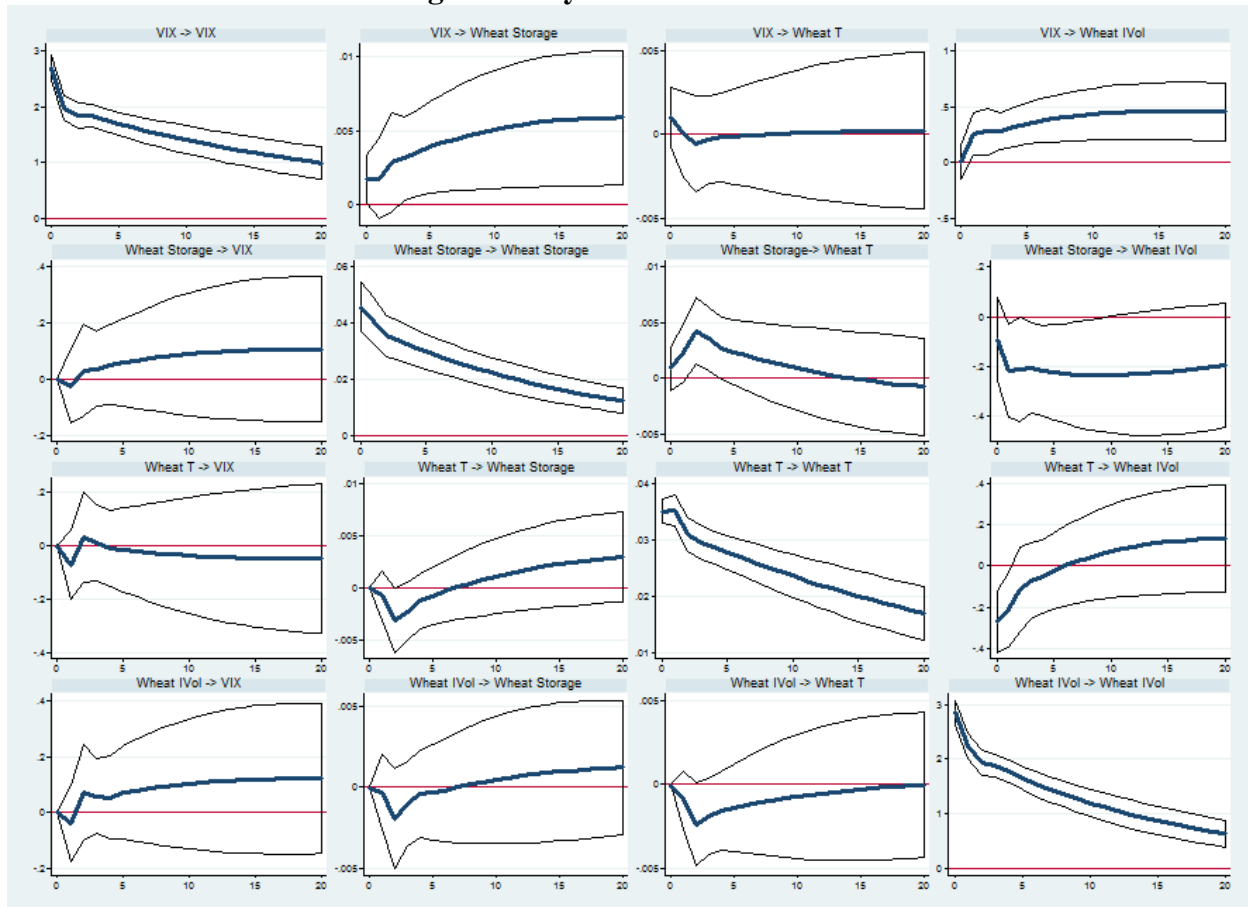


**Figure 3 – Panel B: Impulse Response Functions for Drivers of Forward-Looking Volatility in the CME Soybean Market**



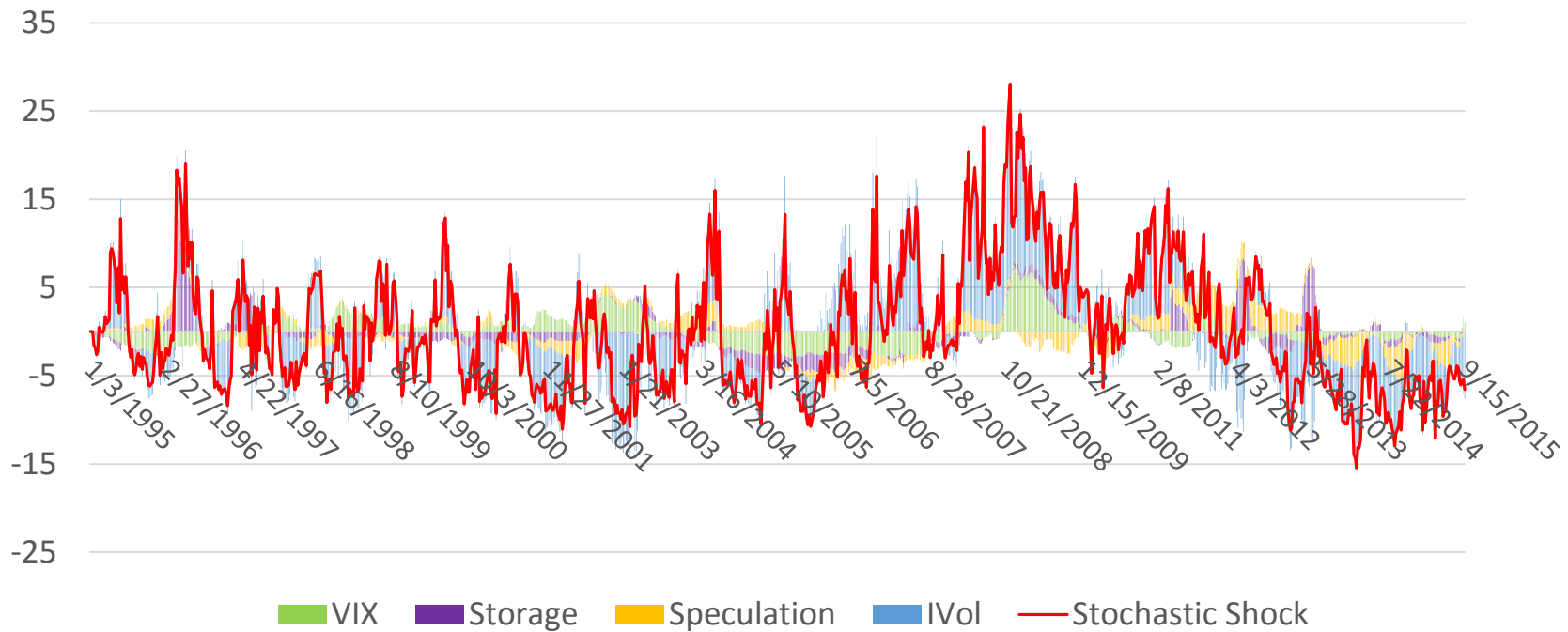
*Note:* Each Panel of Figure 3 plots the 20-week impulse responses of our model variables (S&P 500 option-implied volatility, *VIX*; *Storage* conditions; financial speculation in crop futures markets, *T*; and option-on-futures-implied volatility, *IVol*). Confidence bands are plotted at the 90 percent level of statistical significance. The SVAR model is estimated using weekly data between January 3<sup>rd</sup>, 1995 and September 15<sup>th</sup>, 2015, with variables ordered as follows: *VIX*, *Soybean Storage*, *Soybean T*, and *Soybean IV*. The U.S. commodities covered are corn (Panel A), soybeans (Panel B), and winter wheat (Panel C). Equities are those included in Standard and Poor’s S&P 500 index.

**Figure 3 – Panel C: Impulse Response Functions for Drivers of Forward-Looking Volatility in the CME Winter Wheat Market**



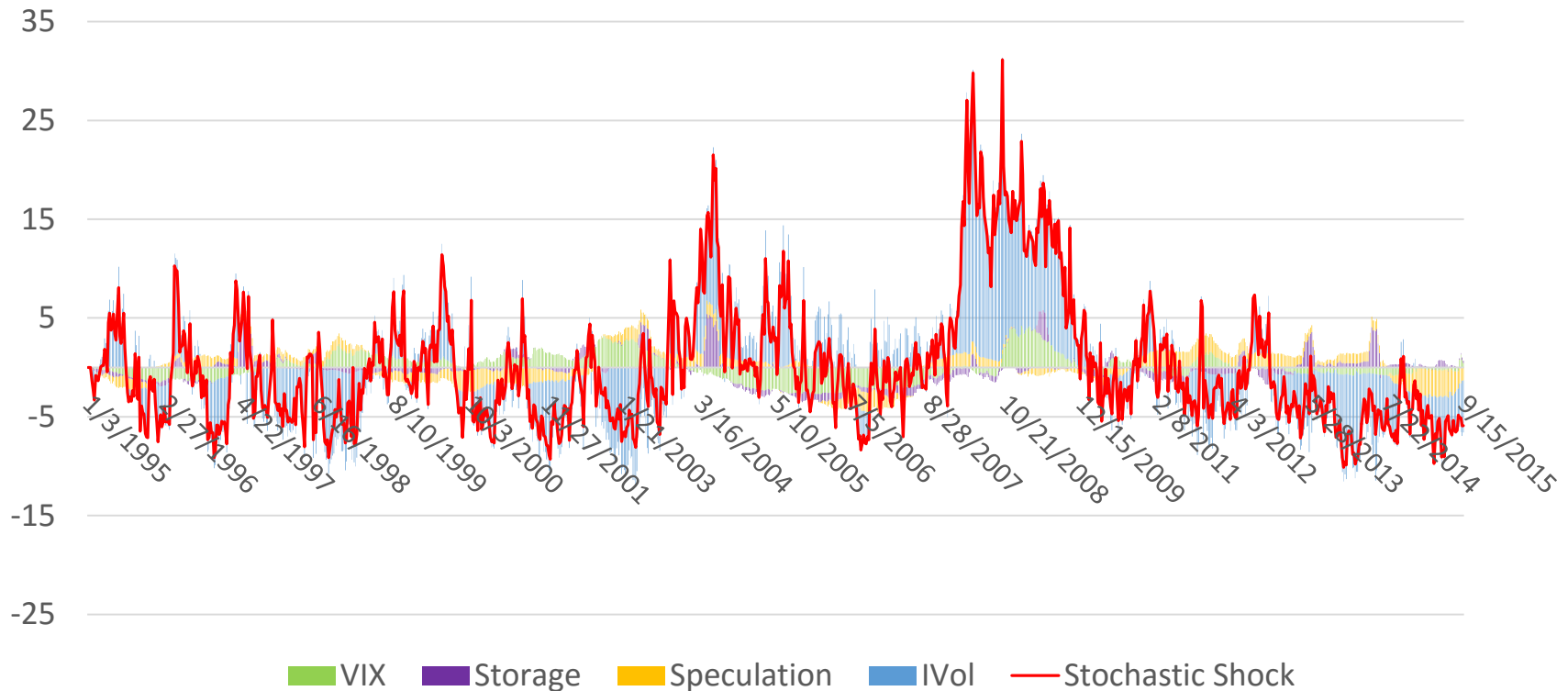
*Note:* Each Panel of Figure 3 plots the 20-week impulse responses of our model variables (S&P 500 option-implied volatility, *VIX*; *Storage* conditions; financial speculation in crop futures markets, *T*; and option-on- futures-implied volatility, *IVol*). Confidence bands are plotted at the 90 percent level of statistical significance. The SVAR model is estimated using weekly data between January 3<sup>rd</sup>, 1995 and September 15<sup>th</sup>, 2015, with variables ordered as follows: *VIX*, *Wheat Storage*, *Wheat T*, and *Wheat IV*. The U.S. commodities covered are corn (Panel A), soybeans (Panel B), and winter wheat (Panel C). Equities are those included in Standard and Poor’s S&P 500 index.

**Figure 4 – Panel A: Historical Decomposition of the Stochastic Shocks to Forward-Looking Volatility in the CME Corn Market**



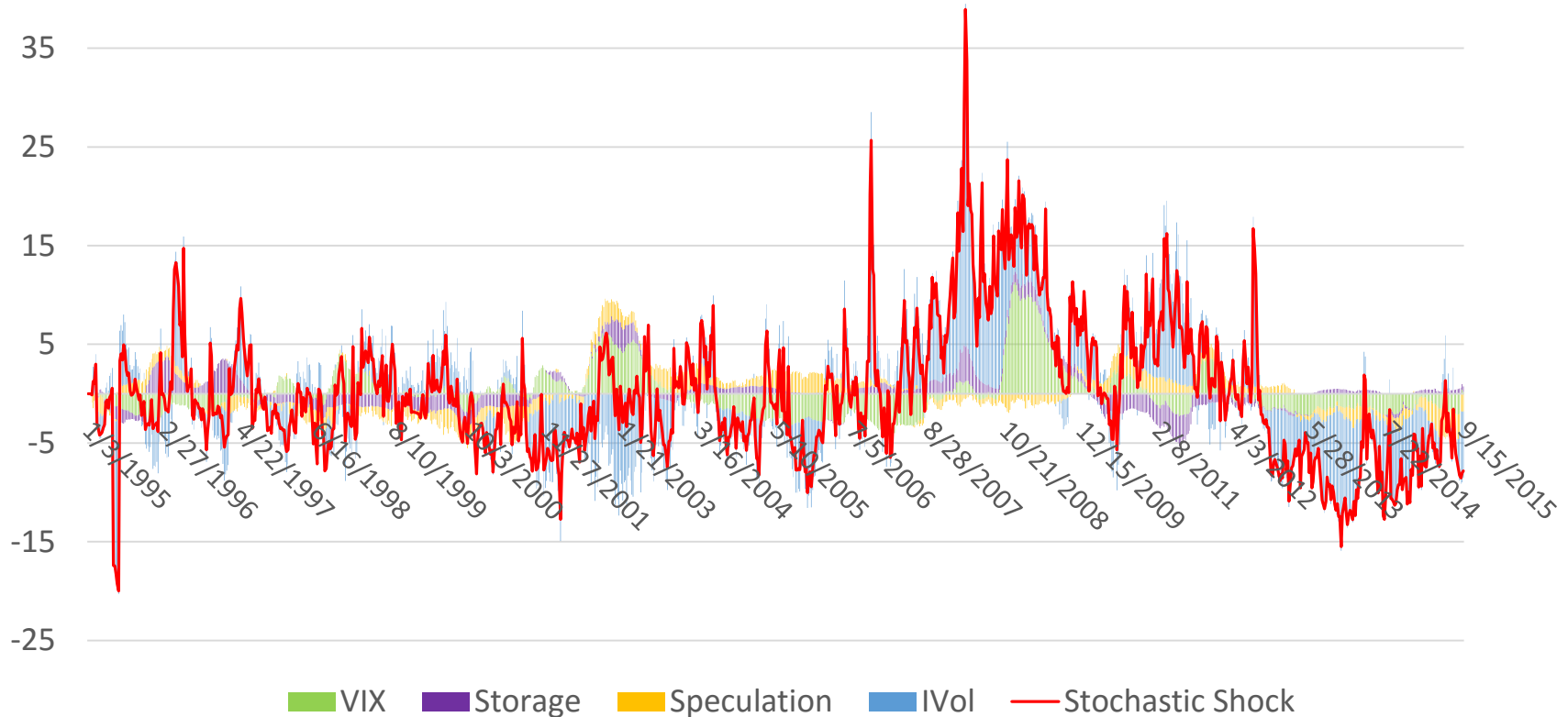
**Note:** Each Panel of Figure 4 plots the historical decomposition of stochastic innovations to commodity implied volatility due to structural shocks to our model variables (S&P 500 option-implied volatility, *VIX*; *Storage* conditions; financial speculation in futures markets, proxied by Working’s *T*; and option-on-futures-implied volatility, *IVol*). The SVAR model is estimated using weekly data between January 3<sup>rd</sup>, 1995 and September 15<sup>th</sup>, 2015, with variables ordered as listed above. The U.S. field crops covered are corn (Panel A), soybeans (Panel B), and Chicago winter wheat (Panel C). Equities are those included in Standard and Poor’s S&P 500 index.

**Figure 4 – Panel B: Historical Decomposition of the Stochastic Shocks to Forward-Looking Volatility in the CME Soybean Market**



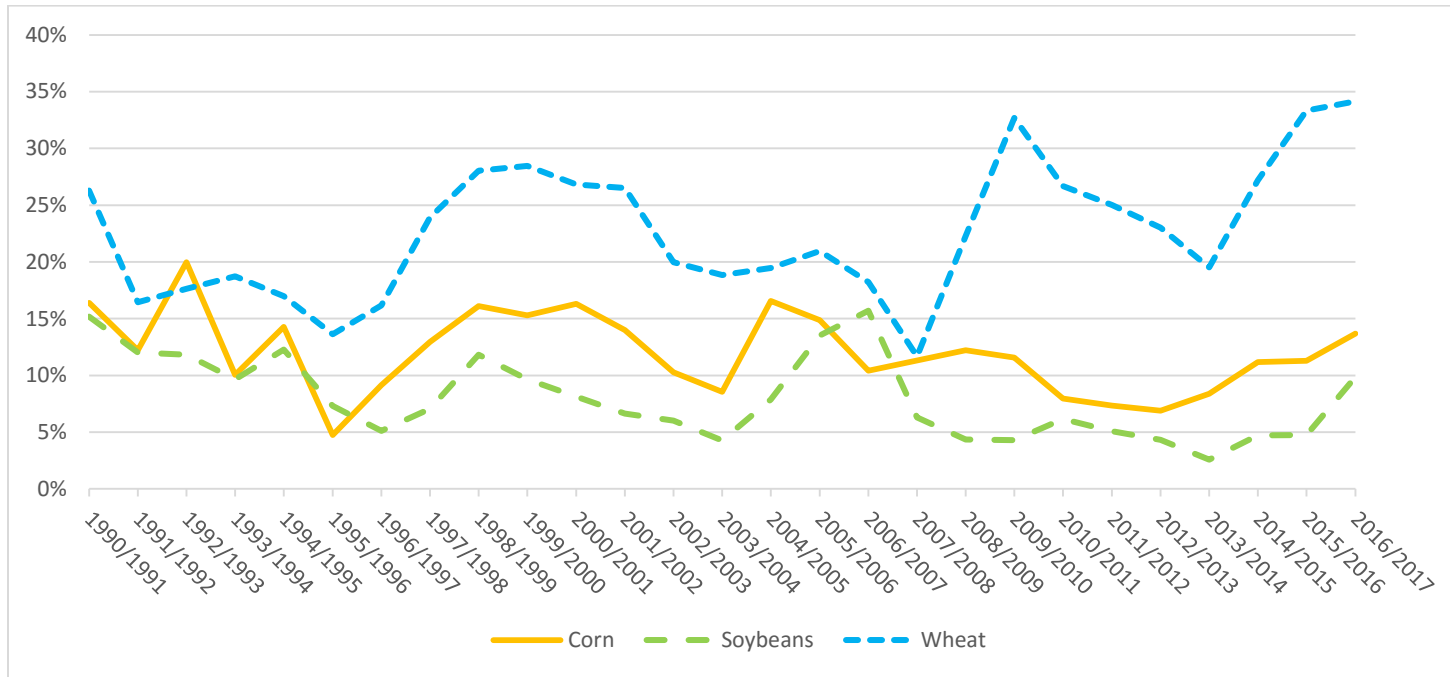
**Note:** Each Panel of Figure 4 plots the historical decomposition of stochastic innovations to commodity implied volatility due to structural shocks to our model variables (S&P 500 option-implied volatility, *VIX*; *Storage* conditions; financial speculation in futures markets, proxied by Working’s *T*; and option-on-futures-implied volatility, *IVol*). The SVAR model is estimated using weekly data between January 3<sup>rd</sup>, 1995 and September 15<sup>th</sup>, 2015, with variables ordered as listed above. The U.S. field crops covered are corn (Panel A), soybeans (Panel B), and Chicago winter wheat (Panel C). Equities are those included in Standard and Poor’s S&P 500 index.

**Figure 4 – Panel C: Historical Decomposition of the Stochastic Shocks to Forward-Looking Volatility in the CME Wheat Market**



**Note:** Each Panel of Figure 4 plots the historical decomposition of stochastic innovations to commodity implied volatility due to structural shocks to our model variables (S&P 500 option-implied volatility, *VIX*; *Storage* conditions; financial speculation in futures markets, proxied by Working’s *T*; and option-on-futures-implied volatility, *IVol*). The SVAR model is estimated using weekly data between January 3<sup>rd</sup>, 1995 and September 15<sup>th</sup>, 2015, with variables ordered as listed above. The U.S. field crops covered are corn (Panel A), soybeans (Panel B), and Chicago winter wheat (Panel C). Equities are those included in Standard and Poor’s S&P 500 index.

**Figure 5 – U.S. Ending Stocks-to-Usage**



*Source:* USDA Production, Supply, and Distribution database.