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Abstract

We analyze empirically the drivers of grain option-implied volatilities (IVs). Forward-looking uncertainty and risk aversion in equity market (jointly captured by the VIX) and the state of commodity inventories (proxied by the net cost of carry for each grain) 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 negative impact on grain IVs.

1. Introduction.

Since the mid-2000's, major domestic food commodities have experienced considerable price spikes and falls. While not unusual in historical terms (Wright, 2000), recent episodes of elevated price volatility in agricultural markets have hurt consumers and attracted the attention of market regulators and researchers worried about their sources and implications. For market participants, understanding 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 increases the efficiency of decision making in the agricultural sector.

The extant empirical research has been principally concerned with *realized* (i.e., past) commodity market volatility—see, e.g., Karali, Power, and Ishdorj (2011), Karali and Power (2013), and references cited therein. 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 grain 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 grain option-implied volatilities (IVs) are driven by uncertainty and risk aversion in the broad economy *vs*. by developments specific to the agricultural space.

For the purpose of this investigation, we use a dataset of financial and fundamental variables. To promote domestic agricultural production, the U.S. Department of Agriculture (USDA) collects and publishes administrative data on the progress and condition of key crops as well as on current and forecasted demand and supply for grains. Linking these USDA figures with other publicly available data between 1995 and 2015 yields a 20-year dataset of key fundamental factors in physical markets, which we augment with proxies for the extents of financialization in grain futures markets and for uncertainty and risk aversion in financial markets.

The first explanatory variable we consider is the option-implied volatility of Standard and Poor's S&P 500 equity index (the VIX), which Bekaert, Hoerova, and Lo Duca (2013) link to uncertainty about global macroeconomic conditions (affecting food consumption demand) and to investor risk aversion. Our other variables are specific to grain markets. The first such variable is the precautionary and speculative demand for grains that is reflected in the state of inventories. Consistent with the forward-looking nature of our IV analysis, we use market expectations of future storage levels embedded in the slope of the term structures of grain futures price. Bruno, Büyükşahin, and Robe (2016) show that this price-based proxy is closely related to the USDA's monthly forecasts of end-of-crop cycle ("ending") stock levels. We construct several additional variables to account for exogenous factors that affect agricultural supply (summarized through progress and condition indices for different crops) and other commodity-specific shocks (such as biofuel mandates for grains, mad cow and swine flu epidemics for livestock, etc.). Finally, we include variables that capture the intensity of financial speculation in each grain 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.[2]

We document that option-implied forward-looking uncertainty and risk aversion in equity market (jointly captured by the VIX) and the state of commodity inventories (proxied by the net cost of carry for each grain) have statistically and economically significant impacts on forward-

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[2] Robe and Wallen (2016) and Covindassamy, Robe, and Wallen (2016) investigate forward-looking volatility in markets for crude oil and for softs, respectively.

looking volatility in the three largest U.S. grain markets: corn, soybeans, and wheat. This result presents an interesting counterpoint to Engle and Figlewski's (2015) finding that, in equity markets, the VIX index is a "viable measure of the common component of IV fluctuations for individual options and portfolios of options" (*ibid*. p.993). In other words, one common factor explains the dynamics of single-stock IVs (and correlations among them) – and the VIX is a good proxy for that factor. In grain markets, the factor captured by the VIX is not the sole driver of IVs: inventories matter too, and they systematically affect traders' volatility expectations.

In the case of corn and winter wheat (though not of soybeans), we also find evidence that increased financial speculation has an immediate but short-lived negative impact on forward-looking volatility. This result complements evidence that hedge fund activity lowers *realized* volatility in several large futures markets (Brunetti, Büyükşahin, and Harris, 2016).

The remainder of the paper proceeds as follows. Section 2 provides descriptive evidence on option-implied volatility patterns in grain (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 our SVAR analysis. Section 6 concludes. A technical Appendix ends the paper.

2. Volatility Expectations in Grain and Equity Markets, 1995-2015

A key intuition in our analysis is that forward-looking volatility (IV) in grain 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 grain and equity IVs and documents their respective evolutions in the past two decades.

2.1. Data

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

Our sample period runs from January 3rd, 1995 to September 15th, 2015. We obtain from Bloomberg the daily futures prices and IVs computed from the prices of European options on those futures, plus volume and open interest for futures and option contracts. The Bloomberg IV series are based on the Tuesday closing prices of the most actively traded contracts, i.e., on at-the-money options (Cui, 2012). In order to minimize the possibility that low liquidity could affect option prices and artificially inflate IVs when a prompt futures contracts approaches its expiration date, we use the preponderance of the futures open interest (rather than calendar dates) to select roll dates for futures and options on futures.

For equities, we use IVs implied by Standard and Poor's S&P 500 equity index option prices. We obtain daily VIX values from Bloomberg, and similarly sample them on Tuesdays.[3,4]

2.2. Patterns

Figure 1 plots, from January 3rd, 1995 to September 15th, 2015, the nearby option-implied volatilities for corn (Panel A), soybeans (Panel B), and Chicago wheat (Panel C). Superimposing

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[3] If a Tuesday is a market holiday, we use the Wednesday immediately after to the holiday and adjust position data accordingly. If that Wednesday is also a holiday, then we select the Monday prior to the Tuesday.

[4] We measure IVs based on 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.

the graphs for grain IVs with the VIX, Figure 1 shows that IVs in grain 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 identifies commodity-specific IV fluctuations that appear unrelated to the behavior of the VIX – indicating that an investigation into grain-specific explanations for those IV patterns should prove fruitful.

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

Our premise is that both physical market fundamentals and financial market variables help explain market expectations of volatility in grain markets. This Section discusses the variables we use in the econometric analysis of Sections 4 and 5.

3.1. Macroeconomic Uncertainty and Investor Risk Aversion

Bekaert, Hoerova, and Lo Duca (2013) show that the VIX index "can be decomposed into a component that reflects actual expected stock market volatility (uncertainty) and a residual, the so-called variance premium, that reflects risk aversion and other non-linear pricing effects, perhaps even Knightian uncertainty." Intuitively, uncertainty levels in financial and grain 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 connected insofar as an intermediary capital factor prices many classes of assets, including commodities (He, Kelly, and Manela, 2016), so that changes in investors risk-bearing desire or capacity are likely to permeate all asset markets.[5] In line with 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 affect grain IVs.[6]

3.2. Precautionary and Speculative Demand: Inventories

Economic theory establishes the importance of inventories for commodity price dynamics – see Myers, Sexton, and Tomek (2010), Vercammen and Doroudian (2014), Wright (2011), and references cited in those recent papers. Intuitively, forward-looking price uncertainty should be low when investor expect that grain inventories will be healthy going forward. In contrast, expectations of storage-related constraints when silos are either empty or almost full should make grain prices more susceptible to possible supply shocks and, thus, less predictable – boosting forward-looking price uncertainty (i.e., IVs). In a similar vein, extremely low or extremely high inventory levels could weaken the co-movements between financial and grain market, thus weakening the link between of global uncertainty and grain IVs.

We consider two possible sources of forecasts for future grain storage levels. First, the USDA's World Agricultural Supply and Demand Estimates (WASDE) include expert forecasts of next-September grain storage levels. These forecasts contain market-moving information (Adjemian, 2012) but are monthly, whereas our analysis is weekly. Absent higher-frequency data on physical grain inventories, we follow a second approach suggested by Working (1933, 1948, 1949) and Fama and French (1987, 1988) and use, as a proxy for the market expectations of future inventory conditions in each grain market, the slope of the term structure of U.S. futures

[5] As long as commodity markets are not segmented from financial asset markets, higher uncertainty levels in financial markets (which we capture through the options-implied volatility in equity markets, the *VIX*) should spill over into commodity markets. Spillovers in the opposite direction are unlikely to happen in the case of grains, as grain markets are relatively small compared to global asset markets.

[6] 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.

prices for that commodity.[7] This slope, expressed in percentage terms and net of interest rate costs, measures the commodity's cost of carry.

We denote the resulting variable, which measures the net calendar spread return or net cost of carry, *SLOPE*. As for the other time series, we use Tuesday futures prices and interest rates to compute *SLOPE*. In our econometric analyses, we use the absolute value of *SLOPE* so that high values of the variable capture extremely low or high inventory levels.

3.3. Output shocks

As noted by Bruno, Büyükşahin, and Robe (2016), "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 grain IVs – especially when commodity inventories are low.

From a practical perspective, Lehecka (2013) shows that the weather's impact in U.S. grain 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 two ways suggested by Bruno, Büyükşahin, and Robe (2016). 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 – based on evidence that grain prices are more sensitive to very bad (*vs*. very good) weather.[8] 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

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[7] Joseph, Garcia, and Irwin (2014) provide solid empirical evidence that this price-based approach remains a valid way of estimating market participants' views of the state of inventories. Bruno, Büyükşahin, and Robe (2016) show that this price-based proxy is closely related to the USDA's forecasts of ending stock levels.

[8] In a related setting, Boudoukh, Richardson, Shen, and Whitelaw (2007) show that only extreme weather materially affects orange production levels and, thus, significantly impact frozen orange juice futures prices.

planted. We solve this problem by centering our condition indices for all weeks when there is a crop growing (by subtracting a grain-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, we investigate the possibility that financial speculation has an impact on forward-looking volatility. To capture the relative importance of financial institutions such as hedge funds in grain futures markets, we use a version of the widely-used Working's (1960) *T* index of speculative intensity. For each grain, we compute this index from the U.S. Commodity Futures Trading Commission's (CFTC) weekly reports on the aggregate end-of-Tuesday positions of different trader categories. The Appendix provides details of our *T* index computations.

Figure 2 plots, from January 3rd, 1995 to September 15th, 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. grain markets (corn, soybeans, Chicago wheat), the respective roles of macroeconomic uncertainty and investor risk aversion (jointly captured by the equity *VIX*), physical grain market fundamentals (affecting commodity supply or demand), and financial speculation (Working's *T*) in explaining a fourth variable: grain price volatility expectations or *IV*.

For our four-variable SVAR, we impose the standard Cholesky decomposition of the variance-covariance matrix to fit a just-identified model. We impose structural restrictions by assuming that the *VIX* is not contemporaneously affected by grain inventory forecasts (*SLOPE*), *T*, or *IVs*. In turn, we assume that inventory forecasts (*SLOPE*) are contemporaneously affected by the *VIX*, but not by financial speculation (*T*) or price uncertainty (*IV*) in grain 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 grain market (*T*) is affected contemporaneously by the *VIX* and by inventory forecasts for that grain (*SLOPE*) but not by that grain's *IV*. Finally, we assume that each grain's *IV* is affected by contemporaneous shocks in *VIX*, *SLOPE*, and *T*. By ordering *T* in third position and before *IV*, we assume that financial speculation in a given grain 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 grain *IV*. We make this assumption in order to test whether the intensity of financial speculation impacts volatility expectations or uncertainty in grain markets.

Finally, we use our proxy for grain supply as an exogenous variable in our SVAR model. Precisely, we use for each grain a weekly crop-specific, centered, asymmetrically-weighted average of the percentages of soybean, wheat and corn plots in "very poor", "poor", "good", or "excellent" condition.

5. Results – Impulse Response Functions

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 all three grains specifications, which eliminates serial correlation in the residuals. For the IRF analyses, we have a large number of observations (1,081) and use a standard non-parametric bootstrapping with replacement in order to compute confidence intervals. We use 1,000 replications and report the results with 90 percent confidence bands.

Figure 3 shows the IRFs from our four-variable SVAR for, respectively, corn (Panel A), soybeans (Panel B), and winter wheat (Panel C) based on the following ordering – the *VIX* followed by three grain-specific variables: expected future *STORAGE* conditions (*SLOPE*), financial speculation *T,* and *IV*. Each chart within these Figures gives the impulse responses over 20 weeks to a one-standard deviation shock to the variable identified 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 the relevant grain futures market's *SLOPE*, *T*, and *IV*.

5.1. VIX

Figure 3 shows that a key driver of forward-looking volatility in grain markets' is the VIX, i.e., forward-looking volatility in financial markets – which itself captures both macro-economic uncertainty and investors' risk aversion. Higher *VIX* levels lead to a statistically significant and long-lasting increase in grain IVs after one (soybean, winter wheat) or two (corn) weeks. The magnitudes of these responses are similar to the IV responses, documented in Section 5.2 below, to a storage (*SLOPE*) shock in the case of corn and wheat, and about a quarter of that magnitude in the cases of soybeans.

5.2. Grain Storage Conditions

Consistent with economic theory, we find that inventory conditions have an economically significant impact on forward-looking price volatility. In all cases, the impact is statistically significant after just a week; it is longer lasting in the case wheat and soybean (more than three months – see Panels B and C in Figure 3) than it is for corn (where the impact is statistically significant for less than a month – see Panel A). In all three grain markets, our point estimates of the *IV* response to a *SLOPE* shock are largest in the first two weeks.

Together with Section 5.1, these results present an interesting contrast to related 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 Dow-Jones stocks (Christoffersen, Fournier, and Jacobs, 2013) 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 commodities, Figure 3 establishes that the *VIX* matters but is not the sole driver of grain IVs: inventories significantly affect traders' volatility expectations (*IV*) as well.

5.3. Financial Speculation in Grain Markets

Panel B in Figure 3 shows a negative, if statistically insignificant, impact of financial speculation (*T*) on near-dated soybean *IV*. Likewise, Panels A and C in Figure 3 show that a one-standard deviation shock to the *T* index for corn and wheat, respectively, decreases *IV*s in those two grain markets. For the latter two, the impact is immediate, statistically significant and strongest contemporaneously. Compared to the impact of *SLOPE* 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 a month at the most.

In total, the results summarized in Figure 3 establish that fundamentals matter and suggest that financial speculation moderates grain-market specific forward-looking volatility. If speculative activity dampens the uncertainty that is idiosyncratic to grain markets, then it may in turn increase the importance of shocks common to all asset markets. If so, then it would help understand Bruno, Büyükşahin, and Robe's empirical finding (2016) 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 grain 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 inventory conditions (namely, expected future stress in the storage space) both boost forward-looking in grain markets (captured through grain IVs), whereas financial speculation in grain 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, for example, Adjemian, Robe, and Bruno (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 grain 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 Grain Markets

In Section 5, we test empirically if the intensity of financial speculation in grain 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*.[9] This Appendix explains how we construct the *T* index.

4.1 Data

Working's (1960) *T* measures speculative intensity in terms of how much speculation (non-commercial positions) exceeds the minimum required to offset any unbalanced commercial hedging at the market-clearing price (i.e., to satisfy hedgers' net demand for hedging at that price). 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.[10,11] 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.

4.2 Measuring the intensity of financial speculation

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

[9] 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. Büyükşahin 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.

[10] 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 4th, 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).

[11] COT reports also provide data on the positions of non-reporting (i.e., small) traders.

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

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 numerators, 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

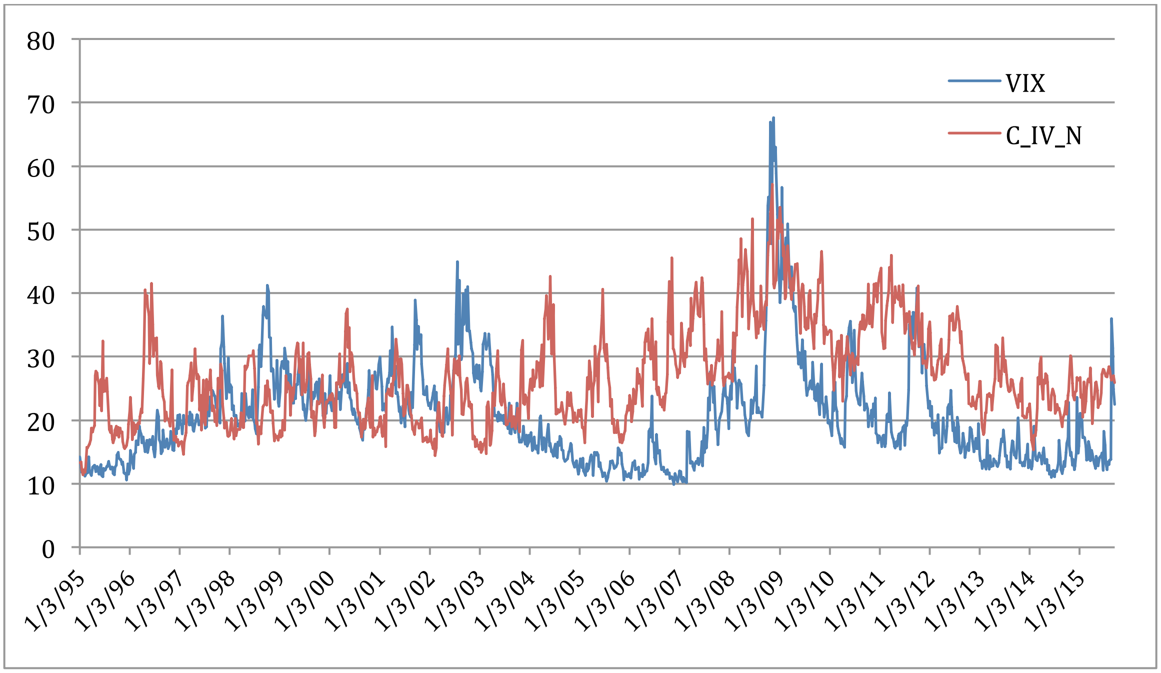


Figure 1 plots in **red**, from January 3rd, 1995 to September 15th, 2015, the forward-looking volatilities (IV) implied by prices of nearby at-the-money call options on futures for corn (Panel A), soybeans (Panel B, next page), and Chicago wheat (Panel C, next page) – *Source*: Bloomberg. In all three 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 grains, near-dated forward-looking volatility is more volatile than longer-dated (6-month out) figures (not displayed). Although all nearby grain 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

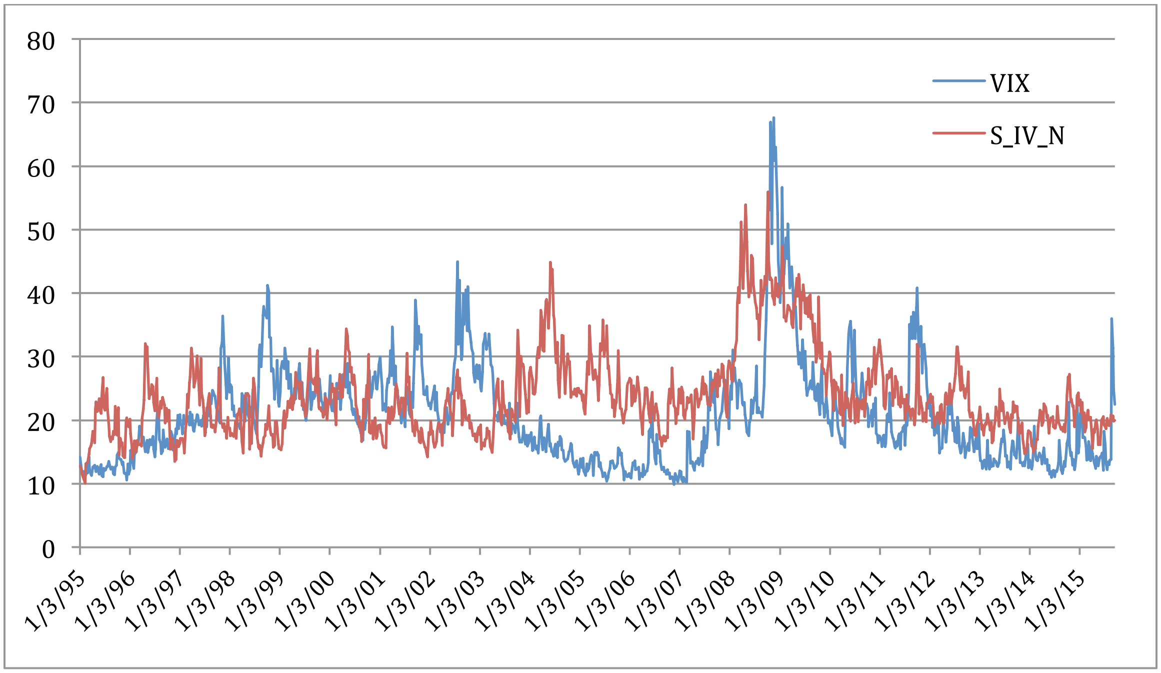


Figure 1 – Panel C: Forward-Looking Volatility in Wheat and Equity Markets

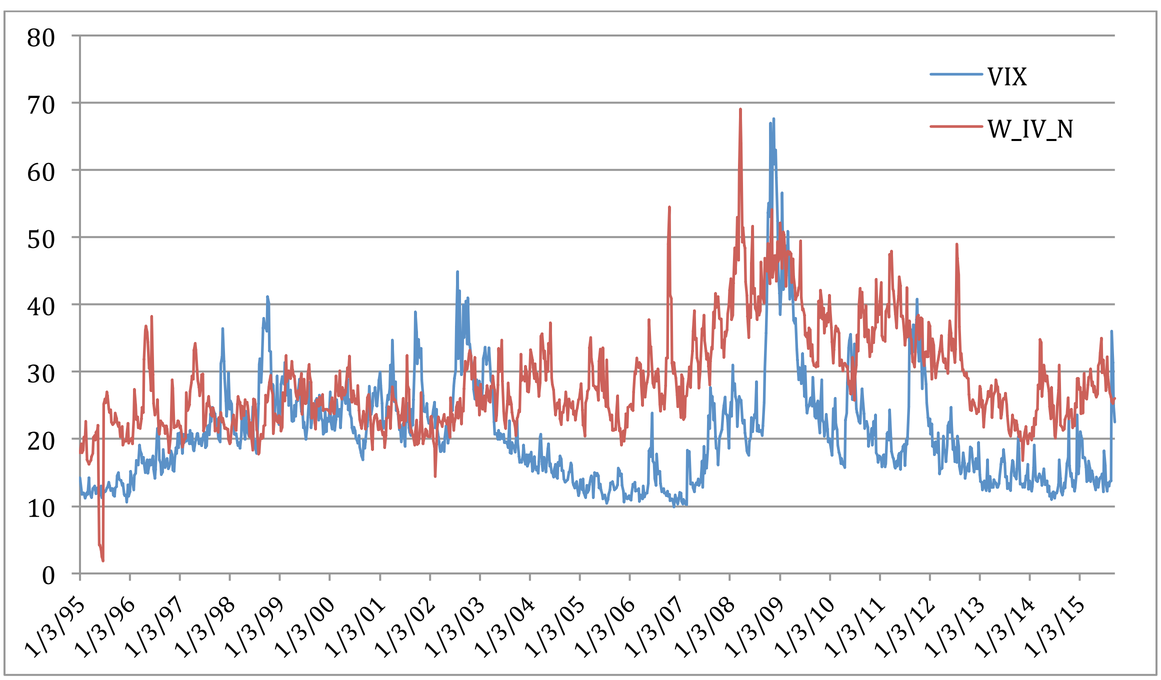


Figure 2 – Financial speculation in Grain Markets

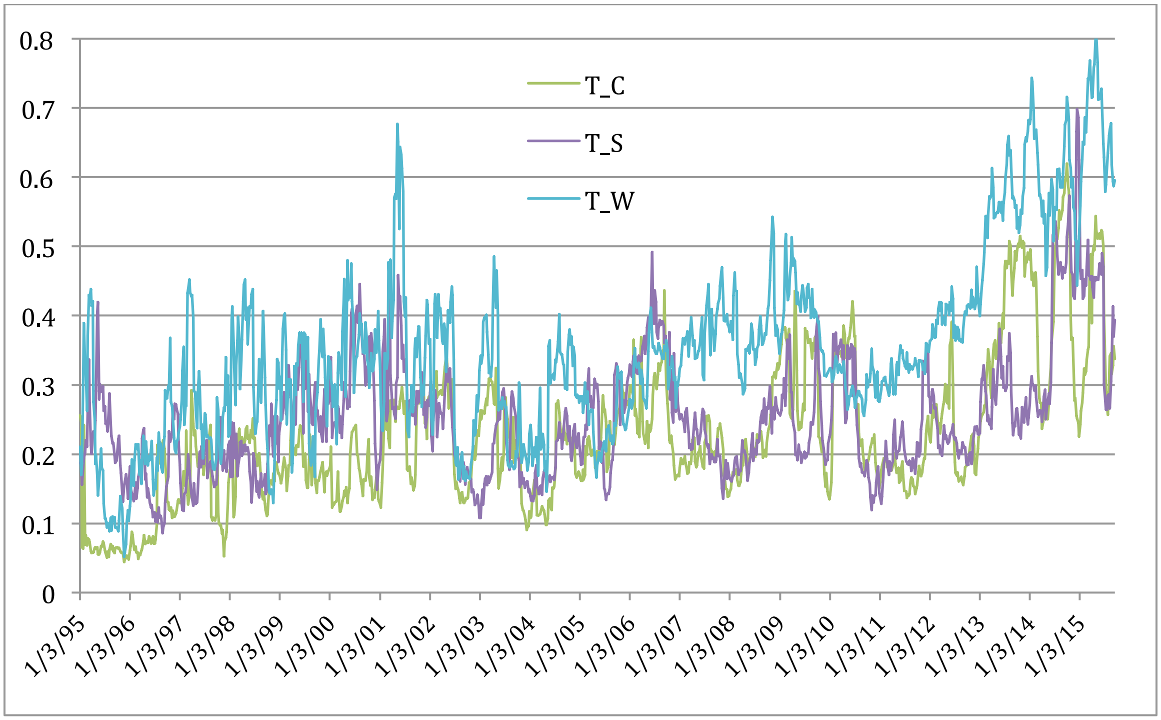
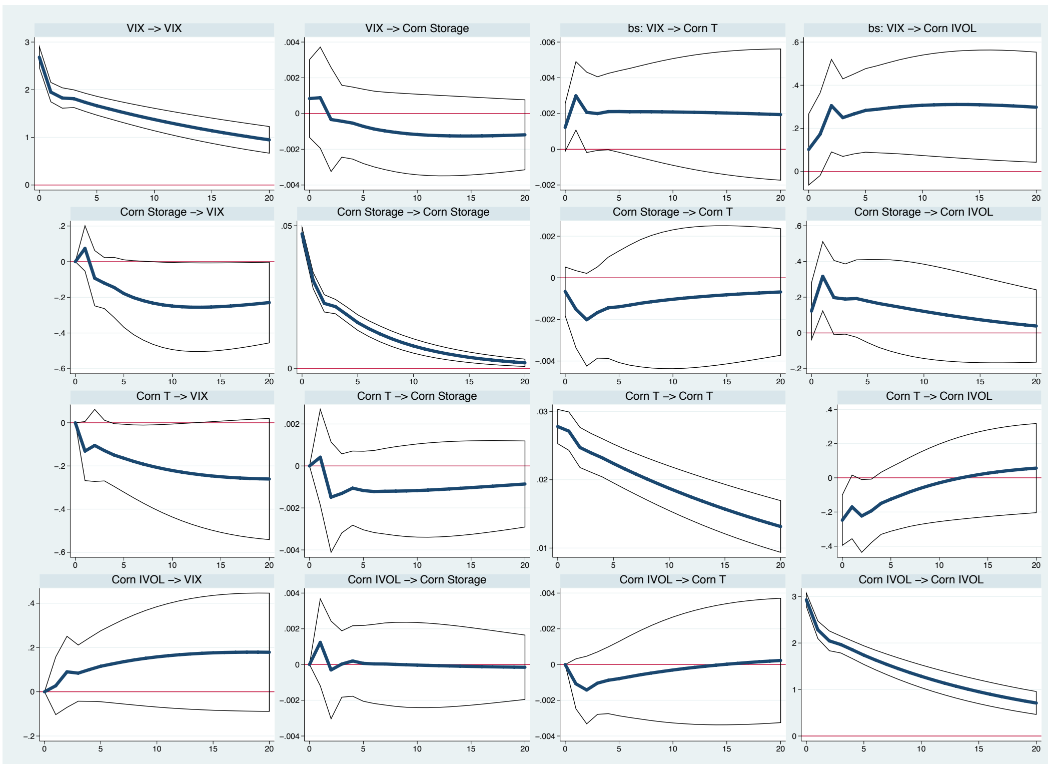


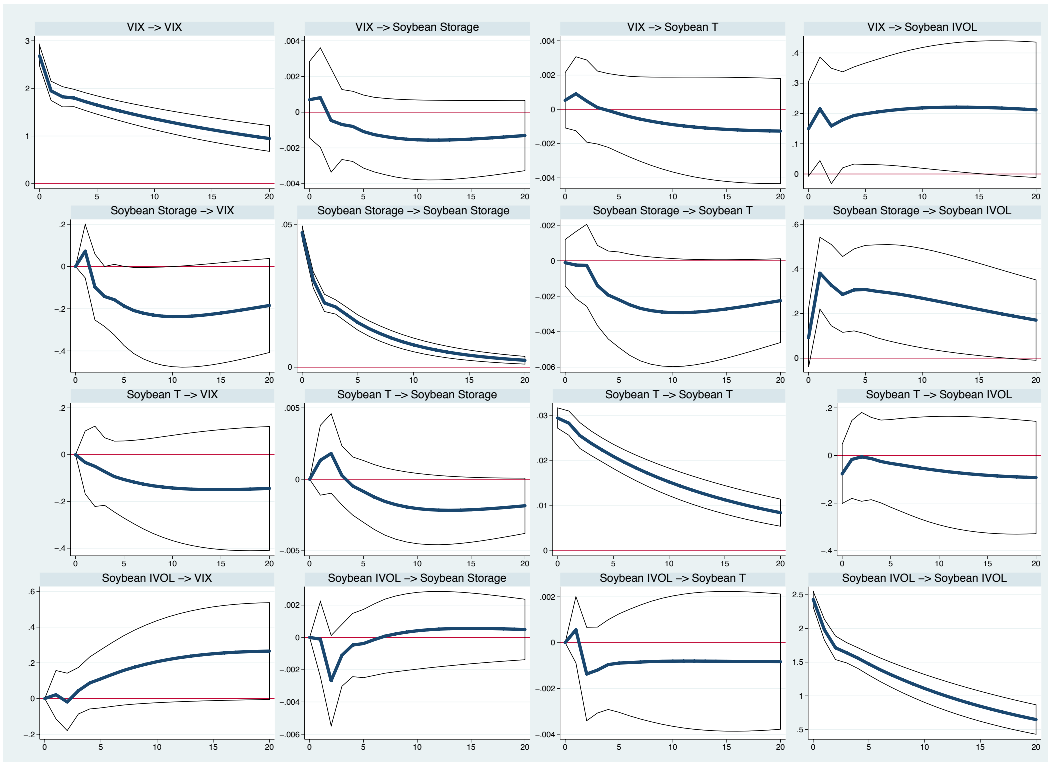
Figure 2 plots, from January 3rd, 1995 through September 15th, 2015, indices of the intensity (adjusted Working's (1960) *T* index *minus* 1) of financial speculation in the U.S. futures markets for corn (**green** series), Chicago wheat (**blue** series), and soybeans (**purple** series). We use data 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: Drivers of Forward-Looking Volatility in Corn Markets



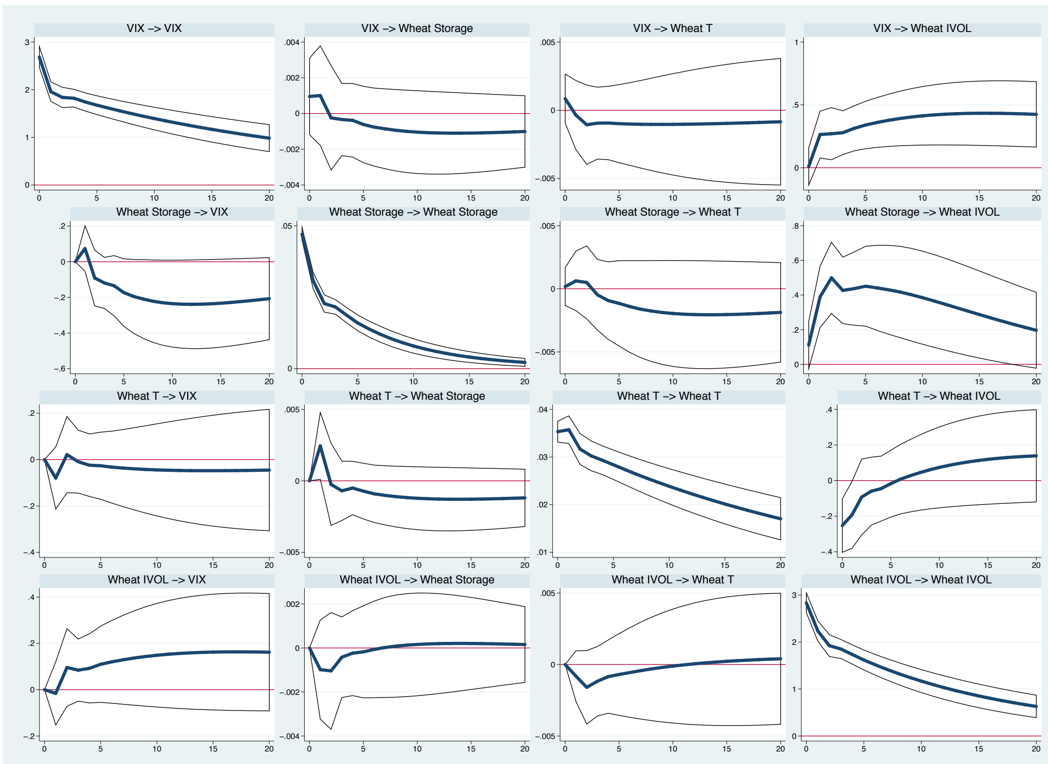
Note: Each Panel of Figure 3 plots the 20-week impulse responses of our model variables (S&P 500 option-implied volatility, *VIX*; *Grains Storage* conditions; financial speculation in grain futures markets, *T*; and option-on-grain-futures-implied volatility, *IVol*). Confidence bands are plotted at the 90 percent level of statistical significance. The SVAR model is estimated using weekly data between January 3rd, 1995 and September 15th, 2015, with variables ordered as follows: *Grains Storage, VIX, Grains T,* and Grains *IV*. The U.S. grains 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: Drivers of Forward-Looking Volatility in Soybean Markets



Note: Each Panel of Figure 3 plots the 20-week impulse responses of our model variables (S&P 500 option-implied volatility, *VIX*; *Grains Storage* conditions; financial speculation in grain futures markets, *T*; and option-on-grain-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 3rd, 1995 and September 15th, 2015, with variables ordered as follows: *Grains Storage, VIX, Grains T,* and Grains *IV*. The U.S. grains 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: Drivers of Forward-Looking Volatility in Winter Wheat Markets



Note: Each Panel of Figure 3 plots the 20-week impulse responses of our model variables (S&P 500 option-implied volatility, *VIX*; *Grains Storage* conditions; financial speculation in grain futures markets, *T*; and option-on-grain-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 3rd, 1995 and September 15th, 2015, with variables ordered as follows: *Grains Storage, VIX, Grains T,* and Grains *IV*. The U.S. grains 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.