“Energy and Speculation: New Dynamics in Agricultural Price Volatility”

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Poster prepared for presentation at the Agricultural & Applied Economics Association’s 2012 AAEA Annual Meeting, Seattle, Washington, August 12-14, 2012

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1. Introduction

RECENT developments in biofuels have altered the relationship between agricultural and energy. Historically energy has been an input to agricultural production. As the amount of corn utilized for ethanol production in the US has increased from 5% in 2001 to over 30% by the end of the decade, the correlation of agricultural commodity prices to energy prices has been transformed (Abbott et al, 2008, 2009). A number of authors have suggested a new era in which energy prices will play a more important role in driving agricultural commodity prices (Gohin and Chantret, 2010; Tyner, 2010). However disagreement in literature exists relative to the extent of influence from the energy to the agricultural markets and the existence of long run relationships (Nazlioglu, 2011; Nazlioglu and Soytas, 2011).

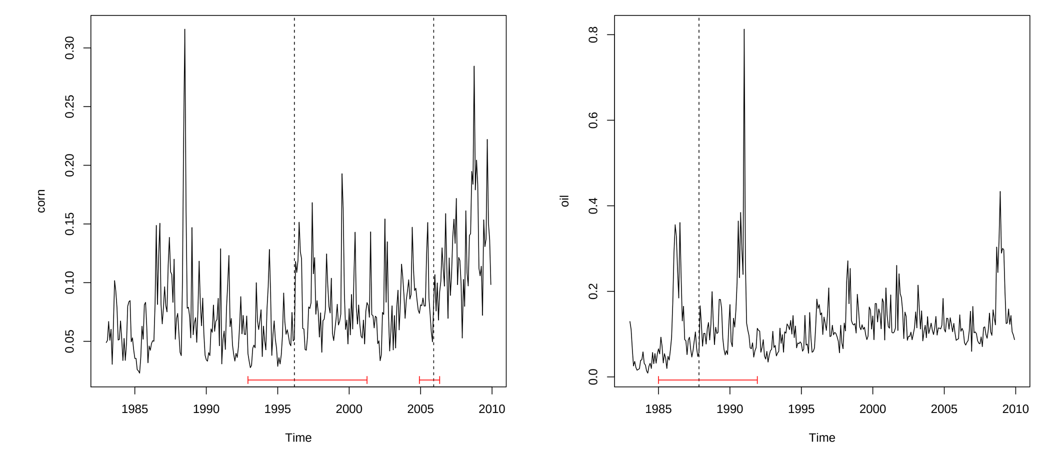
A new potential connection between energy and agricultural markets will likely manifest itself in short-run volatilities. The volatility of agricultural prices was historically determined by supply side shocks. The recent strengthening of the connection between energy and agriculture markets bears the question whether it has created a shift in the volatility of commodity prices by introducing marketable demand-side volatility in the market. Du, Yu, and Hayes (2009) find evidence of volatility spillovers among crude oil, corn and wheat markets after the fall of 2006. Further, Hertel and Beckman (2010) argue that in the future agricultural price volatility, particularly for biofuel feedstocks, will depend critically on renewable energy policies.

2. Methodological Approach

According to Serra (2011), the degree of the estimated transmission between energy and agricultural markets depends on the methodology used. To avoid influencing the results by choosing a specific model of stochastic volatility we use the standard deviation of effective daily log price returns as a measure of volatility over time.[1] The series of daily standard deviations is converted to a monthly basis (multiplied by $\sqrt{30}$) to examine the influence of factors such as interest rates, speculation, monthly stocks, and the effects of biofuel policies. Workings (1960) speculative index is constructed for major agricultural and energy commodities to measure (the excess of) speculation in the commodity futures market.

We use a vector autoregressive (VAR) model to allow for endogeneity among all the time series variables. One of the difficulties with the VAR approach is the large number of parameters that must be estimated.[2] We therefore adopt a Bayesian VAR model which incorporates prior information into the model to allow us to *shrink* the parameter space without appealing to artificial, ex ante restrictions (such as applying a Cholesky decomposition).

Following Koop and Korobilis (2010), we utilize different Bayesian VAR (BVAR) approaches to estimate the relationship among the endogenous, time series variables. Table 2 displays the results for two BVAR models: 1) a model with non-informative priors (this is comparable to a classical, unrestricted VAR approach); and 2) a model with a stochastic search variable selection (Koop and Korobilis, 2010). The SSVS prior (George, Sun, and Ni, 2008) automatically shrinks the parameter space by allowing the data to determine which time-varying coefficients are important to the model. Basically, the SSVS prior shrinks uninformative coefficients to zero. Based upon the model results we will offer a series of posterior impulse response function plots to visually inspect the shocks to the endogenous variables.



(a) (b)

Figure 1: *Structural Breaks Test for (a) Monthly Corn Volatility and (b) Monthly Oil Volatility, 1983-2009*

3. Preliminary Results

To analyze the volatilities we conducted the following analyses: Augmented Dickey Fuller (ADF) tests and structural break tests to evaluate structural changes, correlation analysis, Granger causality tests, and finally the regression analysis.

The ADF tests are used to determine if the individual volatility series are characterized by mean reversion or stationarity. The test results suggest that we reject the null hypothesis of a unit root at a one percent level for all commodities volatilities (except for barley, corn, and wheat) with 16 lags. However, the ADF results do offer evidence against the null when we include a trend for corn and wheat with 16 lags.

Table 1: *Mean Values of Correlation Analysis for Corn Over Time*

	1981–1990	1991-2000	2001–2011
Ag Commodities	0.60	0.36	0.335
	(0.51, 0.69)	(0.09, 0.68)	(0.14, 0.62)
Crude Oil	-0.04	-0.18	0.36
	N/A	N/A	N/A

Note: Average correlations with ranges in parentheses where applicable.

Limiting our analysis to corn and crude oil, the structural break tests indicate that 2006 marks the change in volatility patterns for historic corn prices as displayed in Figure 1, panel (a).[3] As displayed in Figure 1, panel (b), we find relatively weak evidence (large confidence interval band displayed in red) for a structural break in 1987 for WTI crude oil.

Agricultural commodities are highly correlated during the period 1981–1990. Correlations with crude oil are low for the period 19812001, and high for 2001-2011. Table 1 presents correlations for the case of corn. Granger causality tests (not provided) preliminarily suggest that only crude oil price volatility Granger cause the volatility of corn.

The parameter estimates for VARs (Table 2) are rarely of direct interest, so attention lyes with the impulse response functions (IRF). A function of the parameters is displayed in the IRFs in Figure 2. The IRFs suggest that a shock to corn price volatility has a small but positive effect on crude oil volatility that persists for approximately sixteen months. Conversely, a shock to crude oil price volatility has positive effect on corn price volatility that persists for approximately ten months. These initial results suggest that there are positive volatility spillovers between crude oil prices, corn prices, and speculation.

In future analyses we plan to examine to examine spillovers in the years prior to the structure break in corn price volatilities (1986-2005) versus the years following the break (2006-2009).

Table 2: *Posterior mean of BVAR Coefficients*

	Non-informative priors			SSVS priors		
	Corn	Oil	Spec	Corn	Oil	Spec
Intercept	-8.3383	-0.7604	0.3615	-4.8911	-1.1314	0.1161
Corn_{t-1}	0.4358	0.2358	0.0189	0.2488	0.0990	0.0091
Oil_{t-1}	-0.1293	0.0202	-0.0099	-0.0480	0.0380	-0.0056
Spec_{t-1}	0.6058	0.1342	-0.1388	0.2714	-0.0520	-0.0682
Corn_{t-2}	0.0609	-0.0325	-0.0106	0.1544	0.0498	0.0011
Oil_{t-2}	0.0809	-0.0325	-0.0106	0.0140	0.0431	-0.0046
Spec_{t-2}	-0.2325	-0.7076	-0.0455	-0.0668	-0.2457	-0.0383
Corn_{t-3}	0.0890	0.0398	0.0247	0.0917	0.0652	0.0110
Oil_{t-3}	-0.0096	0.0096	-0.0167	0.0311	0.0053	-0.0077
Spec_{t-3}	-0.0053	0.3247	0.0286	0.0979	0.1425	0.0034
Corn_{t-4}	-0.0202	0.1684	0.0091	0.0285	0.0846	0.0055
Oil_{t-4}	0.0217	-0.0966	0.0034	0.0567	-0.0243	-0.0007
Spec_{t-4}	0.1874	0.7278	0.0522	0.0407	0.2863	0.0251

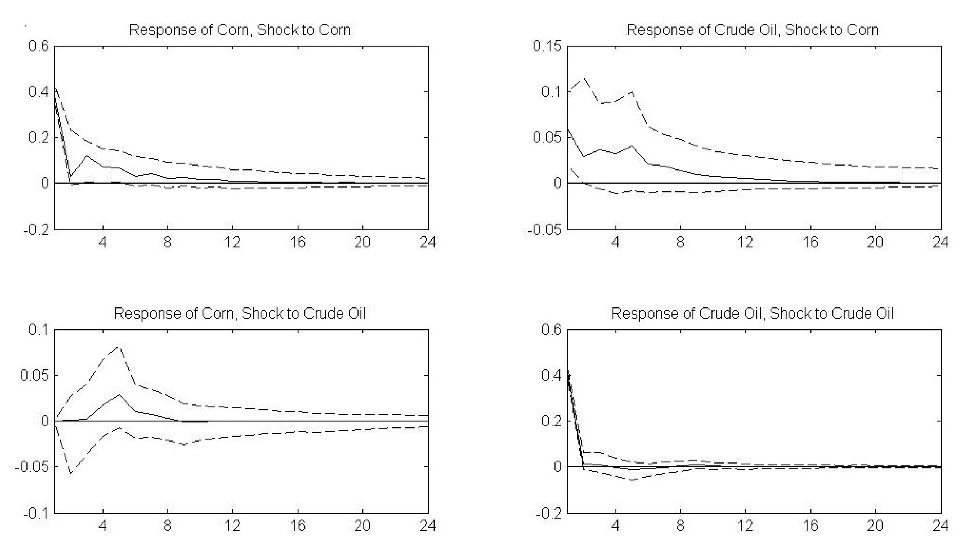


Figure 2: *Impulse Response Functions Based Upon SSVS Priors*

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[1] Agricultural commodities prices include the daily spot prices of corn, barley, wheat (No.2 Hard, Kansas), and soybeans. Crude oil prices are based upon West Texas Intermediate daily spot prices.
[2] For example, if the VAR contains five dependent variables with four lags then there are 105 parameters to estimate. Without placing some *ex ante* restrictions on the estimated parameters, models such as ours that contain only 288 observations can become quickly over-parameterized.
[3] This structural break was also confirmed through Perron's test (not provided).

2012 AAEA Annual Meeting August 12-14, 2012, Seattle, WA