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A Structural Approach to Disentangling Speculative and Fundamental Influences on the Price of Corn

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A Structural Approach to Disentangling Speculative and Fundamental Influences on the Price of Corn

Corn prices experienced enormous volatility over the last decade. In this paper, we apply a structural vector autoregression model to quantify the relative importance of various contributing factors in driving corn price movements. The identification of structural parameters is achieved through a data-determined approach—the PC algorithm of Directed Acyclic Graphs. We find that, in general, unexpected shocks in aggregate global demand and speculative trading activities do not have a statistically significant effect on corn price movements. By contrast, shocks in the crude oil market have large immediate effects that persist in the long-run. The forecast error variance decomposition suggest that at the two-year horizon, variations in crude oil prices account for over 50% of the total corn forecast error variances. We also find that, consistent with theory, unexpected shocks in market-specific fundamentals also have large negative effects on price movements. In addition, unexpected residual shocks play an important role in corn price movement, especially in the short-run.

Key words: corn, volatility, structural vector autoregressions, crude oil, speculative activities, graph theory

Introduction

Led by crude oil, global commodity prices have undergone large fluctuations since 2006. Corn prices, for example, nearly tripled between 2000 and 2008, rising from less than $2/bu. to over $5.50/bu. in nominal terms. Though corn prices plummeted dramatically from their peak in mid-2008, in 2011 they skyrocketed again, peaking at $7.60/bu. in August 2012.[1] Similar levels of volatility were observed in other grain commodity prices during this time. The resulting food price volatility has led to economic difficulties among the poor and irreversible damage from nutritional deficiencies among children in developing countries, and may have been responsible for political turmoil in many countries (Bellemare 2011). The extensive and negative consequences from the recent episode of food price fluctuations highlight the critical importance of understanding the causes behind heightened price volatility.

Studies attempting to pinpoint the underlying causes behind these large price volatilities over the past several years do not agree in their conclusions. Common contributing factors implicated in the recent volatility include, among others, strong demand from emerging countries such as China and India, diversion of a substantial amount of grains out of the food system by biofuel production, poor harvests due to weather shocks, the weak US dollar, and financial speculation (Abbott, Hurt, and Tyner 2011). It is fair to say that the recent large commodity price volatilities are likely driven by a combination of factors. However, addressing the relative importance of these contributing factors is of key importance to policymakers. The recent regulatory effort to impose position limits on futures trading (the Dodd-Frank Act) is a response to the argument that speculative trading in futures markets is primarily responsible for driving commodity prices away from fundamentals.

Empirical research disentangling the forces of large price fluctuations in commodity markets has largely followed one of two paths. One stream employs a partial approach by testing the empirical relationship between a specific driving factor of price variability and price movements using either time-series or cross-sectional regression techniques. Such analyses have investigated the extent to which investment activities of commodity index traders (CITs) allegedly drove prices away from fundamentals by creating demand side pressure through a "weight of money" effect (e.g., Stoll and Whaley 2010, Sanders and Irwin 2011, Hamilton and Wu 2013). In general, little evidence is found to support the relationship between CITs and futures prices movement. Notably, this research does not attempt to determine the primary factors behind recent large price volatilities in commodity markets.

The other stream of research applies a structural approach, such as a structural vector autoregression (SVAR) model. Kilian (2009) is among the first to apply an SVAR model to disentangle demand and supply shocks in commodity markets. In his seminal paper, Kilian decomposes the real price of crude oil into three components: crude oil supply shocks, shocks to the global demand for all industrial commodities, and demand shocks specific to the crude oil market. The ordering of the VAR model is based on exclusion restrictions that incorporate zero instantaneous responses of oil supply to demand shocks mainly due to information and institutional knowledge delays. In following papers, instead of imposing exclusion restrictions, Kilian and Murphy (2012a, b) incorporate sign restrictions and bounds on the implied demand/supply elasticities to identify a set of solutions to the structural parameters of the SVAR model. They conclude that business cycle fluctuations in demand were the primary drivers behind real price shocks in oil since the 1970s. Similar procedures have been employed by Juvenal and Petrella (2011) and Melolinna (2012), among others, to investigate crude oil price movements.

In attempting to explain the recent spikes in agricultural commodity prices, the SVAR model has also become an increasingly popular approach. McPhail, Du, and Muhammad (2012) use similar exclusion restrictions as in Kilian (2009) and investigate the role of global demand, speculation, and energy shocks on corn price volatility between 2000 and 2009. They conclude that energy market shocks are the most important driver of long-run corn price volatility. Qiu, Colson, Escalante, and Wetzstein (2012) extend the work by McPhail, Du, and Muhammad (2012) on corn price movements by considering an SVAR model including the demand and supply for gasoline, ethanol and corn, with the identification of the model obtained through the usual Cholesky decomposition. They conclude that increased biofuel production only have a short-run effect on corn prices. Janzen, Smith, and Carter (2013) consider four structural factors driving cotton prices: real economic activity, co-movement induced by speculative trading, demand for inventories, and shocks to current net supply. Their identification of the SVAR model is achieved through a combination of normalization, recursion, and identification through heteroskedasticity. They find minimal co-movement between cotton and non-agricultural commodity prices (crude oil, copper, and silver). They also find market-specific supply and demand factors to be the main determinants of cotton price fluctuations, rather than global real economic activity. Carter, Rausser, and Smith (2013) examine the effect of US ethanol mandates on corn prices through a four-variable SVAR model that includes inventory supply (end-of-year stocks), inventory demand (real futures price of corn), supply of storage (convenience yield), and global real economic activity. The model is identified by imposing exclusion restrictions and placing bounds on certain parameters in the contemporaneous relationship matrix. They conclude that the US ethanol mandate has had a considerable impact on annual global corn prices, without which the price of corn would have been 40% lower in 2012. By contrast, Baumeister and Kilian (2013) find little evidence that oil price shocks have caused more than a negligible increase in retail food prices in recent years using a two-variable VAR system. Bruno, Büyükșahin, and Robe (2013) investigate both commodity-equity and cross-commodity return comovements by employing a four-variable SVAR model that includes macroeconomic factors, physical food market fundamentals, financial speculation, and cross-market return correlations. Using exclusion restrictions as the identification strategy, they find that rather than directly affecting the cross-market comovements, financial speculation helps to transmit the macroeconomic shocks into grain markets.

Building on the SVAR models employed in previous research, the present paper expands on the current examination of grain price movements by providing estimates of the dynamic effects of various shocks and the individual contributions of these shocks on the price of corn over the period of 2000-2013. The analysis extends the current literature in several ways. First, given the importance of the various contributing factors in determining grain prices, it brings together the following five structural shocks: market-specific fundamentals, global business cycles, oil price fluctuations, financial speculation, and residual variations. While other studies have used some subset of these factors (e.g., McPhail, Du, and Muhammad 2012, Carter, Rausser, and Smith 2012, Janzen, Smith, and Carter 2013), these five critical factors have not been accounted for together in one framework. Second, unlike previous studies that rely on subjective judgment and prior knowledge of underlying model structure (exclusion restrictions and sign restrictions), the important contemporaneous causal pattern among the proposed structural factors is identified using a data-determined technique (e.g., Swanson and Granger 1997, Bessler and Yang 2003, Haigh and Bessler 2004, Wang and Bessler 2006, Mjelde and Bessler 2009).[2] The directed acyclic graph (DAG) approach is applied to the five structural shocks to understand their contemporaneous relationship. The resulting impulse response functions and forecast error variance decomposition from the SVAR model may thus provide a more unambiguous and objective view of the degree to which various factors affect the price movements of corn. In addition, modeling the causal relationships among structural factors contemporaneously may itself prove important as it may contain information regarding how information is transmitted among these factors.

The remainder of the paper proceeds as follows. First we discuss the contributing factors considered in this study to motivate the five-variable SVAR model. Then, in section three, the SVAR model is discussed, as well as the DAG technique that explores contemporaneous correlations among the structural factors in the model. We then discuss the data, results from the recursive VAR and DAG analysis, as well as the interpretation from the resulting SVAR model. The last section concludes the paper, highlighting its important policy implications. Results from the SVAR model suggest that consistent with previous studies, unexpected shocks in crude oil prices have a large and persistent effect on corn price movements. Further, residual shocks and market-specific supply/demand shocks play an especially important role in short-term corn price fluctuations. By contrast, speculative and global real economic activities are unlikely to be a major driving force of corn price volatility.

Sources of Corn Price Variability

The first factor we consider that drives corn price variability is the global real economic activity common to all commodities. Many studies suggest that the rapid economic growth in developing countries, notably China and India, is the main driving force of commodity price spike (e.g. von Braun 2008). Using a capital asset pricing model-type model, Gilbert (2010a) finds that common macroeconomic factors such as demand growth, monetary expansion, and exchange rates should be seen as the main drivers of agricultural food prices movement since 1971. The argument is consistent with the observation that a large number of commodities, including food, energy and metal products, experienced similar large price volatilities at around the same time. When the economy is booming, the demand for most commodities is likely to increase.

The price of corn can be driven by the price of crude oil in two ways. The first and traditional channel is the impact large fluctuations in crude oil prices have on the price of fertilizers and transportation costs, which constitute a substantial proportion of crop production costs. The second and more recent channel is due to the rise in ethanol production during the last decade, which has forged links between corn and crude oil prices through demand linkages (e.g., Mallory, Irwin, and Hayes 2012). This linkage has its roots in both policies and market incentives. For example, the Renewable Fuel Standard (RFS) sets a minimum annual blending requirement for ethanol usage in 2005 which was later expanded in 2007. At least partially influenced by these mandates, ethanol production capacity underwent a massive wave of expansion through 2010. High crude oil prices have also created market incentives for ethanol use as a gasoline extender and octane enhancer. The ethanol mandate, in conjunction with market incentives for ethanol production, has had a large impact on corn consumption. The estimated impact of the increased demand for biofuels on corn prices range from 30% in real terms by Rosegrant et al. (2008) to 70% by Lipsky (2008). In addition, considerable volatility in the crude oil market has been transmitted to the corn market (e.g. Trujillo-Barrera, Mallory, and Garcia 2012). Indeed, as argued by Wright (2011), demand for corn from ethanol production is the largest exogenous shock on corn prices in recent years.[3]

Closely related to oil supply shocks is the market-specific fundamental supply and demand conditions. Elementary economic theory suggests that the price of a good is determined by its quantity demanded and supplied. Shocks in the underlying fundamentals, such as droughts and climate change that cause supply disruptions, directly affect the price of grains. Wright (2011) argues that the price behavior in recent years is not "as unusual as" many have asserted, particularly when viewed through the prism of a "scarcity" argument. For storable commodities, this suggests that price volatility will be high when the inventory is low. Wright (2011) shows that when the inventory falls below a certain threshold, the price becomes very inelastic and even small demand or supply shock can induce large price fluctuations.

Fundamental supply and demand factors may not explain all the variations in grain prices. Indeed, as argued by Gilbert (2010b), attributing the cause of price booms to pure fundamental factors requires an "act of faith in relation to the unquantifiable impacts" from fundamentals. Thus, we consider an additional variable that may have had an impact on grain price volatilities over the past few years—futures market speculation. While the notion that speculative activities distort commodity prices is not new, recent concerns and criticisms have been particularly intense, due to the broad range of commodities involved and the fact that commodity price run-ups and run-downs occurred after the 2007 subprime crisis. Caballero, Farhi, and Gourinchas (2008) argue that the financial crises in different industries are not isolated; instead a collapse in one financial market forces investors to seek alternative investment opportunities, thus triggering a chain of interlinked crises, including the commodity price bubble that burst in mid-2008. One group of speculators, namely commodity index traders (CITs), has been alleged to be responsible for funds moving from financial to commodity futures markets. Specifically, through a massive influx of funds to commodity futures market, CITs are argued to have created large buy-side pressure, driving commodity prices away from their fundamentals (Masters 2008, 2009). Empirically, Gilbert (2010b) estimates that commodity prices would have been more than 10% lower in 2008 if CITs were not present. Robles, Torero, and von Braun (2009) implement Granger causality tests based on rolling-window samples, and report that speculative activity partly explains the price spike since January 2008. However, most studies fail to find a linkage between commodity price movements and index trading activities (e.g., Stoll and Whaley 2010, Sanders and Irwin 2011, Hamilton and Wu 2013). A potential limitation of these studies is that they have in general relied on a partial approach involving the single factor of CIT positions. It is possible that speculative impacts can be estimated more accurately in a multivariate structural framework.

Econometric Methodology

We consider a five-variable structural vector autoregressive model. The five-component vector of endogenous variables (y_t) consists of global real economic activity (rea_t), price of crude oil ($POil_t$), speculative trading in futures market ($speculation_t^i$), market-specific fundamentals ($inventory_t^i$), and price of corn ($PCorn_t$). The model may be represented as

(1) $$A_0 y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t,$$

where p is the lag order, A_i , $i = 0, \ldots, p,$ are 5×5 matrices of coefficient parameters, and u_t is a five-component vector of serially and mutually uncorrelated structural innovations. Without a loss of generality, the variance-covariance matrix of structural errors is typically normalized such that $E(u_t u_t') \equiv \Sigma_u = I_k$ as long as the diagonal elements of A_0 remain unrestricted. The price of corn is thus affected by shocks in global business cycles, the oil market, speculation in futures market and market-specific supply and demand conditions. In addition, following Kilian and Murphy (2012a), the shocks derived from the price of grain equation are used to measure residual variations not accounted by the other four variables in the system. We can derive the reduced-form representation of the model as,

(2) $$y_t = A_0^{-1} A_1 y_{t-1} + \cdots + A_0^{-1} A_p y_{t-p} + A_0^{-1} u_t, \text{ or}$$
(3) $$y_t = B_1 y_{t-1} + \cdots + B_p y_{t-p} + \varepsilon_t,$$

where $B_1 = A_0^{-1} A_1$, …, $B_p = A_0^{-1} A_p$ and $\varepsilon_t = A_0^{-1} u_t$. Clearly, the reduced-form errors are a weighted average of the structural errors. In the context of our current model, the relationship between reduced-form errors and structural shocks may be written as:

$$(4) \qquad \underbrace{\begin{pmatrix} u_t^{Global\ demand\ shock} \\ u_t^{Oil\ price\ shock} \\ u_t^{Speculative\ trading\ shock} \\ u_t^{Corn\ market-specific\ shock} \\ u_t^{Residual\ shock} \end{pmatrix}}_{u_t} = \underbrace{\begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} \\ a_{21} & a_{22} & a_{23} & a_{24} & a_{25} \\ a_{31} & a_{32} & a_{33} & a_{34} & a_{35} \\ a_{41} & a_{42} & a_{43} & a_{44} & a_{45} \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix}}_{A_0} * \underbrace{\begin{pmatrix} \varepsilon_t^{rea} \\ \varepsilon_t^{POil} \\ \varepsilon_t^{spec} \\ \varepsilon_t^{stocks} \\ \varepsilon_t^{PCorn} \end{pmatrix}}_{\varepsilon_t}.$$

Equation (3) can be consistently estimated using standard techniques. However, to obtain the response of y_t to structural innovations u_t, which are useful to disentangle the relative effects of the variables, we need to recover the elements of A_0^{-1} from reduced-form parameters. Solving for the elements in A_0^{-1} is equivalent to determining the contemporaneous relationship among the endogenous variables. This can be achieved by solving $K\,(K+1)/2$ equations using the information from the variance and covariance matrix of reduced-form residuals ε_t for a K-dimension vector y_t (i.e. $\Sigma_\varepsilon = A_0^{-1}A_0^{-1\prime}$). Note that since Σ_ε is symmetric, only up to $K\,(K+1)/2$ unknowns in A_0^{-1} maybe uniquely identified. The traditional approach to solve the $K\,(K+1)/2$ nonlinear equations is to orthogonalize the reduced-form errors using the Cholesky decomposition. This involves setting A_0^{-1} as a lower triangular matrix with positive main diagonals P such that $\Sigma_\varepsilon = PP'$. Using this approach essentially imposes recursive or exclusion restrictions on time series variables y_t to achieve a just-identified system. For instance, consider a two-variable system with the ordering being y_t^1 and y_t^2. By using the Cholesky decomposition, we assume that y_t^1 affects y_t^2 contemporaneously, while the opposite does not hold. However, this recursively identified model structure makes sense only if the underlying model admits such a causal chain, which in reality rarely holds and largely depends on the subjective view of researchers. Kilian (2011) summarizes various possible ways to identify the recursive ordering: (1) economic theory; (2) specify an encompassing model that includes as special cases various alternative structural models implied by different economic models; (3) information delays; (4) physical constraints; (5) institutional knowledge; (5) assumptions about market structure; (6) homogeneity restrictions on demand; (7) extraneous parameter estimates; and (8) high-frequency data.

Most procedures to identifying structural innovations either impose arbitrary restrictions (recursive VAR) or require the researcher to have prior knowledge of the underlying model that may prove to be arbitrary (exclusion restrictions or sign restrictions). Following Swanson and Granger (1997), this study employs a data-determined approach to place restrictions on elements of the A_0^{-1} matrix based on the conditional and unconditional correlations among reduced-form VAR innovations. Swanson and Granger (1997) argue that many structural models of the errors in reduced-form VAR imply testable over-identifying constraints, which might be disentangled by examining partial correlations among the errors. Unlike other studies, this procedure requires minimal prior knowledge of the underlying model structure and can potentially reduce the element of subjective judgment when imposing constraints on contemporaneous correlations in an SVAR model. While the procedure proposed by Swanson and Granger (1997) may only allow for causal chains (i.e., A causes B causes C), the possibility of examining every possible ordering of causal patterns (e.g. A and B cause C) was developed by Demiralp and Hoover (2003) using graph-theoretic methods. Specifically, they examine the validity of applying the PC algorithm of Directed Acyclic Graph (DAG) procedure to direct the contemporaneous causal patterns. The PC algorithm of Spirtes, Glymour, and Scheines (2000) is the most widely used DAG technique and is embedded in the Tetrad IV software. The DAG approach, in conjunction with the Swanson and Granger (1997) procedure, has been applied in a number of studies in applied economics, including among others Bessler and Yang (2003), Haigh and Bessler (2004), and Wang and Bessler (2006). Here we follow Wang and Bessler (2006) and provide a brief description of the DAG technique using the PC algorithm.

A directed graph is an assignment of causal flows among a set of variables based on observed correlations and partial correlations. Under the context of the current study, five possible relationship exists between two variables: (1) a no edge relationship, or $(X\ Y)$, (2) an undirected edge, or $(X - Y)$, (3) a directed edge $(X \rightarrow Y)$, (4) a directed edge $(X \leftarrow Y)$, and (5) a bi-directed edge $(X \leftarrow\rightarrow Y)$. Arrows are used to indicate causal flows. Starting with an undirected edge between all possible pairs of variables, the PC algorithm tests for independence among variables and works backward until all edges are specified. Specifically, the technique follows two steps—elimination and direction. In the elimination stage, for a pair of variables X and Y, we remove the edge connecting X and Y if one of the following two conditions are satisfied: (1) the unconditional correlation $\rho(X, Y)$ is not statistically significant, and (2) the conditional correlation given a third variable Z: $\rho(X, Y|Z)$ is not statistically significant. In the latter case, there are $N - 2$ possible conditional correlations for an N-variable system. Instead of using standard t statistics as in Swanson and Granger (1997), Fisher's z statistic is used to test the significance of conditional correlations. The elimination works backward until every pair of variables is examined.

In the direction stage, consider a three-variable pair $X - Z - Y$ such that edges exist between X and Z as well as between Y and Z. However, there is no conditional or unconditional correlation between X and Y. If Z is not the conditioning variable that leads to the removal of the edge connecting X and Z, i.e. $\rho(X, Y|Z) \neq 0$, the triplets should be directed as $X \rightarrow Z \leftarrow Y$. If $X \rightarrow Z - Y$, and there is no arrowhead at Z, then $Z - Y$ should be oriented as $Z \rightarrow Y$. If there is a direct path from X to Y via way of other variables, and an edge between X and Y, direct $X - Y$ as $X \rightarrow Y$. A demonstration of the validity of this algorithm is provided in Spirtes, Glymour, and Scheines (2000).

The PC algorithm has been tested on simulated data in a number of studies such as Spirtes, Glymour, and Scheines (2000). Monte Carlo studies conducted by Demiralp and Hoover (2003) show that under the context of a VAR model, the DAG approach based on the PC algorithm performs well with a variety of model structures and can be an effective tool when specifying the contemporaneous causal patterns among variables.

Data

The data used in this study run from January 2000 to July 2013 at a monthly frequency, resulting in 163 observations. The nominal price of corn is obtained based on average prices received by US farmers as recorded by the National Agricultural Statistical Service (NASS) of the US Department of Agriculture (USDA). The nominal price of crude oil is represented by the refiners' acquisition cost of crude oil, which is available through the US Department of Energy. Both nominal price series are deflated by the US Consumer Price Index (CPI) to obtain the real price of corn and crude oil, where the CPI in January 2000 is set to 100.[4]

Though the importance of macroeconomic factors has been widely asserted, directly incorporating macroeconomic variables in empirical models has been hindered by the low frequency of macroeconomic indicators because these variables are typically only available on an annual or quarterly basis (e.g., GDP). In addition, currently available indicators of economic growth tend to be partial measurements of a specific region, unable to reflect global economic activities. Here we follow Kilian (2009) and use an index based on the dry cargo shipping rate as a measure of global real activity. The motivation for using this index is that the demand for transport services is primarily determined by world economic growth (e.g., Klovland 2004). Kilian shows this indicator can capture shifts in the demand for industrial commodities driven by the global business cycle. Unlike other partial macro-economic indicators that are typically available at an annual or quarterly basis (e.g., GDP), the index can be constructed on a monthly frequency, providing a larger sample size more suitable for evaluating the demand shocks arising from fluctuations in the global business cycle.

The inventory data are obtained from the World Agricultural Supply and Demand Estimates (WASDE) report released by the USDA. Every month, the WASDE report provides an estimate of the US end-of-marketing-year and world end-of-year stocks and uses. The estimated stocks-to-use ratio measures the level of carryover stock as a percentage of the total demand to use, and thus closely represents the tightness of the current supply-demand relationship in the corn market. Estimates are provided for both old crop and new crop in the WASDE reports. Here we use the ending stocks-to-use ratio calculated from old crop estimates to reflect market-specific fundamentals.

Financial speculation is measured by Working's speculative T index defined as:

(5) $$T = 1 + SS/(HL + HS) \text{ if } HS \geq HL, \text{ or}$$
(6) $$T = 1 + SL/(HL + HS) \text{ if } HS < HL,$$
where SL and SS are long and short positions held by speculators, and HL and HS long and short positions of hedgers. The index attempts to measure whether speculation is excessive relative to the level of hedging activity in the market. Peck (1980, p.1037) notes that the speculative index " ...reflects the extent by which the level of speculation exceeds the minimum necessary to absorb long and short hedging, recognizing that long and short hedging positions could not always be expected to offset each other even in markets where these positions were of comparable magnitudes." In a number of recent studies, the index has been used to gauge the effect of speculative activities in futures markets (e.g., Du, Yu, and Hayes 2011, McPhail, Du, and Muhammad 2012, Büyükşahin and Robe 2013). While the Working's T primarily concerns the futures market, it also impacts the cash prices given the no-arbitrage linkage between cash and future prices. [5]

Working's T is constructed using the CFTC *Supplemental Commitment of Trader* (SCOT) and *Commitment of Trader* (COT) reports. The reports reflect combined futures and options positions as of Tuesday's market close, where options are adjusted to the delta-equivalent futures positions. Traditionally, commercial and non-commercial trader positions from COT reports are used as positions held by hedgers and speculators, respectively, to construct the index. However, this may be inappropriate given the large, allegedly speculative positions held by CITs since 2004.

As demonstrated in Sanders, Irwin, and Merrin (2010), categorizing CIT activities into speculators' positions may have a large impact on Working's index. We therefore add CIT positions to the speculator category using data from the SCOT reports, which are publicly available since January 2006. Additional data were collected by the over 2004-2005 at the request of the U.S. Senate Permanent Subcommittee on Investigations (USS/PSI 2009) and these data are also used in the present analysis.[6] Since CIT activity only accounts for a small fraction of the total open interest between 2000 and 2003 (Aulerich, Irwin, and Garcia 2013), we assume CIT positions during this time period are zero, drawing speculator and hedger positions from the COT reports instead. One issue that arises in constructing the index is how to classify the non-reporting traders. Here we follow Sanders, Irwin, and Merrin (2010) and allocate the non-reporting traders' positions to the commercial and non-commercial trader categories using the same ratio as reporting traders.

Figure 1 plots the time series of five variables used in the analysis. As can be seen, the real price of corn experienced rather large volatility throughout the period. While corn prices were stable around \$2.00/bushel between 2000 and the end of 2006, three large price spikes appear between 2007 and 2012. The first spike occurred in mid-2008, with a bushel of corn priced at over \$4.00 in real terms. In August 2011, the real price of corn increased sharply again, reaching \$5.13/bushel—roughly two-and-a-half times the low in mid-2000. A third spike occurred shortly afterwards in August 2012, when corn prices reached \$5.59/bushel in real terms. In the next section, we apply our framework to identify the factors behind this dramatic volatility in corn prices.

Results

Before estimating the SVAR model, the stationarity property of the data series needs to be examined. Using the Augmented Dickey Fuller test, Phillips-Perron unit root test, and the revised ADF tests (DF-GLS) by Elliott, Rothenberg, and Stock (1996) with various lags,[7] we found that only Working's T and oil prices appeared to be stationary with a trend. The nonstationarity of corn prices, inventory, and global real economic activity clearly warrants additional attention as spurious regression may lead to false conclusions. However, as demonstrated by Sims, Stock, and Watson (1990), the estimated coefficients from a VAR model with possibly non-stationary variables are still consistent and the asymptotic distribution of individual estimated parameters remain standard, as the VAR in levels take implicitly account of the cointegrated relationships. In addition, the impulse response functions are also consistent except in the long run. Hamilton (1994, p 544-p.568) provides a similar argument.[8] We thus proceed with estimating the VAR model in levels.

We begin by estimating the reduced-form, five-variable VAR system with two lags as selected by the Akaike information criteria (AIC).[9] To account for potential seasonality, monthly dummies are included in the estimation as exogenous variables. The Lagrange multiplier test suggests that residuals from reduced-form VAR are not autocorrelated at the 5% significance level. Examination of eigenvalues indicates that the estimated VAR satisfies the stability condition.

Table 1 reports the Granger causality test results after estimating the reduced-form VAR. Here, Granger causality tests are used to examine whether lagged explanatory variables help to predict the real price of corn. If the joint hypothesis that all the coefficients on the lagged values of one variable are zero can be rejected, then this variable is said to Granger cause the price of corn. We use the Toda and Yamamoto (1995)—TY methodology to test for Granger causality. The TY technique is applicable irrespective of the stationarity and cointegration properties of the system. The method involves using a modified Wald statistics for testing the significance of the parameters of a VAR model. As can be seen in the table, statistical significance exists for the price of oil and the stocks-to-use ratio of corn at a 10% significance level, while lagged speculative trading activity and global real economic activity do not help to predict the price of corn.

Directed contemporaneous correlations

The second step is to apply the DAG technique to the residuals from the reduced-form VAR model using the PC algorithm of Spirtes, Glymour, and Scheines (2000) to recover the structural innovations in equation (1). As stated, the PC algorithm starts with a completed undirected graph connecting the five innovations from the reduced-form VAR. Edges between variables are removed based on either zero unconditional or conditional correlations based on Fisher's z test. Here a significance level of 10% is used. In Monte Carlo simulations, Spirtes, Glymour, and Scheines (2000) demonstrate that the significance level should be inversely correlated with the sample size. For instance, a significance level of 0.20 is preferred for sample sizes less than 100. For sample sizes between 100 and 200 observations, which is the case in our study, a *p*-value of 0.10 is recommended.

Figure 2 reports the pattern from TETRAD IV's application to the reduced-form VAR model. At the elimination stage, four sets of edge relationships are first removed based on zero unconditional correlations: (1) real economic activity and speculative trading, (2) stocks-to-use ratio of corn and the real price of oil, (3) real economic activity and the stocks-to-use ratio of corn, and (4) real economic activity and the price of corn. Based on vanishing partial correlations, edges between speculative trading and the price of oil as well as between speculative trading and stocks-to-use ratio are removed. The conditioning variable leading to the removal of edges is the real price of corn in both cases. Now, given the triplets (stocks-to-use ratio)—(price of corn)—(price of oil), since the edge between stocks-to-use ratio and price of oil is not removed because of zero partial correlation conditioning on the price of corn, the triplets can be directed as (stocks-to-use ratio)→(price of corn)←(price of oil). The final result suggests that, corn prices are caused by oil prices, market-specific fundamentals, and speculative activities in futures markets in contemporaneous time, but not by aggregate global demand. Note that in the Granger causality test, we find that lagged speculative activities do not help to predict corn price movements.

Note in the directed acyclic graph shown in figure 2 there is bidirectional relationship between the real price of corn and the real price of crude oil. Under ideal conditions in the PC algorithm, a bidirected edge between two variables usually indicates a latent common cause. However, in small samples the PC algorithm tends to produce false positive double headed edges.[10] Here given the prior knowledge that crude oil market is much larger compared to corn, and previous studies that have found that one-way volatility spillover exist from crude oil to corn market (e.g., Trujillo-Barrera, Mallory, and Garcia 2012), we expect that the contemporaneous causality occurs from the crude oil prices to corn prices. To more formally support this one-way causality, we compute the BIC value for two different structures, one with an arrowhead drawn from corn to oil, as shown in figure 3(a), and the other with an arrowhead drawn from oil to corn (figure 3(b)). The BIC value associated with the structure in figure 3(a) is -22.24, while for figure 3(b), the BIC is -22.48. Therefore, the one-way causality from the price of oil to the price of corn is preferred over causality in the other direction.

We next impose the over-identifying constraints identified by the DAG technique on the structural parameters in matrix A_0 in equation (1). Specifically, the relationship between structural innovations and reduced-form errors are specified as:

$$(7) \qquad u_t \equiv \begin{pmatrix} u_t^{Global\ demand\ shock} \\ u_t^{Oil\ price\ shock} \\ u_t^{Speculative\ trading\ shock} \\ u_t^{Corn\ market-specific\ shock} \\ u_t^{Residual\ shock} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 \\ 0 & 0 & a_{33} & 0 & 0 \\ 0 & 0 & 0 & a_{44} & 0 \\ 0 & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix} * \begin{pmatrix} \varepsilon_t^{rea} \\ \varepsilon_t^{POil} \\ \varepsilon_t^{spec} \\ \varepsilon_t^{stocks} \\ \varepsilon_t^{PCorn} \end{pmatrix}.$$

Here we normalized the variance covariance matrix of the structural innovations as an identity matrix ($E(u_t u_t') \equiv \Sigma_u = I_k$) and leave the diagonal elements of A_0 unrestricted. The advantage of normalizing is that a unit innovation in the structural shocks will have a size of one standard deviation. The corresponding impulse responses are changes caused by a one standard deviation shock in the explanatory variables.

Analysis of structural impulse response functions

Figure 4 plots the dynamic responses of real corn prices to one standard deviation shocks in the structural innovations by setting the over-identifying constraints as specified in equation (7). All structural shocks are assumed to be positive. In the figure, the solid line represents the mean effect while the dotted lines show the 95% confidence of the response.

As figure 4(b) demonstrates, unanticipated increases in oil prices have an immediate large positive effect on the real price of corn that is highly statistically significant. This effect increases rather substantially starting from month 3, and peaks at month 14, after which it starts to decline only slightly. The response of real corn prices is significant even two years after the shock occurs, suggesting that the effect of oil market shock is rather persistent. This result is not surprising given that during our sample period, corn prices are increasingly connected to crude oil prices due to corn-based ethanol production. Wright (2011) argues that the effect of ethanol mandate is equivalent to a large exogenous supply shock that significantly drove up corn prices. Similar results are reported in Carter, Rausser, and Smith (2013) who find that without the mandate on corn-ethanol production, the price of corn would have been much lower between 2006 and 2012. In addition, market incentives may also play a role since high crude oil prices over the past few years have improved the competitiveness of ethanol in terms of gasoline blending. While our results do not differentiate between the channels through which ethanol production linked crude oil and corn prices, the large and persistent effects of unexpected shocks in crude oil markets clearly reflect the increasingly important role of energy prices on corn price movements.

Unexpected shocks in speculative trading on average have a negative impact on corn prices up to month 12, becoming positive afterwards (figure 4(c)). However, the effect is only statistically significant up to a 3-month horizon. The results thus indicate that real corn price changes are only slightly sensitive to the size of speculative trading positions in the corn futures markets for a short period. Given that a large portion of Working's T index is affected by CIT positions as shown in Sanders, Irwin, and Merrin (2010), results from the SVAR model also suggest that CIT's have played a rather small role in determining corn price movements. This result is generally consistent with numerous other studies, which find that commodity index traders or speculators in general did not push up corn prices over the past decade. Instead, results from this analysis suggest that speculative activities have a short-term damping effect on corn prices.

As seen in figure 4(d), an unexpected corn market-specific fundamental supply and demand shock at the annual level has a negative effect on the real price of corn. When the ending stocks-to-use ratio increases or when the market projects a higher inventory relative to total use at the end of marketing year, the positive shock will soon be incorporated in corn prices. It appears that this negative effect of market specific shock strengthens until 5 months, after which it becomes relatively stable. This effect is statistically significant up to a one-year horizon as the variation becomes rather large afterwards.

The last plot in figure 4 shows the effect of residual shocks not explained by the aforementioned shocks. Kilian and Murphy (2012a) argue that this type of shock does not have a direct economic interpretation. Relating to the oil market, they argue that residual shocks may refer to unexpected changes to strategic reserve, change in storage preferences of oil companies, change of inventory techniques, etc. In the context of corn markets, one type of residual shock may be due to short-term inventory fluctuations not directly related to annual inventories, as the SVAR model uses monthly estimates of end-of-marketing year stocks-to-use ratio. This dimension of the shock may have a short-term large effect as the market becomes increasingly volatile. As seen in the plot, a one standard deviation unexpected residual shock has immediate large statistically significant impact on corn prices, which gradually decreases starting from month 2. The effect remains positive for the two-year horizon considered in the graph. However, after month 14, the effect becomes statistically insignificant.

Perhaps the most striking result of impulse response analysis arises in the lack of response of the real price of corn to unexpected shocks in global real economic demand (figure 4(a)). The mean response is never significant at the 95% level, suggesting that an unanticipated change in global demand will not have any immediate or persistent effect on the real price of corn. While counterintuitive, there are several possible explanations. First, previous studies find that unanticipated aggregate demand shocks often cause a large and persistent increase in the real price of oil. For instance, Kilian and Murphy (2012a) find that in the long run 87% of the variation in the real price of oil can be explained by the aggregate global demand shock. In our model, it is plausible that any global demand shocks only play a role after being absorbed in the crude oil market instead of directly affecting real corn prices. Second, the global demand shock may have been reflected in the unexpected shocks in corn market-specific fundamentals. For instance, an unanticipated increase in aggregate global demand may be reflected by a decrease in ending stocks-to-use ratio of corn, negating the effect of global demand shocks. As a robustness check, we exclude real economic activity from the SVAR model and our results are very similar.

Variance decomposition of forecast errors

Forecast error variance decomposition (FEVD) shows the percentage of variance of the forecast error attributable to a specific shock at a given horizon. It provides an estimate of the relative contribution of each structural innovation in affecting the SVAR variables. The results of FEVD for the real price of corn are presented in table 2 for various horizons. At the immediate horizon, most of the forecast error variance comes from the residual shock, accounting for over 70% of total variation. This finding is consistent with much applied research in which it is common for a variable to explain much of its forecast error variance at short horizons (Enders 2010). The contribution of residual shocks declines quickly as the forecasting horizon expands. At the one year horizon, residual shocks explain about one-third of the total forecast error variance in real corn prices. Similar to the impulse response findings, unexpected shocks in the crude oil market contribute significantly to the forecast error variance of real corn prices. However, their relative importance is weak at immediate horizons, contributing only 5.61% at two months. Starting at month six, the effect quickly accelerates, eventually accounting for over 50% of the forecast error variance at the two-year horizon.

Stock to use ratios also affect the real corn price. The largest contribution of unexpected shocks in market-specific fundamentals comes from the 10-month to one year forecast horizon, accounting for about 20% of the total variation. This effect is rather consistent and remains at about the same percentage even at the two year-ahead forecast. Speculative activities account for about 15% of the forecast variance at the 2-month horizon, which significantly declines afterwards. At the two-year forecast horizon, speculative activities only account for about 3% of the error variance. In addition, shocks in global real economic activity only explain a very small portion of the forecast error variance, typically less than 1% at all horizons.

Conclusions

Corn prices experienced historically high volatility over the last decade. In this paper we apply a structural vector autoregression model to quantify the relative importance of various contributing factors in driving corn price movements. Unlike previous studies that require prior knowledge of the underlying model structure, we use a data-determined approach to identify the contemporaneous correlations among variables so that specification errors due to subjective judgment may be minimized. This is achieved by applying the PC algorithm of Directed Acyclic Graphs. Specifically, we examine five structural shocks, including aggregate global demand shocks, crude oil market shocks, speculative trading shocks, corn market-specific shocks, and residual shocks (consisting of all other shocks).

We find in the reduced-form VAR that lagged crude oil prices and market-specific fundamentals help to predict corn prices, but the effects of speculative trading and aggregate global real economic activity are not statistically significant. In the analysis of contemporaneous residuals, it is clear that crude oil prices, speculative activities, and market-specific fundamentals affect the real corn price, but real economic activities do not. These contemporaneous linkages were incorporated in the SVAR system by setting over-identifying constraints on the matrix reflecting instantaneous correlations. We find that in general, unexpected shocks in aggregate global demand and speculative trading activities do not have a statistically significant effect on corn price movements at a long run. By contrast, shocks in the crude oil market have large effects that persist. The forecast error variance decomposition suggest that at the two-year horizon, variations in crude oil prices account for over 50% of the total corn forecast error variances. We also find that, consistent with theory, unexpected shocks in market-specific fundamentals (i.e., positive shocks to the stocks-to-use ratio) have very large negative effects on corn price movements. In addition, unexpected residual shocks play an important role in corn price movement, especially at immediate horizons.

This study presents two main findings. First and foremost, unexpected shocks in the oil market had a dominant and persistent effect on corn price movements between 2000 and 2013, a period in which both commodities experienced unprecedented large price changes. Clearly, the strong linkages have emerged from a combination of policy and market incentives which stimulated the production of ethanol. It is also important to note that the magnitude of these effects may have been magnified by the presence of low ending stocks-to-use ratios which were often observed after 2006. Second, speculative activities are unlikely to be a major driving force of corn prices. While the reduced-form VAR analysis supports no temporal causality from speculative behavior to corn prices, the DAG analysis does indicate that there is contemporaneous causality from speculative trading activities to corn prices. However, the SVAR analysis employing the DAG identification strategy suggest that rather than driving the prices up, speculative activities in the futures market have a slight dampening effect on corn prices. Given that the Working's T index also reflects CIT positions, our results further suggest that a particular group of speculators—financial index traders—are unlikely to be behind spikes in corn prices. This result is consistent with a number of other studies, which find that speculative trading cannot explain the large price fluctuations observed in corn markets (e.g., Stoll and Whaley 2010). These findings suggest that policy initiatives to reduce volatility by curbing speculative activities in commodity futures markets (e.g. the Dodd Frank act) are unlikely to have their intended effects.

While the results in general are consistent with other structural analyses of commodity price movements, our findings differ in several important ways. Unlike McPhail, Du, and Muhammad (2012) who show that speculative activities played an important role in driving short-run corn price movements, we find a smaller linkage. The limited influence of speculative activity on the corn price also is supported by the insignificant Granger causality findings based on lagged effects. While our results on the linkage between oil prices and corn prices are consistent with Carter, Rausser, and Smith (2012), who find ethanol production played an important role in corn price movements, our analysis provides insights on the relative significance of the contributing factors to the recent commodity volatility. Oil prices and stocks to end use are critical factors accounting for over 70% of the corn price error variance at a two-year horizon. In contrast, real economic activity and speculative activities account for less than 1% each of the corn price error variance at the same horizon. The failure to find an influence of speculative activity speaks to a contentious on-going policy debate. The limited effect of world economic activity highlights in a policy context that a traditional link between increased income and improved nutrition through the consumption corn and its end-products was swamped by energy and other market-specific fundamentals.

One limitation of the present analysis is that we neglect structural breaks in the data series. Overall, it is rather difficult to precisely measure the changing effect of influencing factors during a sample period when a combination of policy and market conditions underwent significant changes, we therefore focus our analysis on the sign of the coefficient and the average impact only. One potential approach to account for structural breaks would be to first split the sample period into two to reflect the ethanol mandate policy change and then estimate separate models for the two sub-periods (Carter, Rausser, and Smith 2013; McPhail, Du, and Muhammad 2012; Baumeister and Kilian 2013). Another approach would be to estimate a time-varying SVAR model that accounts for both gradual and one-time changes in the data series (e.g. Baumeister and Peersman 2013).

References

Abbott, Philip C, Christopher Hurt, and Wallace E Tyner. 2011. What's Driving Food Prices in 2011? Farm Foundation Issue Report. Oak Brook, IL.

Aulerich, Nicole M, Scott H Irwin, and Philip Garcia. 2013. "Bubbles, Food Prices, and Speculation: Evidence from the CFTC's Daily Large Trader Data Files." NBER Working Paper c12814.

Baumeister, Christiane, and Lutz Kilian. 2013. "Do Oil Price Increases Cause Higher Food Prices?". No. 2013/10. CFS Working Paper.

Baumeister, Christiane, and Gert Peersman. 2013 "Time-varying effects of oil supply shocks on the US economy." American Economic Journal: Macroeconomics 5, no. 4: 1-28.

Bellemare, Marc. 2011. Rising Food Prices, Food Price Volatility, and Political Unrest. In *Sanford School of Public Policy, Duke University*.

Bessler, David A, and Jian Yang. 2003. "The Structure of Interdependence in International Stock Markets." *Journal of International Money and Finance* no. 22 (2):261-287.

Bruno, Valentina G., Bahattin Büyükşahin, and Michel A. Robe. 2013. "The Financialization of Food?" Bank of Canada Working Paper.

Büyükşahin, Bahattin, and Michel A Robe. 2013. "Speculation, Commodities and Cross-Market Linkages." *Journal of International Money and Finance,* forthcoming.

Caballero, Ricardo J, Emmanuel Farhi, and Pierre-Olivier Gourinchas. 2008. "Financial Crash, Commodity Prices, and Global Imbalances." *Brookings Papers on Economic Activity*.

Carter, Colin, Gordon Rausser, and Aaron Smith. 2013. "The Effect of the US Ethanol Mandate on Corn Prices." *Department of Agricultural and Resource Economics, University of California, Davis.*

Demiralp, Selva, and Kevin D Hoover. 2003. "Searching for the Causal Structure of a Vector Autoregression." *Oxford Bulletin of Economics and statistics* no. 65 (s1):745-767.

Du, Xiaodong, Cindy L Yu, and Dermot J Hayes. 2011. "Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis." *Energy Economics* no. 33 (3):497-503.

Elliott, Graham, Thomas J. Rothenberg, and James H. Stock. 1996 "Efficient Tests for an Autoregressive Unit Root." Econometrica 64, no. 4: 813-836.

Enders, Walter. 2010. *Applied econometric time series*: John Wiley & Sons.

Gilbert, Christopher L. 2010a. "How to understand high food prices." *Journal of Agricultural Economics* no. 61 (2):398-425.

Gilbert, Christopher L. 2010b. Speculative influences on commodity futures prices 2006-2008. United Nations Conference on Trade and Development Discussion Paper NO. 197.

Haigh, Michael S, and David A Bessler. 2004. "Causality and Price Discovery: An Application of Directed Acyclic Graphs." *The Journal of Business* no. 77 (4):1099-1121.

Hamilton, James D. Time Series Analysis. Princeton: Princeton university press, 1994.

Hamilton, James D, and Jing Cynthia Wu. 2013. Effects of index-fund investing on commodity futures prices. Working paper, University of California, San Diego.

Irwin, Scott H, and Dwight R Sanders. 2011. "Index funds, financialization, and commodity futures markets." *Applied Economic Perspectives and Policy* no. 33 (1):1-31.

Janzen, Joseph P, Aaron D Smith, and Colin A Carter. 2013. Commodity Price Comovement: The Case of Cotton. In *Working Paper, UC Davis*.

Juvenal, L, and I Petrella. 2011. Speculation in the oil market, Federal Reserve Bank of St. Louis, Working Paper.
Kilian, Lutz. 2009. "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market." *The American economic review* no. 99 (3):1053-1069.
Kilian, Lutz. 2011. Structural Vector Autoregressions. CEPR Discussion Papers.
Kilian, Lutz, and Daniel P Murphy. 2012a. "The Role of Inventories and Speculative Trading in the Global Market for Crude Oil."
Kilian, Lutz, and Daniel P Murphy. 2012b. "Why agnostic sign restrictions are not enough: understanding the dynamics of oil market VAR models." *Journal of the European Economic Association* no. 10 (5):1166-1188.
Klovland, Jan Tore. 2004. *Business cycles, commodity prices and shipping freight rates: Some evidence from the pre-WWI period*: Citeseer.
Lipsky, John. 2008. "Commodity prices and global inflation." *New York: Council on Foreign Relations*.
Mallory, Mindy L, Scott H Irwin, and Dermot J Hayes. 2012. "How market efficiency and the theory of storage link corn and ethanol markets." *Energy Economics*.
Masters, Michael W. 2008. Testimony before the Committee on Homeland Security and Governmental Afairs, Unites States Senate.
Masters, Michael W. 2009. Testimony before the Commodities Futures Trading Commission. http://www.cftc.gov/ucm/groups/public/@newsroom/documents/file/hearing080509_masters.pdf.
McPhail, Lihong Lu, Xiaodong Du, and Andrew Muhammad. 2012. "Disentangling Corn Price Volatility: The Role of Global Demand, Speculation, and Energy." *Journal of Agricultural and Applied Economics* no. 44 (3):401-410.
Melolinna, Marko. 2012. Macroeconomic shocks in an oil market var. European Central Bank.
Mitchell, Donald. 2008. A note on rising food prices. In *World Bank Policy Research Working Paper Series No. 4682*.
Mjelde, James W, and David A Bessler. 2009. "Market integration among electricity markets and their major fuel source markets." *Energy Economics* no. 31 (3):482-491.
Peck, Anne E. 1980. "The role of economic analysis in futures market regulation." *American Journal of Agricultural Economics* no. 62 (5):1037-1043.
Pindyck, Robert S, and Julio J Rotemberg. 1990. "The Excess Co-Movement of Commodity Prices." *The Economic Journal* no. 100 (403):1173-1189.
Qiu, Chen, Colson, G., Escalante, C., and M. Wetzstein, 2012. "Considering macroeconomic indicators in the food before fuel nexus." *Energy Economics* no. 34(6): 2021-2028.
Robles, M, M Torero, and J von Braun. 2009. "When speculation matters." *IFPRI-Issue Brief* (57).
Rosegrant, Mark W, Tingju Zhu, Siwa Msangi, and Timothy Sulser. 2008. "The impact of biofuel production on world cereal prices." *International Food Policy Research Institute, Washington, DC Electronic file*.
Sanders, Dwight R, and Scott H Irwin. 2011. "The impact of index funds in commodity futures markets: A systems approach." *Journal of Alternative Investments* no. 14 (1):40-49.
Sanders, Dwight R, Scott H Irwin, and Robert P Merrin. 2010. "The adequacy of speculation in agricultural futures markets: Too much of a good thing?" *Applied Economic Perspectives and Policy* no. 32 (1):77-94.

Sims, Christopher A., James H. Stock, and Mark W. Watson. 1990. "Inference in linear time series models with some unit roots." *Econometrica: Journal of the Econometric Society* no. 58(1) : 113-144.

Spirtes, Peter, Clark N Glymour, and Richard Scheines. 2000. *Causation Prediction & Search 2e*. Vol. 81: MIT press.

Stoll, Hans R, and Robert E Whaley. 2010. "Commodity index investing and commodity futures prices." *Journal of Applied Finance* no. 20 (1):7-46.

Swanson, Norman R, and Clive WJ Granger. 1997. "Impulse response functions based on a causal approach to residual orthogonalization in vector autoregressions." *Journal of the American Statistical Association* no. 92 (437):357-367.

Tang, Ke, and Wei Xiong. 2010. Index investment and financialization of commodities. National Bureau of Economic Research.

Trujillo-Barrera, Andres, Mindy Mallory, and Philip Garcia. 2012. "Volatility Spillovers in US Crude Oil, Ethanol, and Corn Futures Markets." *Journal of Agricultural and Resource Economics* no. 37 (2):247.

von Braun, Joachim. 2008. High and rising food prices: Why are they rising, who is affected, how are they affected, and what should be done. Paper read at International Food Policy Research Institute (IFPRI), presentation at a US Agency for International Development (USAID) conference on “Addressing the Challenges of a Changing World Food Situation: Preventing Crisis and Leveraging Opportunity,” Washington, DC, April.

Wang, Zijun, and David A Bessler. 2006. "Price and quantity endogeneity in demand analysis: evidence from directed acyclic graphs." *Agricultural Economics* no. 34 (1):87-95.

Wright, Brian D. 2011. "The economics of grain price volatility." *Applied Economic Perspectives and Policy* no. 33 (1):32-58.

Endnotes

[1] The discussion and subsequent analysis uses monthly average prices of corn. The data are available at http://www.farmdoc.illinois.edu/manage/uspricehistory/us_price_history.html.

[2] Qiu, Colson, Escalante, and Wetzstein (2012) considers the causality implied from the Direct Acyclic Graph. However, their SVAR model is identified through the usual Cholesky decomposition, rather than the DAG approach.

[3] A number of studies also examined another pathway through which crude oil prices affect corn prices. They show that there is excessive or unexplained co-movement between the price of crude oil and prices of agricultural commodities. For instance, Tang and Xiong (2010) found that the prices of commodities included in major commodity indices (GSCI and DJ-UBS indices) possess increasingly significant correlation with crude oil prices. An earlier study byPindyck and Rotemberg (1990)) revealed a similar pattern. This dimension of research was pursued in Janzen, Smith, and Carter (2013), who include the price of oil to examine the co-movement effects on cotton prices.

[4] The CPI is obtained from the US Bureau of Labor Statistics. See http://www.bls.gov/cpi/. We also consider the nominal prices in the model. In addition, nearby corn futures prices are also considered as a robustness check.

[5] Given the recent non-convergence problem between cash and future prices, we also consider alternative model using nearby corn futures prices, and the results appear to be qualitatively similar.

[6] To obtain non-CIT commercial and non-commercial trader positions during 2004-2005, we use the ratios of CIT positions drawn from commercial and non-commercial trader positions between 2006 and 2008, and subtract these positions from the original commercial/non-commercial positions.

[7] According to Elliott, Rothenberg, and Stock (1996, p.813), the "DF-GLS" test "has substantially improved power when an unknown mean or trend is present."

[8] Hamilton (1994, p.544) argues that "One should be concerned about the possibility of a spurious regression whenever all the variables in a regression are I(1) and no lags of the dependent variable are included in the regression." In the current analysis, we have variables that are I(0), and also include lags of the dependent variables in the system.

[9] We consider the VAR model with nearby futures prices, and found the results to be rather similar. Models using nominal prices are also estimated, with qualitatively similar results being identified.

[10] See Tetrad Manual: http://www.phil.cmu.edu/projects/tetrad/new_manual.pdf

Tables and Figures

Table 1. Granger Causality Test from Reduced Form VAR Model for Corn Prices, January 2000 – July 2013

Variable	Test Stat	Degree of Freedom	p-value
Real Economic Activity	1.62	2	0.45
Price of Oil	5.01	2	0.08
Working's T	1.73	2	0.42
Stocks-to-Use	4.63	2	0.09
All	11.58	8	0.17

Notes: This table examines whether the lagged values of one variable help to predict corn prices using the Toda and Yamamoto (1995) procedure.

Table 2. Corn Price Forecast Error Variance Decomposition at Various Horizons, January 2000 – July 2013 (in Percentage)

Horizon	Real Economic Activity	Price of Oil	Working's T	Stocks-to-Use	Price of Corn
2	0.18	5.61	14.80	5.36	74.05
4	0.21	11.63	13.82	12.63	61.71
6	0.36	20.21	11.23	17.50	50.71
8	0.33	28.19	9.16	19.55	42.76
10	0.26	34.68	7.60	20.14	37.32
12	0.23	39.72	6.40	20.12	33.52
18	0.53	48.62	4.16	19.58	27.11
24	0.93	52.38	3.11	19.64	23.94

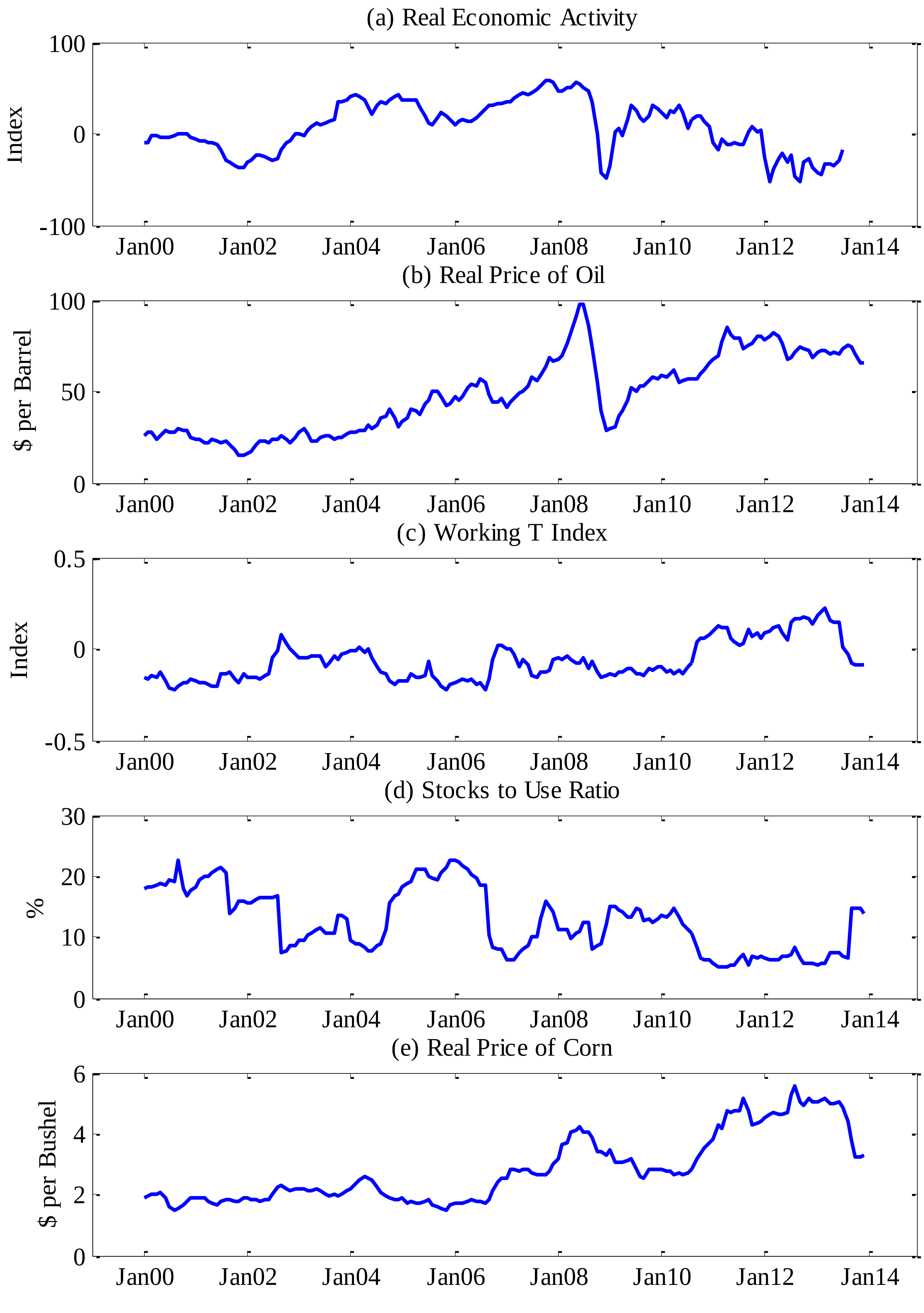


Figure 1. SVAR data, January 2000 – July 2013

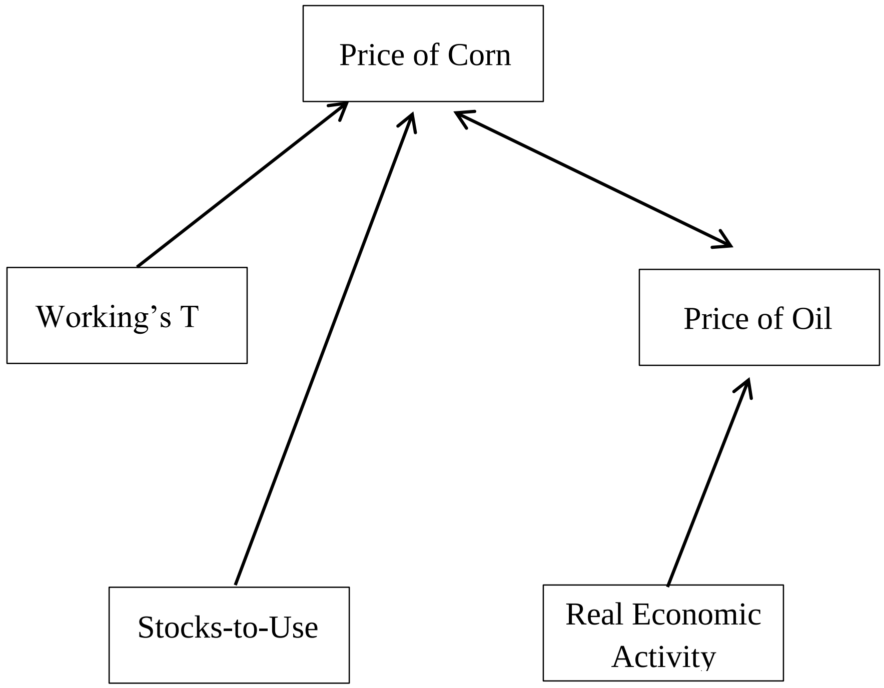
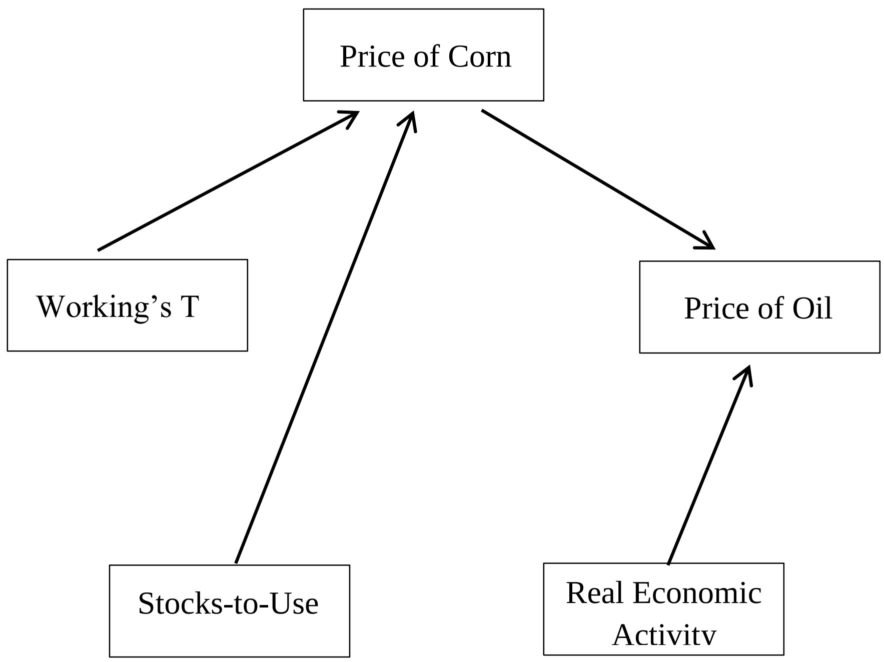


Figure 2. Contemporaneous correlations identified by DAG

(a) Causality from price of corn to price of oil



(b) Causality from price of oil to price of corn

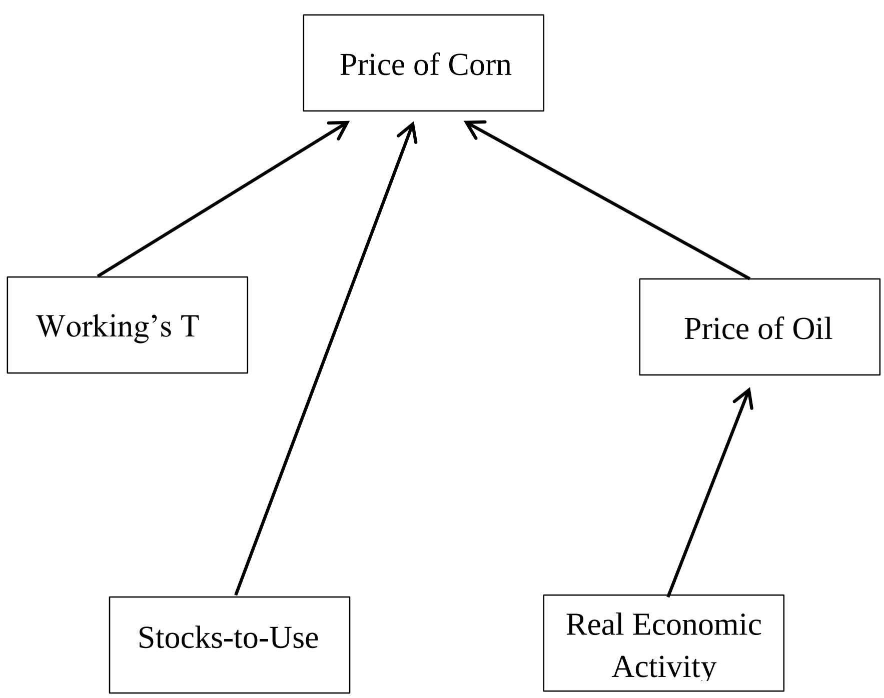
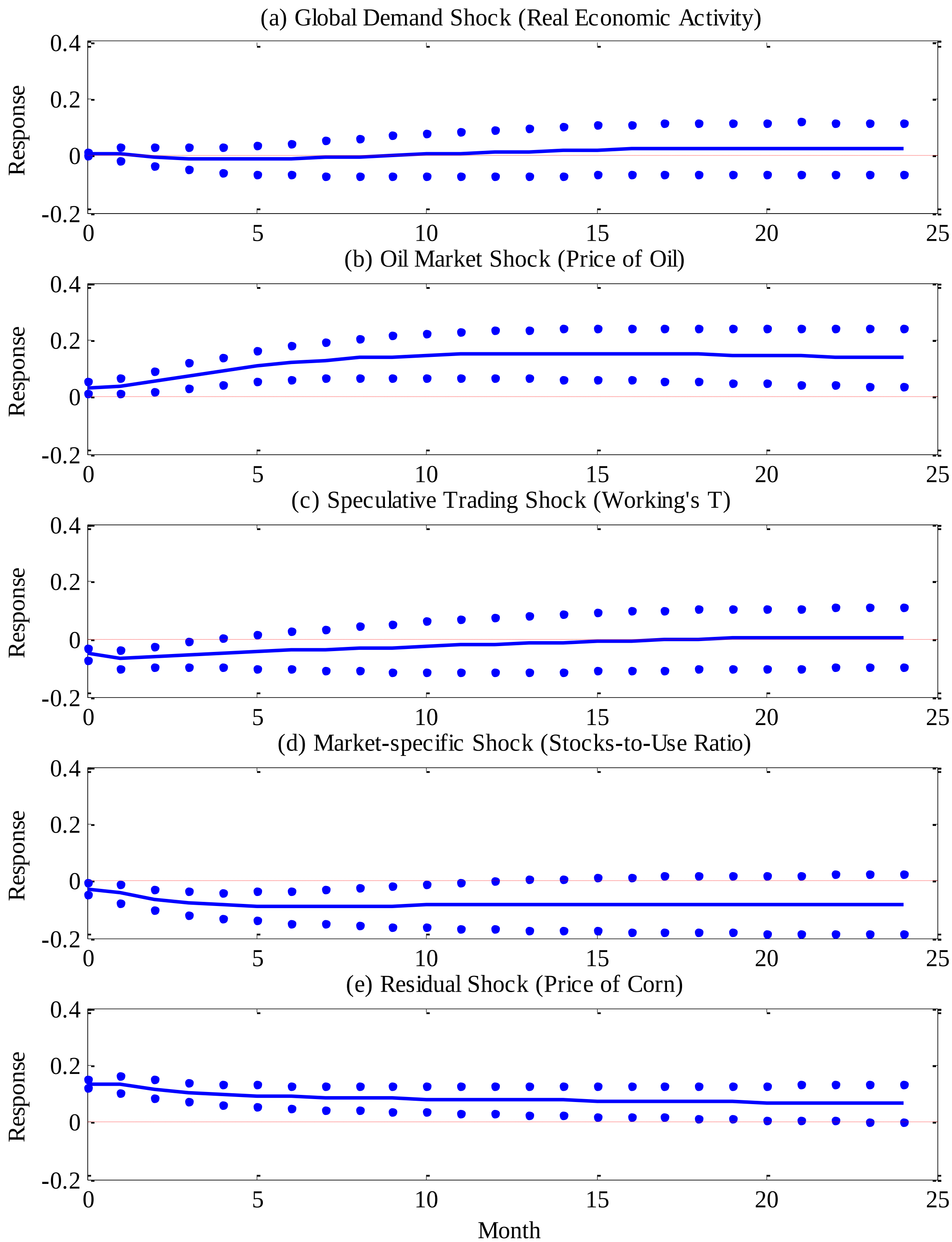


Figure 3. DAG one-way causality of contemporaneous correlations



Notes: solid line represents point estimate and dots represent 95% confidence intervals.

Figure 4. Response of real corn prices ($/bushel) to various shocks (one standard deviation)