Long-Run and Short-Run Co-Movements between Oil and Agricultural Futures Prices

By

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July, 2015

Abstract:

The relationship between oil prices and the prices of agricultural feedstocks for biofuel has received considerable attention in the recent literature. Here we extend the recent common trend-common cycle analysis of Myers et al. (2014), which investigated long-run and short-run co-movements between fuel and agricultural spot prices, to the case of futures prices. It is often argued that the speculative nature of futures trading leads to excess co-movement between different futures price series. Our results do not support this hypothesis and show there is even less co-movement between futures prices for oil and agricultural biofuel feedstocks than there is between spot prices for these same commodities. This suggests variations in agricultural futures prices are dominated by factors not related to changes in oil prices, such as agricultural supply response and the non-biofuel demand for feedstocks.

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Introduction

The relationship between prices for fuels (crude-oil, gasoline, and ethanol) and agricultural feedstocks for biofuel (particularly corn and soybeans) has become an important economic and policy issue. There is now considerable evidence that the growth in biofuel production has increased the demand for, and price of, agricultural feedstocks—but the evidence on the extent to which changes in fuel prices get transmitted to agricultural feedstock prices is more mixed (Zilberman et al., 2013). This is important because if there is strong price transmission then higher (lower) fuel prices can be expected to lead to higher (lower) food prices, changing the incentives for agricultural production and putting pressure on the food security of low income households (Runge and Senauer, 2007; Mitchell, 2008). However, if variations in fuel prices do not transmit readily to agricultural prices then many of these concerns are misplaced and oil price shocks can be expected to have much smaller and more short-lived effects on agricultural and food prices.

A recent study by Myers et al. (2014) investigates long-run and short-run co-movement between spot prices for crude oil, gasoline, and ethanol and spot prices of corn and soybeans. Results suggest that spot fuel prices transmit to spot agricultural feedstock prices in the short run, but that the relationship dissipates in the long run. In particular, long-run equilibrium spot fuel and spot agricultural prices were found to be driven by separate stochastic trends and therefore "meander away" from one another over long time horizons. Furthermore, shocks to long-run equilibrium spot fuel prices only explain a relatively small portion of the forecast error variance in long-run equilibrium spot agricultural prices. These results suggest that while spot fuel and spot agricultural prices co-move to some extent over intermediate time horizons, in the long run

spot agricultural prices are determined primarily by agricultural supply conditions (e.g., productivity growth, acreage expansion etc.) and the non-biofuel demand for agricultural feedstocks (e.g., the derived demand for livestock feed as incomes grow), with fuel prices playing a relatively minor role in long-run agricultural spot price determination.

An interesting additional question is whether similar kinds of relationships exist between futures prices for fuels and futures prices for biofuel feedstocks. Futures prices differ from spot prices because they reflect the aggregated expectations of market participants regarding the *future* value of the underlying commodity at the maturity date specified on the futures contract. A futures contract is therefore a different asset than the underlying physical commodity, even when quality specifications and delivery location are the same. Furthermore, participation in futures trading does not require production, consumption, or ownership of the physical commodity and so opens up additional opportunities for low-cost speculative trading activity. Some have argued that this additional speculative activity can have an important influence on futures price determination, leading to futures prices that co-move in excess of co-movement in the spot prices of the underlying physical commodities (e.g., Juvenal and Petrella, 2011).

This paper builds on Myers et al. (2014) by investigating long-run and short-run co-movements between futures prices for crude oil and futures prices for biofuel feedstocks, specifically corn and soybeans. We do not include gasoline prices in the analysis because Myers et al. (2014) show that gasoline and crude oil prices co-move strongly in both the short-run and long-run. We also do not include ethanol futures prices in the analysis because ethanol futures only began trading in 2005, which would limit the length of time series data available for analysis. Finally, Myers et al. (2014) include exchange rates in their spot price analysis to account for the possibility that exchange rates provide an important link between energy and agricultural prices, both of which are traded goods. In the futures price analysis reported here,

however, we do not include exchange rates because Myers et al. (2014) found that including the exchange rate explicitly did not have a significant influence on inferences regarding price transmission between fuel and biofuel feedstock prices. We also investigated including other potential biofuel feedstock prices (e.g., wheat, soybean oil, other oil seeds, etc.) in the futures price analysis but found results followed an almost identical pattern to those using corn and soybean prices only (see Myers et. al, 2012 for details). For all of these reasons we focus here on co-movements between just three futures prices (crude oil, corn, and soybeans).

It is important to investigate futures price as well as spot price co-movement between fuel and agricultural biofuel feedstocks because of the potentially different market participants and price relationships that can occur in futures versus spot commodity markets. The contribution of the current paper is that it investigates long-run and short-run relationships between futures prices for oil and biofuel feedstock prices, and compares these results to those from the previous spot price analysis. Results lead to some new insights into the influence of futures market trading on commodity price co-movements, and on the relationship between oil and agricultural commodity prices.

Empirical Approach

To characterize the relationships among a set of *n* different fuel and agricultural futures prices, let $\mathbf{p}_t$ be an (nx1) vector of the logarithms of each commodity futures price.[1] Because each futures contract has a fixed maturity date, a time series of futures prices will have jumps in time to maturity as the series switches from one futures contract to the next as the maturity date

[1] Log transformations are commonly used in commodity price modeling because they are consistent with the statistical properties of most price data and facilitate interpretation of coefficients in terms of proportional relationships between prices.

for the first contract expires. This feature will be taken into account in the empirical analysis which follows.

We follow the empirical approach in Myers et al. (2014). The first step is to decompose each (log) price into a permanent component $\boldsymbol{\tau}_t$ and a transitory or cyclical component $\boldsymbol{\eta}_t$ such that:

(1) $$\mathbf{p}_t = \boldsymbol{\tau}_t + \boldsymbol{\eta}_t .$$

The permanent component is defined as $\boldsymbol{\tau}_t = \mathbf{p}_t + \lim_{s\to\infty}\sum_{k=1}^{s}\left[\Delta\hat{\mathbf{p}}_{t+k|t} - E(\Delta\mathbf{p}_t)\right]$ where $\Delta\hat{\mathbf{p}}_{t+k|t}$ is the *k*th step ahead best linear unbiased forecast of $\Delta\mathbf{p}_t$ conditional on information available at time *t*. By definition, $\boldsymbol{\tau}_t$ is a vector of prices expected in the very long-run (i.e., as the forecast horizon goes to infinity) conditional on information available at time *t* but adjusted back to time *t* by subtracting any known trend or drift. Futures prices should be nonstationary based on no-arbitrage arguments and there is considerable existing evidence to support this hypothesis. In this case it can be shown that $\boldsymbol{\tau}_t$ follows a pure random walk (possibly with drift) and is therefore itself nonstationary (see Beveridge and Nelson, 1981 and Stock and Watson, 1988). Because $\boldsymbol{\tau}_t$ is the current value of the price that is consistent with expected full adjustment over an infinite time-horizon we call it the "long-run equilibrium value" of the series. By definition, $\boldsymbol{\eta}_t$ is then stationary and represents transitory deviations around long-run equilibrium values.

Because the components of $\boldsymbol{\tau}_t$ are nonstationary they may also be cointegrated. Suppose all prices are nonstationary and there are $r < n$ cointegration relationships among the *n* prices in the system. Then $\boldsymbol{\tau}_t$ can be expressed in terms of a smaller number $k = n - r$ of "common trends" so that the long-run equilibrium prices can be written as $\boldsymbol{\tau}_t = \mathbf{A}\tilde{\boldsymbol{\tau}}_t$ where $\tilde{\boldsymbol{\tau}}_t$ is a (*k* x 1)

vector of common trends (random walks) and $\mathbf{A}$ is an (n x k) loading matrix that has full column rank (Hecq, Palm and Urbain, 2000).

Similarly, Vahid and Engle (1993) have shown that the cyclical part of the series may also have common components. In particular, assuming all prices are nonstationary then $\Delta\mathbf{p}_t$ is said to be co-dependent with common serial correlation features (hereafter just "co-dependent") if there are $c < n$ linear combinations of $\Delta\mathbf{p}_t$ that are innovations with respect to information available at time $t - 1$ (i.e., linear combinations of $\Delta\mathbf{p}_t$ that are not serially correlated). These linear combinations are called "co-feature vectors" and they imply that the cyclical component can be written as $\boldsymbol{\eta}_t = \mathbf{B}\tilde{\boldsymbol{\eta}}_t$ where $\tilde{\boldsymbol{\eta}}_t$ is an (l x 1) vector of common cyclical components with $l = n - c$, and $\mathbf{B}$ is an (n x l) loading matrix for the common cycles that has full column rank (see Vahid and Engle, 1993).

Allowing for both cointegration and co-dependency the decomposition (1) can be expressed:

(2) $$\mathbf{p}_t = \mathbf{A}\tilde{\boldsymbol{\tau}}_t + \mathbf{B}\tilde{\boldsymbol{\eta}}_t .$$

If there is no cointegration or co-dependency then $\tilde{\boldsymbol{\tau}}_t$ and $\tilde{\boldsymbol{\eta}}_t$ will be of full dimension n. However, when cointegration and/or co-dependency exist imposing the common trend and common cycle restrictions in (2) will help identify the nature of long-run and short-run relationships between the prices in the system.

Measures of Long-Run and Short-Run Co-Movement

Myers et al. (2014) suggest measuring the extent of long-run co-movement between two prices p_{it} and p_{jt} by the size of the correlation coefficient between the innovations in their

permanent component, $Corr(\Delta\tau_{it}, \Delta\tau_{jt})$. If the long-run equilibrium values of the prices move closely together this correlation will be close to one, while if movements in the long-run equilibrium prices are completely unrelated this correlation will be zero. The correlation between the innovations in the permanent components therefore has a natural interpretation as a measure of long-run co-movement between prices.

The number of common trends *k* in $\tilde{\boldsymbol{\tau}}_t$ influences long-run co-movement between prices. For example, suppose that p_{it} and p_{jt} are both driven by a single common trend (i.e., they are cointegrated). Then the equilibrium values of both prices would move together perfectly and $Corr(\Delta\tau_{it}, \Delta\tau_{jt}) = 1$. In this case the long-run equilibrium prices maintain a fixed relationship with one another and there is "perfect long-run co-movement" between the prices. Alternatively, if the two prices are not driven by a common trend (i.e., are not cointegrated) then $Corr(\Delta\tau_{it}, \Delta\tau_{jt}) < 1$ and the two prices will be unrelated in the very long-run (infinite horizon forecasts of any linear combination of the prices will have infinite variance). In the limiting case when the permanent components of the two prices are separate *uncorrelated* random walks then the long-run equilibrium values of the prices move completely independently and $Corr(\Delta\tau_{it}, \Delta\tau_{jt}) = 0$. In this case there is "no long-run co-movement" in the prices. Intermediate outcomes $0 < Corr(\Delta\tau_{it}, \Delta\tau_{jt}) < 1$ indicate long-run equilibrium values of prices move together over intermediate time intervals because innovations in their permanent component are correlated, even though these prices would eventually meander apart and become unrelated in the long-run. In this case there is "intermediate-run co-movement" and values of $Corr(\Delta\tau_{it}, \Delta\tau_{jt})$ close to one indicate stronger intermediate-run co-movement while values close to zero indicate weaker intermediate run co-movement.

Myers et al. (2014) suggest measuring short-run co-movement between any two prices p_{it} and p_{jt} by the unconditional correlation between their transitory components, $Corr(\eta_{it}, \eta_{jt})$. Because the transitory components are stationary this unconditional correlation is well-defined and provides a convenient summary measure of the extent to which prices co-move in the short run as they converge back to long-run equilibrium values. Just as the number of common trends *k* influence the extent of co-movement between long-run equilibrium prices, the number of common cycles *l* in $\tilde{\boldsymbol{\eta}}_t$ influences the extent of co-movement between the transitory components. For example, suppose that Δp_{it} and Δp_{jt} are both driven by a single common cycle (i.e., they are co-dependent). Then their transitory components would move together perfectly, and $Corr(\eta_{it}, \eta_{jt}) = 1$. In this case there is "perfect short-run co-movement" between the prices. Alternatively, if the two prices are not co-dependent then each price is driven by separate cyclical components, and $Corr(\eta_{it}, \eta_{jt}) < 1$. In the limiting case of no relationship between the transitory components then $Corr(\eta_{it}, \eta_{jt}) = 0$ and there is "no short-run co-movement" between the series. In the intermediate case of $0 < Corr(\eta_{it}, \eta_{jt}) < 1$ values close to one indicate stronger co-movement in adjustments towards long-run equilibrium while values close to zero indicate weaker short-run co-movement.

Together, the estimated correlation matrices of $\Delta\boldsymbol{\tau}_t$ and $\boldsymbol{\eta}_t$ provide detailed information on the ways in which the prices are related to one another over different forecast horizons.

Estimation and Testing

Estimation and testing for nonstationarity and cointegration are now standard and will not be detailed here.[3] Estimation and testing for co-dependence is outlined in Vahid and Engle (1993) and their procedures are adapted to the current case of fuel and agricultural feedstock prices in Myers et al. (2014). We do not detail the co-dependency testing procedures again here but note that estimation and testing is conditional on cointegration restrictions and so based on a vector error correction (VEC) representation:

$$\Delta\mathbf{p}_t = \boldsymbol{\mu} + \boldsymbol{\alpha}\mathbf{z}_{t-1} + \sum_{i=1}^{q} \boldsymbol{\Gamma}_i \Delta\mathbf{p}_{t-i} + \boldsymbol{\varepsilon}_t \tag{3}$$

where $\mathbf{z}_t = \boldsymbol{\beta}'\mathbf{p}_t$ is the (r x 1) vector of equilibrium errors from the r cointegrating relationships and $\boldsymbol{\beta}$ contains the cointegrating vectors. Testing for co-dependence is based on the canonical correlations between $\Delta\mathbf{p}_t$ and $\mathbf{w}_t = \{\mathbf{z}_{t-1}, \Delta\mathbf{p}_{t-1}, ..., \Delta\mathbf{p}_{t-q}\}$ as outlined in Myers et al. (2014). If co-dependence is found the co-feature vectors form a (n x c) matrix $\tilde{\boldsymbol{\beta}}$ such that each element of $\tilde{\boldsymbol{\beta}}'\Delta\mathbf{p}_t$ is an innovation with respect to the information set $\mathbf{w}_t$. Once the number of cofeature vectors has been established via testing we estimate $\tilde{\boldsymbol{\beta}}$ by imposing the co-dependency restrictions on the VEC model (3) and estimating the resulting "pseudo-structural form" using maximum likelihood. The appropriate pseudo-structural form is derived by first noting that $\tilde{\boldsymbol{\beta}}$ is not unique and so can be normalized to:

$$\tilde{\boldsymbol{\beta}} = \begin{bmatrix} \mathbf{I}_c \\ \tilde{\boldsymbol{\beta}}^*_{(n-c)\times c} \end{bmatrix} \tag{4}$$

for a set of unknown parameters $\tilde{\boldsymbol{\beta}}^*$. Then the co-dependency restrictions imply (up to a constant term) the following restrictions on the VEC model (3):

[3] More details are available in Hamilton (1994) and many other econometric texts.

(5) $$\begin{bmatrix} \mathbf{I}_c & \tilde{\boldsymbol{\beta}}^{*\prime} \\ \mathbf{0}_{(n-c)\times c} & \mathbf{I}_{n-c} \end{bmatrix} \Delta \mathbf{p}_t = \begin{bmatrix} \mathbf{0}_{(c\times r)} \\ \boldsymbol{\alpha}^* \end{bmatrix} \mathbf{z}_{t-1} + \sum_{i=1}^{q} \begin{bmatrix} \mathbf{0}_{(c\times n)} \\ \boldsymbol{\Gamma}_i^* \end{bmatrix} \Delta \mathbf{p}_{t-i} + \boldsymbol{\varepsilon}_t$$

where the * differentiates parameters from their unrestricted counterparts, $\boldsymbol{\alpha}^*$ is $(n-c)\times r$, and the $\boldsymbol{\Gamma}_i^*$ are $(n-c)\times n$. Equation (5) can then be estimated using maximum likelihood and imposes the following restrictions on the VEC model (3):

(6) $$\boldsymbol{\alpha} = \begin{bmatrix} \mathbf{I}_c & \tilde{\boldsymbol{\beta}}^{*\prime} \\ \mathbf{0}_{(n-c)\times c} & \mathbf{I}_{n-c} \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{0}_{(c\times r)} \\ \boldsymbol{\alpha}^* \end{bmatrix} \text{ and } \boldsymbol{\Gamma}_i = \begin{bmatrix} \mathbf{I}_c & \tilde{\boldsymbol{\beta}}^{*\prime} \\ \mathbf{0}_{(n-c)\times c} & \mathbf{I}_{n-c} \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{0}_{(c\times n)} \\ \boldsymbol{\Gamma}_i^* \end{bmatrix} \text{ for } i = 1, 2, \ldots q.$$

These restrictions will be useful for computing the permanent-transitory decomposition under co-dependency restrictions.

Computing the Decomposition

Once the parameters of the model have been estimated, either with or without cointegration and co-dependency restrictions as indicated by test results, decomposing each price into permanent and transitory components is straightforward as shown in Myers et al. (2014). In particular, the decomposition for the VEC representation (3) can be computed as:

(7a) $$\boldsymbol{\tau}_t = (\mathbf{I}_n - \mathbf{P})[\boldsymbol{\Gamma}(1) - \boldsymbol{\alpha}\boldsymbol{\beta}']^{-1}\boldsymbol{\Gamma}(L)\mathbf{p}_t$$

(7b) $$\boldsymbol{\eta}_t = -(\mathbf{I}_n - \mathbf{P})[\boldsymbol{\Gamma}(1) - \boldsymbol{\alpha}\boldsymbol{\beta}']^{-1}\boldsymbol{\Psi}(L)\Delta\mathbf{p}_t + \mathbf{P}\mathbf{p}_t$$

where $\boldsymbol{\Gamma}(L) = \mathbf{I}_n - \boldsymbol{\Gamma}_1 L - \ldots - \boldsymbol{\Gamma}_q L^q$, $\boldsymbol{\Gamma}(1) = \mathbf{I}_n - \boldsymbol{\Gamma}_1 - \ldots - \boldsymbol{\Gamma}_q$,

$\boldsymbol{\Psi}(L) = \boldsymbol{\Psi}_0 + \boldsymbol{\Psi}_1 L + \ldots + \boldsymbol{\Psi}_{q-1} L^{q-1}$ with $\boldsymbol{\Psi}_j = \sum_{i=j+1}^{q} \boldsymbol{\Gamma}_i$, and where

$\mathbf{P} = [\boldsymbol{\Gamma}(1) - \boldsymbol{\alpha}\boldsymbol{\beta}']^{-1}\boldsymbol{\alpha}\{\boldsymbol{\beta}'[\boldsymbol{\Gamma}(1) - \boldsymbol{\alpha}\boldsymbol{\beta}']^{-1}\boldsymbol{\alpha}\}^{-1}\boldsymbol{\beta}'$.

These formulas already impose cointegration restrictions directly, so decompositions computed using (7) will satisfy all appropriate cointegration restrictions. If there is no cointegration (r = 0)

these formulas are still applicable if we set $\boldsymbol{\alpha\beta}' = \mathbf{0}$ and $\mathbf{P} = \mathbf{0}$. If short-run co-dependency behavior is found then the decomposition (7) is still applicable, except that values for $\boldsymbol{\alpha}$ and the $\boldsymbol{\Gamma}_i$ must satisfy the restrictions in (6) with $\tilde{\boldsymbol{\beta}}^*$, $\boldsymbol{\alpha}^*$, and $\boldsymbol{\Gamma}_i^*$ estimated using the pseudo-structural form (5). Imposing these restrictions ensures that the transitory component $\boldsymbol{\eta}_t$ computed from (7b) exhibits all of the behavior implied by the co-dependency restrictions.

Evaluating Potential Nonlinearities and Regime Shifts

As argued by Myers et al. (2014), it is possible that co-movement in commodity prices involves nonlinearities that are not well captured by the linear cointegration and co-dependency models discussed so far. For example it could be that the price relationships experienced a structural change due to the growth of biofuels, or that when production of biofuel reaches certain threshold levels then the nature of the price relationships change. One way to model such nonlinearities is to allow model parameters to change over different ranges of values for underlying threshold variables, such as biofuel production levels, commodity stock levels, and time.

To allow for such regime changes, suppose the estimation equations for the multivariate price model take the general form $\Delta\mathbf{p}_t = \mathbf{f}(\mathbf{w}_t;\boldsymbol{\theta}) + \boldsymbol{\varepsilon}_t$ where $\mathbf{w}_t$ is as defined previously and $\boldsymbol{\theta}$ an associated parameter vector. Then we can define a multiple threshold model as:

(8) $$\Delta\mathbf{p}_t = \mathbf{f}(\mathbf{w}_t;\boldsymbol{\theta}_j) + \boldsymbol{\varepsilon}_t \qquad \mathbf{x}_t \in R_j(\boldsymbol{\delta})$$

where j indexes a set of multiple regimes defined by values of the exogenous threshold variable vector $\mathbf{x}_t$ lying in a set of nonintersecting and exhaustive sets $R_j(\boldsymbol{\delta})$ defined by the parameter vector $\boldsymbol{\delta}$. After identifying and estimating the separate models for each regime, the cointegration, co-dependency and permanent-transitory decomposition analyses can then be

applied regime by regime to isolate the extent of long-run and short-run co-movement in different regimes (see Myers and Jayne, 2012).

Given the well-known difficulties of testing formally for threshold effects (see Davies, 1987; Hansen, 1996; and Balagtas and Holt, 2008) we follow Myers et al. (2014) and use the Gonzalo and Pitarakis (2002) BIC-like criterion function:

$$(10) \qquad Q_T(m) = \max_{\boldsymbol{\delta}} \left\{ \frac{2}{T}\left[L_T(\boldsymbol{\delta}) - L_T\right] - \frac{\ln(T)}{T} md \right\}$$

to evaluate the existence of threshold nonlinearities. Here L_T is the log-likelihood value for the single regime (no threshold) model, $L_T(\boldsymbol{\delta})$ is the full sample log-likelihood value for the multi-regime model with thresholds $\boldsymbol{\delta}$, d is the number of parameters to be estimated in the single regime model, and m is the number of threshold parameters. The criterion is based on a likelihood ratio statistic but imposes a penalty for over-parameterization that is similar to the BIC criterion for evaluating lag length. Threshold and regime selection is then based on:

$$(11) \qquad \hat{m} = \arg\max_{0 \le m \le M} Q_T(m)$$

where M is the maximum number of thresholds to be considered. Gonzalo and Pitarakis provide simulation evidence to suggest this criterion performs well in selecting the appropriate number of thresholds and regimes.

Data and Preliminary Analysis

The application uses end-of-month current and one-month lags of the prices for the nearest maturing futures contract for CBOT corn, soybeans, and West Texas Intermediate (WTI) crude oil (hereafter “oil”) traded on NYMEX. The one-period lags are used to construct a series of futures price differences that always have the same maturity date (i.e., futures price “changes”

are always computed using the same underlying futures contract, not from the difference in prices between two contracts with different maturity dates). The sample period is January 1990 through August 2012.

Table 1 shows the nearby contract expiration months for each month of the year. In the corn futures market there are five contracts for delivery in March, May, July, September, and December. For soybeans there are seven contracts for delivery in January, March, May, July, August, September, and November. There are oil futures contracts for every month so the nearby futures price data are always taken from a contract expiring in the subsequent month. Using this approach recorded price changes are always changes in futures prices for contracts for the same maturity date, which avoids introducing spurious variation in futures price change data that are due only to changes in time to maturity.

To give some initial insights into the data we plot nearby futures prices for oil, corn, and soybeans over the sample period, each normalized to a value of one in January 1990 (see figure 1). As can be immediately observed, nearby futures prices for corn and soybeans move closely together over the entire sample period. Nearby oil futures prices appear to co-move with the agricultural futures during some periods, but also go through periods where there is little observed co-movement. This suggests a detailed investigation into the extent and nature of co-movement between these series should provide some interesting insights.

Model Estimation and Testing Results

Because of the considerable existing evidence that commodity futures prices are nonstationary, and because stationary futures prices would imply the existence of systematic profitable futures trading strategies, we do not report detailed tests for nonstationarity. However,

augmented Dickey-Fuller and Phillips-Perron tests strongly support nonstationarity of all three nearby futures price series.

Given nonstationarity it is important to test for cointegration because this will impose restrictions on the permanent-temporary decomposition. We undertook both Engle-Granger and Johansen trace tests for cointegration. The results are reported in Table 2 and show strong evidence of a single cointegration relationship between nearby corn and soybean futures prices, but no cointegration between the nearby futures price for oil and either of the agricultural futures prices. These findings are similar to those found for spot oil and agricultural prices in Myers et al. (2014).

We also need to estimate the cointegrating vector. Results from both least squares regression, and Johansen's VEC maximum likelihood method for estimating the cointegrating vector, are reported in table 3. Both estimates suggest strongly that the cointegrating vector is (1, -1), with the Johansen procedure (which provides consistent standard errors) showing a very tight confidence interval around this value. Remembering that the prices are in logarithms, this shows that nearby corn and soybean futures prices remain proportional to one another in the long-run. This result is consistent with economic intuition and we impose the long-run proportionality (cointegration) constraint from here on.

The next step is to test for co-dependency. The canonical correlation statistics for testing at least one and then at least two co-dependency relationships, along with their associated p-values, are shown in table 4. The result suggests two co-dependency relationships which implies one common transitory component is driving all of the price series.

Estimating the resulting pseudo-structural form with one cointegration and two co-dependency restrictions imposed revealed that the agricultural price differences could be excluded from the oil co-dependency relationship (likelihood ratio p-value = 0.985). This

suggests that changes in nearby futures prices for oil are already innovations with respect to the information set $\mathbf{w}_t = \{\mathbf{z}_{t-1}, \Delta\mathbf{p}_{t-1}, ..., \Delta\mathbf{p}_{t-q}\}$. In other words, oil futures prices follow a pure random walk with all price movement due the permanent component (the series has no transitory component). This is exactly what we would expect for futures prices generated from a well-functioning futures market because it means futures price changes are unpredictable based on past information, without even short-run temporary predictable cycles. On the other hand, corn and soybean futures are found to have small transitory components that suggest at least some predictability of short-run cyclical price movements. However, the majority of the price variation still comes from the (unpredictable) permanent component of these series so predictability of price changes remains low and short-run.

Full results for the restricted pseudo structural form estimated via maximum likelihood are provided in table 5. The first two equations for oil and corn are the two co-dependency relationships, showing that oil price changes are pure innovations and a linear combination of corn and soybean futures price changes, given by $(1, -\tilde{\beta}^*_{SOY}) = (1, -0.687)$ are also innovations with respect to the defined information set. The third equation (for soybeans) is an error-correction equation using the difference in log corn and soybean futures prices as the lagged equilibrium error term (i.e. imposing long-run proportionality between corn and soybean futures prices as the cointegration restriction). This specification is supported by previous testing results but we note that the results suggest very little ability to forecast futures price changes (see the very low R^2 in the soybean equation). The pseudo-structural form estimates are of little interest by themselves and are only shown for completeness and to provide additional insight into the structure of the empirical model. The main use of the estimates in the current application comes in operationalizing the permanent-transitory decomposition.

Decomposition and Co-Movement Results

The pseudo-structural form estimates are used decompose the three nearby futures price series into permanent (long-run equilibrium) and transitory (short-run stationary) components using the decomposition defined in equation (7). Test results showed that the oil futures prices have no transitory component (all price movements represent permanent changes). However, the corn and soybean futures process have both permanent and transitory components. The correlation matrix for changes in the permanent components of each series is shown in table 6. The corn and soybean futures prices are cointegrated and therefore driven by the same common trend. Therefore, as expected, the permanent components of the corn and soybean futures are perfectly correlated, showing perfect long-run co-movement. The oil futures are driven by a separate trend (not cointegrated with corn and soybean futures) but it is still possible that the two trends are correlated, showing that the oil and agricultural futures prices move together over intermediate time horizons. However, table 6 shows that the correlation coefficient between innovations in the two permanent components is only 0.01, indicating very weak long-run co-movement between oil futures prices and either corn or soybean futures prices.

Following Myers et al. (2014), we investigate this issue further by computing the (horizon independent) forecast error variance decomposition from a bivariate model of long-run equilibrium oil and corn prices. Results show that less than 1% of the variation in the innovations in the permanent component of corn futures prices is accounted for by variation in the innovations in the permanent component of oil futures prices. This result continues to hold if we use corn futures price changes themselves, instead of changes in the permanent component of the corn futures changes, to do the decomposition. The finding of very weak co-movement between long-run equilibrium oil and agricultural futures prices is therefore robust to model specification.

Turning to short-run co-movements, table 7 shows the estimated correlation matrix of transitory deviations around long-run equilibrium values for the three series. The oil futures prices have no transitory component and the corn and soybean futures prices are driven by the same common cycle. Therefore, table 7 shows no results for oil and that the transitory components of the corn and soybean futures prices are perfectly correlated (as expected). The results show perfect short-run co-movement between corn and soybean futures prices, but no short-run co-movement between oil futures and futures prices for the agricultural commodities. It might seem odd that the corn and soybean series co-move perfectly in both the short run and the long run, but the prices themselves are not perfectly correlated (though they are clearly highly correlated). This happens because, although the two prices are driven by the same common trend and same cyclical component, the prices themselves are different linear combinations of these two components, and therefore do not need to be perfectly correlated.

Overall the evidence supports strong co-movement between corn and soybean futures prices in both the long run and the short run. On the other hand, oil futures only co-move very weakly with the permanent component of corn and soybean futures prices and have no transitory component. Therefore there is very little co-movement between oil futures prices and either of the agricultural futures prices in either the long run or the short run.

These results suggest that fluctuations in agricultural futures prices are dominated by factors related to agricultural supply and the non-energy demand for biofuel feedstocks and are little influenced by oil futures price movements in either the long run or the short run. The results are similar to, but even stronger than, the co-movement results found for spot oil, corn, and soybean prices in Myers et al. (2014). For spot prices, the permanent components of oil and corn/soybean prices are more correlated (0.49 versus 0.01 found here for futures prices) and the forecast error variance decomposition of the innovations showed a larger proportion of the

variance in the permanent component of spot corn price is due to the permanent component of spot oil prices (24% versus less than 1% found here for futures prices). Evidently, the nature of futures price determination leads to even less co-movement between oil and agricultural prices over any length of run than is found in spot prices. The implication is that there is nothing about the speculative nature of futures markets, or the ease of participation in futures trading for those not involved in production or trade of the physical commodities, that leads to more co-movement between oil and agricultural prices. In fact, the reverse is true with even less co-movement than in the case of spot prices.

Nonlinearities and Regime Shifts

We evaluated the possibility of nonlinearities using time as the threshold variable and the Gonzalo-Pitarakis criterion function approach described above. There is some evidence of a regime shift in the model parameters (i.e., structural change) in March 2003 (GP criterion = 0.125). However, the GP criterion is only slightly greater than zero, indicating the evidence of structural change is weak. Furthermore, undertaking separate model estimation, decomposition and co-movement analysis for the two regimes before and after the structural break leads to the same conclusions as the full sample analysis—strong long-run and short-run co-movement between corn and soybean futures prices but very weak co-movement between oil futures and either of the agricultural prices. Therefore we only report complete results for the full sample analysis.

Conclusions

Common trend-common cycle decompositions were used to evaluate long-run and short-run co-movement among futures prices for oil, corn, and soybeans. Cointegration tests supported

the hypothesis that corn and soybean futures prices are cointegrated and therefore driven by a single common trend, but oil futures prices are not cointegrated with the agricultural prices and follow their own long-run trend. Co-dependency tests suggested that oil futures price changes are uncorrelated with past futures price information and so have no transitory component. However, corn and soybean futures prices were found to have small transitory components that are driven by the same common cycle.

The pseudo-structural form was estimated under these cointegration and co-dependency restrictions and results used to decompose each of the series into permanent and transitory components. Correlation analysis of the two components across different commodities revealed that corn and soybean futures prices co-move strongly in both the long run and the short run. However, oil futures prices have only very weak co-movement with the agricultural futures prices over any time horizon.

These results are similar to but stronger than the results found for oil, corn, and soybean spot prices in Myers et al. (2014). Evidently there is even less co-movement between futures prices for oil and agricultural feedstocks than there is between spot prices for the same commodities. This is an important result because it is often argued that the speculative nature of futures trading can generate price movements that go beyond those that can be supported based on supply and demand fundamentals, and in this sense may lead to excess co-movement between futures price series. Our results are not consistent with this hypothesis. Instead, our results indicate that variation in agricultural futures prices are dominated by factors not related to changes in oil prices, factors such as agricultural supply response and the non-biofuel demand for feedstocks. One implication of these results is that in the long run we can expect oil and agricultural futures prices to “meander apart” and be determined by largely separate economic fundamentals. This suggests that, taking a long-run view, concerns about commodity futures

speculation and higher oil futures prices leading to food shortages and agricultural commodity price booms may have been over-emphasized. Our results suggest that, in the long run, corn and soybean prices will be driven more by factors such as productivity growth, acreage response, and the non-ethanol demand for biofuel feedstocks, rather than by changes in oil prices. This does not imply that increased ethanol production has not had an influence on corn prices. But it does imply that changes in oil futures prices do not readily transmit to agricultural futures prices in either the short run or the long run. Our findings are also important because they suggest that futures trading has no adverse effects in terms of generating more co-movement in oil and agricultural futures prices than can be supported by co-movement in the underlying spot prices.

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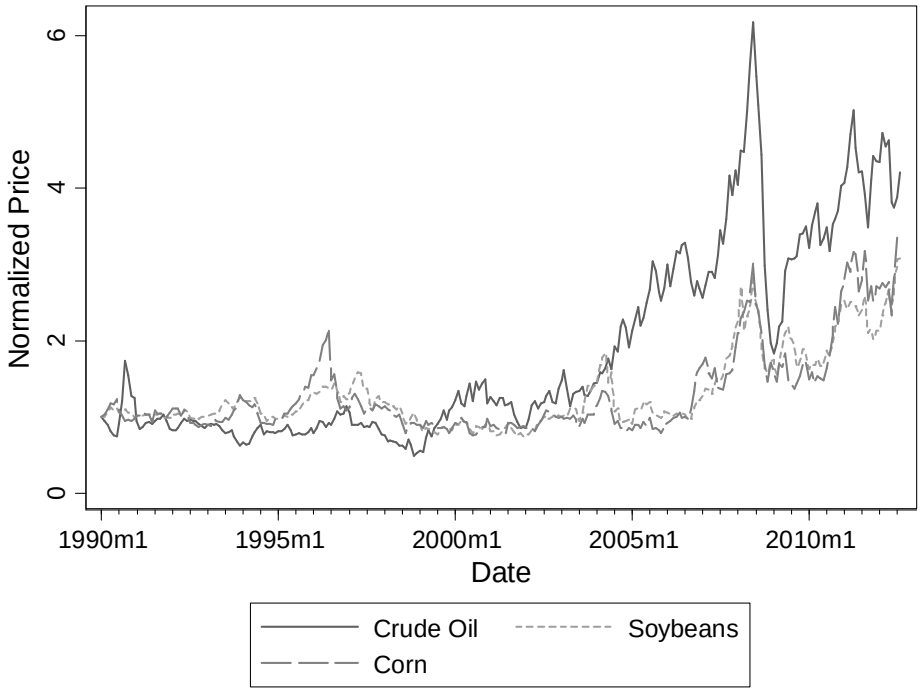

Figure 1. Normalized Monthly Oil, Corn, and Soybean Futures (log) Prices

Table 1. Nearby Futures Contract by Last Day of Month

Actual Month	Nearby Contract Month					
	Corn		Soybeans		WTI Crude Oil	
January	March	Year t	March	Year t	February	Year t
February	March	Year t	March	Year t	March	Year t
March	May	Year t	May	Year t	April	Year t
April	May	Year t	May	Year t	May	Year t
May	July	Year t	July	Year t	June	Year t
June	July	Year t	July	Year t	July	Year t
July	September	Year t	August	Year t	August	Year t
August	September	Year t	September	Year t	September	Year t
September	December	Year t	November	Year t	October	Year t
October	December	Year t	November	Year t	November	Year t
November	December	Year t	January	Year t+1	December	Year t
December	March	Year t+1	January	Year t+1	January	Year t+1

Source: Barchart.com

Table 2. Cointegration Test Results

Cointegrating Relationship	*Engle Granger Statistic*	*5% Critical Value*	*Maximum No. of Cointegrating Relationships*	*Trace Statistic*	*5% Critical Value*
Corn-Oil	-2.802	-3.359	0*	10.505	15.41
			1	0.495	3.76
Soybeans-Oil	-2.586	-3.359	0*	8.665	15.41
			1	0.526	3.76
Corn-Soybeans	-4.392	-3.359	0	20.638	15.41
			1*	0.866	3.76
Corn-Soybeans-Oil	-4.391	-3.772	0	29.808	29.68
			1*	9.265	15.41
			2	0.424	3.76

Notes: All variables are in logarithms. Engle-Granger tests the null of no cointegration. Trace statistics based on appropriate dimensional VEC estimations with two lagged differences included in each model (as suggested by lag selection criteria). * indicates the number of cointegrating vectors supported by the Trace statistic.

Table 3. Estimates of the Cointegrating Vector

Method	*Crude Oil Price*	*Corn Price*	*Soybean Price*	*Constant*
OLS	0	1	-1.014	-0.970
Johansen VEC	0	1	-1.066	1.317
			(0.090)	

Notes: All variables are in logarithms. No standard errors are shown for the OLS result because these are known to be inconsistent. Number in parentheses for Johansen's VEC procedure is a consistent standard error. Also using Johansen's VEC procedure a likelihood ratio test fails to reject excluding oil price from the cointegrating vector (p-value = 0.903).

Table 4. Co-dependency Test Results

Co-dependency Relationship	*No. of Co-dependency Relationships*	*Canonical Correlation Statistic*	*p-value*
Oil-Corn-Soybeans	> 0	7.670	0.174
	> 1	18.820	0.092

Notes: All variables are in logarithms and co-dependency restrictions are on the first differences of the variables. Results suggest 2 co-dependency relationships.

Table 5. Pseudo-Structural Form Estimates

Parameter	*Crude Oil Price Eqn.*	*Corn Price Eqn.*	*Soybean Price Eqn.*
Constant	0.005	-0.007	0.028
	(0.006)	(0.004)	(0.031)
$\tilde{\beta}^*_{SOY}$	-	0.687	-
		(0.285)	
α^*	-	-	0.027
			(0.035)
$\Gamma^*_{1,OIL}$	-	-	-0.010
			(0.046)
$\Gamma^*_{1,CORN}$	-	-	0.122
			(0.080)
$\Gamma^*_{1,SOY}$	-	-	-0.136
			(0.087)
$\Gamma^*_{2,OIL}$	-	-	0.000
			(0.046)
$\Gamma^*_{2,CORN}$	-	-	-0.077
			(0.079)
$\Gamma^*_{2,SOY}$	-	-	0.158
			(0.085)
R^2	-	0.457	0.029

Notes: All variables are in logarithms and the dependent variables are first differences. α^* is the restricted speed of adjustment parameter on lagged equilibrium errors from the cointegration relationship. The $\Gamma^*_{j,OIL}$ are parameters on the *j*th lagged first difference of the log crude oil price in the relevant equation (and so on for other commodities).

Table 6. Correlation Matrix of Innovations in Long-Run Equilibrium Components

	Oil	*Corn*	*Soybeans*
Oil	1.00		
Corn	0.01	1.00	
Soybeans	0.01	1.00	1.00

Table 7. Correlation Matrix of Transitory Components

	Oil	*Corn*	*Soybeans*
Oil	-		
Corn	-	1.00	
Soybeans	-	1.00	1.00