The Australian Journal of
Agricultural and
Resource Economics

AARES
AUSTRALASIAN AGRICULTURAL & RESOURCE ECONOMICS SOCIETY

Australian Journal of Agricultural and Resource Economics, 66, pp. 363–382

Do crop prices share common trends and common cycles?*

Puneet Vatsa[†]

Global crop prices decidedly co-move: research supporting this view abounds. What is unclear is how strong the co-movement is between them. This paper tests for a strong form of co-movement amongst global crop prices before and after the global financial crisis (GFC) using a multivariate decomposition framework based on a serial-correlation common feature. More specifically, we analyze common trends (i.e., long-run co-movement) and common cycles (i.e., short-run co-movement) amongst the global prices of five major crops: corn, palm oil, rice, soybean, and wheat. We show that corn and soybean prices are closely associated in the long and the short run—they respond similarly to persistent and transitory shocks. Furthermore, their associations have strengthened since the GFC. In contrast, the co-movement of rice prices with the other crop prices has weakened during the 2010s. Overall, the cycles are relatively muted after the GFC, indicating that the five crop prices are trend-dominated during this period; the observed prices adhere closely to their long-run trends.

Key words: common trends and cycles, global crop prices, time series.

JEL classifications: C3, C32, G01, Q02, Q11, Q21

1. Introduction

Co-movement of prices of major crops is well documented. This co-movement, at least in the long run, stands to reason—crops have common uses, utilise similar inputs and thus have non-zero cross-price elasticities. They are also affected by common factors such as inflation, interest rates, industrial production, exchange rates and crude oil prices (Baffes & Haniotis, 2016; Camp, 2019; Pindyck & Rotemberg, 1990). Nevertheless, due to geographical factors, differences in energy intensities, seasonal patterns and uses to which they are put, crop prices may diverge from time to time while adhering to long-run equilibria. Transaction costs and product delivery lags may also impede market integration and price convergence, leading to transitory deviations amongst crop prices (Goodwin et al., 2021).

Furthermore, co-movement may be stronger amongst subsets of crop prices. For example, because the United States accounts for a significant proportion of the global production of soybean and corn, crops that are used

*The author thanks the editor and the reviewers for offering valuable and constructive feedback on an earlier draft, which has helped to improve the manuscript significantly.

[†]Puneet Vatsa (puneet.vatsa@lincoln.ac.nz) is a Lecturer at Department of Global Value Chains and Trade, Faculty of Agribusiness and Commerce, PO Box 85084, Lincoln University, Lincoln 7647, New Zealand.

doi: 10.1111/1467-8489.12464

for producing vegetable oils and as feedstock for biofuels, their prices may exhibit strong co-movement. Rice, on the other hand, is an important food staple used predominantly for direct human consumption and produced mainly in China, India and South-East Asia. Consequently, its price may behave differently. This was evident during the first half of 2021—while prices of most major crops rose steeply, rice prices were relatively stable. However, if the past is any indication of the future, the divergence in crop prices may be short-lived. It also bears emphasis that co-movement amongst prices of crops used as biofuel feedstock and those of food crops may signify a link between energy and food markets (Myers et al., 2014). These links can induce volatility in food markets and threaten food security in low- and middle-income countries. Thus, it is important to understand the short- and long-run behaviours of and co-movement amongst specific crop prices.

Asking *whether* crop prices co-move is somewhat simplistic. They decidedly do. What is not fully understood is how strong the co-movement is amongst crop prices. Furthermore, do they co-move in both the short and the long run? Are there specific crops whose prices exhibit stronger co-movement relative to others? Do crop prices respond similarly to persistent and transitory shocks? Have the linkages amongst crop prices changed since the global financial crisis (GFC)? This paper is devoted to answering these questions using a common-features-based framework that allows us to decompose the global prices of five major crops—corn, palm oil, rice, soybean and wheat—into their trend and cyclical components and illuminate their co-movement in the long and the short run.

Previous studies have largely used univariate decomposition techniques to study commodity price cycles, trends and co-movement (see, e.g., Cuddington, 1992; Cuddington & Jerrett, 2008). These techniques, such as the Hodrick-Prescott filter (Hodrick & Prescott, 1997), the Hamilton (2018) filter, and the Beveridge-Nelson decomposition (Beveridge & Nelson, 1981), are applied to one commodity at a time to isolate trends and cycles, which are then co-examined to study long- and short-run associations; the results are often presented as superimposed illustrations that show the similarities and differences amongst the trends and cycles derived from separate unrelated models (see, e.g., Cuddington & Jerrett, 2008). However, because each variable is decomposed separately, this approach can overlook the variables' tendencies to respond similarly to different shocks in the short and the long run. These tendencies determine whether and to what extent variables co-move. Thus, univariate methods are inherently limited in their ability to explain co-movement.

The present study is the first to examine common trends and common cycles amongst major food crops using a multivariate decomposition framework: the results inform the stylised facts on crop prices' trends, cycles and co-movement; they are relevant to the design of agricultural and food policy for different time horizons, especially when one-size-fits-all policy frameworks overlook the needs of crop-specific industries; and they should be of strong interest to industry stakeholders engaged with specific crops and to investors seeking to optimise portfolios comprising agricultural commodities.

The decomposition approach comprises three steps. Each step is contingent upon the preceding ones. First, we test for long-run co-movement amongst the five crop prices. To this end, we test for cointegration, which is a well-known example of a common feature—when non-stationary series comprising stochastic trends are cointegrated, they have one or more linear combinations that are stationary (Johansen, 1988, 1996). The linear combinations are free of stochastic trends, which are the common features amongst non-stationary series. Second, we test for the serial-correlation common feature, which implies short-run co-movement amongst the series in question (Engle & Kozicki, 1993; Vahid & Engle, 1993). The presence of a serial-correlation common feature implies that the series share common cycles; that is, they co-move in the short run. Third, we decompose each of the five crop prices simultaneously into their long-run trend and short-run cyclical components—this approach, in sharp contrast to univariate decomposition methods, imparts a more informative and parsimonious structure to the econometric specification, as it leverages information on all the variables of interest.

Considering the significance of the GFC to commodity price dynamics, we formally test for breakpoints and sample-split dates to identify structural shifts and regime changes. Then, we apply the approach mentioned above to two sub-samples: the pre-GFC period and the post-GFC period. In both cases, we find evidence of common trends and cycles amongst the crop prices, implying long- and short-run co-movement amongst them. However, the strength of the co-movement varies between the long and the short run, between different groups of crops and across different regimes (i.e. before and after the GFC).

2. Previous research: commodity price co-movement and decomposition

Studies on the co-movement amongst commodity prices abound (Ai et al., 2006; Allen et al., 2018; Ciaian & Kancs, 2011; Lence & Falk, 2005; Nazlioglu & Soytas, 2012; Peri & Baldi, 2010). Nevertheless, analyses of trends and cycles in commodity prices are limited (Cashin & McDermott, 2002; Cuddington, 1992; Cuddington & Urzúa, 1989; Myers et al., 2014; World Bank, 2020).

Considering that trend, cyclical and seasonal components are unobserved constituents of time series, authors have applied several decomposition techniques to isolate them. For example, Cuddington and Urzúa (1989) and Cuddington (1992) used dummy-augmented trend and difference-stationary models and the Beveridge-Nelson decomposition method (Beveridge & Nelson, 1981) to decompose commodity prices into trend and cyclical components; Cuddington and Jerrett (2008) applied band-pass filters to identify short-run and super cycles; and the frequency domain approach (Corbae et al., 2002) was used in a special report by World Bank (2020).

Crop prices experience seasonal variations. Applying decomposition frameworks that ignore seasonality may leave it embedded in the cyclical components, thereby masking the true cyclical behaviour of crop prices. A recent approach proposed by Hamilton (2018) overcomes this limitation of other decomposition framework such as the Hodrick-Prescott filter—Hamilton's (2018) approach is robust to seasonal patterns in the data, requires only a few observations to extract the cyclical components and can be estimated in a straightforward way using ordinary least squares regressions. Nevertheless, these are univariate decomposition techniques.

Using univariate techniques, one may isolate the cycles and subsequently use them in regression frameworks or correlational analyses; however, this approach does not reveal the presence of common features, a form of codependence amongst the variables (Engle & Kozicki, 1993; Vahid & Engle, 1993). When it exists, this codependence indicates that the variables co-move in the short-run; that is, they have similar cyclical components. This highlights the importance of jointly treating the variables to leverage information on each of them simultaneously. Moreover, analyses of cycles derived from univariate decomposition techniques do not address common trends amongst the variables. Given the high degree of interconnectedness in commodity markets, the presence of common trends is a distinct possibility. Therefore, analyses of common cycles that disregard common trends would yield incomplete information about co-movement, leading to incorrect conclusions.

In this paper, we overcome the limitations identified above associated with univariate decomposition techniques. By applying Vahid and Engle's (1993) multivariate decomposition framework to uncover trends and cycles in major crop prices, we present a novel perspective on the long- and short-run synchronisation amongst them. Testing for a strong form of codependence, this framework lends itself well to simultaneously analysing short- and long-run co-movement: it obviates the need to estimate separate models to isolate trends and cycles amongst the time series in question; it reduces the complexity of multivariate models, as variables that move together may have common components, the presence of which simplifies the econometric models while maintaining their predictive power; and it addresses the commonalities amongst the cyclical components in conjunction with commonalities amongst the long-run trends.

Multivariate models have been extensively used to study commodity price co-movement (see, e.g., Pindyck & Rotemberg, 1990; Ai et al., 2006; Peri & Baldi, 2010; and Baffes & Haniotis, 2016). In these papers, the decomposition of commodity price series is ignored. Only one paper, Myers et al. (2014), addresses common trends and common cycles amongst biofuels, crude oil and crop prices. Thus, from an econometric standpoint, their study is similar to ours, as they use cointegration and tests for codependence to isolate trends and cycles in the observed price series.

The application of cointegration, a popular technique, deserves special mention. Although cointegration is useful for studying long-run trends and co-movement amongst variables, it does not address their short-run cycles. In this paper, cointegration serves as a foundation for decomposing crop prices and analysing their long- and short-run co-movement. In essence, we coalesce two strands of literature, one that is predicated on the decomposition of time series (but in univariate frameworks) and the other that leverages multivariate frameworks (but does not involve time-series decomposition). Notwithstanding the strong interest in understanding long- and short-run co-movement amongst crop prices, there is scant research on this subject. Myers et al. (2014), who have studied the two forms of co-movement in a unified common-feature-based framework, have taken only corn and soybean prices into account. Their focus is on examining the linkages between energy prices (oil, gasoline and ethanol), exchange rates and the aforementioned crop prices. Moreover, they have used only the pre-GFC data and thus do not explain how crop and energy price linkages have changed since the GFC.

The present paper extends the literature on crop price dynamics in three important ways. First, by examining five major crops that account for a substantial share of the global arable land, it broadens the scope and provides a more exhaustive investigation of crop price co-movements. Second, analysing up-to-date time series and using formal structural break tests, it offers insights into how crop price dynamics differ between the pre- and post-GFC periods. Third, focusing exclusively on crop prices, it points to potential channels that may underpin their co-movement in the short and the long run.

Although it is easy to see why crop prices are often treated as a homogeneous group, a discussion of why they may exhibit different patterns is in order. Farming of crops is geographically dispersed: for example, India and China are the largest rice producers, whereas Brazil and the United States dominate the soybean market. Crops have different energy intensities: rice is significantly more energy-intensive than wheat. Their input requirements are different: while fertilisers account for significant proportions of the operating expenses for producing corn, they constitute a relatively small proportion of the cost of producing soybean. Their optimal growing environments vary: sowing, harvesting and delivery of different crops happen at separate times of the year. Weather affects their supply variously: a drought in Russia may compromise wheat supply, while leaving soybean supply unchanged. Crops also have different uses: rice and wheat are food staples across the world; significant proportions of corn are used as a feed grain for livestock and feedstock for producing biofuel; and palm oil is an ingredient in a multitude of consumer, pharmaceutical and industrial products.

Considering the above, variations in the responses of crop prices to macroeconomic, weather and policy shocks are to be expected. Some shocks may exert a long-lasting influence on crop prices, whereas others may have a transitory effect. For example, in the United States, the Energy Independence and Security Act of 2007 mandates a substantial proportion of gasoline and diesel to be replaced by biofuel alternatives by 2022 (Hawkins et al., 2012)—such mandates are likely to have a persistent impact on corn prices. Similarly, the discovery of novel uses for crops such as palm oil may permanently alter their prices. On the other hand, weather-related supply shocks such as drought, forest fires and floods may have transitory effects on crop prices. Therefore, it is plausible that crop prices may exhibit different patterns in the long relative to the short run. How they respond to different shocks may also determine the extent to which they co-move at different horizons. Thus, the debate on what determines crop prices should be reframed as what determines crop prices in the short and the long run—the underlying factors may be different.

Understanding trends and cycles may inform the design of stabilisation policies, especially in developing countries with large agrarian populations. Common trends and cycles amongst crops should also be of strong interest to stakeholders in industries that utilise crops as feedstock: crop prices directly or indirectly affect numerous industries worldwide. With the financialisation of the commodities sector, investors seeking to diversify their portfolios would benefit from understanding the strength of crop price co-movement at different horizons. The method applied in this paper allows us to examine each of the five crops' responses to persistent and transitory shocks: the former give rise to common trends, whereas the latter engender common cycles. In the following section, we discuss the three-stage empirical framework in detail.

3. Estimation framework

In the first stage, we use the maximum likelihood based on Johansen (1988) cointegration test to determine the number of common trends amongst the five crops. If the components of the vector $x_t = (x_{1\,\mathrm{t}}, x_{2\,\mathrm{t}}, \ldots, x_{nt})$ are integrated of order *1*, and there is a vector $\beta = (\beta_1, \beta_2, \ldots, \beta_t)$ such that the linear combination $\beta = (\beta_1 x_{1t} + \beta_2 x_{2t} + \cdots + \beta_n x_{nt})$ is integrated of order *0*, then the components of x_t are said to be cointegrated (Engle & Granger, 1987). Johansen (1988) showed that for an $(n \times 1)$ vector x_t, there can exist $r < n$ linearly independent cointegrating vectors, implying the presence of $(n - r)$ common trends. Also, $\beta' x_t$ is $I(0)$, where β is the $(r \times n)$ matrix of the cointegrating coefficients. Vahid and Engle (1993) proposed a serial-correlation common features test for determining the number of common cycles amongst cointegrated variables.

Co-movement amongst stationary series cannot be attributed to cointegration as defined above—it must be due to the presence of common cycles. In this case, linear combinations of cycles that are not cyclical should exist. Vahid and Engle (1993) called a linear combination of the elements of Δx_t, an innovation apropos all observed information prior to time t, a cofeature vector.

The second stage involves estimating the number of cofeature vectors by testing for the significance of the canonical correlations between Δx_t and $(\beta' x_{t-1},\ \Delta x_{t-1},\ \Delta x_{t-2},\ \ldots,\ \Delta x_{t-k+1})$, where β is an (n x r) matrix comprising the cointegrating vectors. They propose the following test statistic to determine the significance of the canonical correlations:

$$C(k,\ s) = -(T - k - 1)\sum_{i=1}^{s} \ln(1 - \rho_i^2) \tag{1}$$

where ρ_i^2 are the s smallest squared canonical correlations between Δx_t and $(\beta' x_{t-1},\ \Delta x_{t-1},\ \ldots,\ \Delta x_{t-k+1})$, T is the number of observations, and k is the lag length of the VAR system; $C(k,s)$ has a χ^2 distribution with $s^2 + snk + sr - sn$ degrees of freedom. However, Engle and Issler (1993) suggest that the F statistic proposed by Rao (1973) yields superior results. Thus, we use the F statistic to ascertain the number of cofeature vectors. Given r linearly independent cointegrating vectors, there can exist, *at most*, $s = (n - r)$ cofeature vectors that eliminate common cycles. Also, given s cofeature vectors, there exist (n - s) common cycles.

Lastly, the five crop price series are decomposed into their trend and cyclical components. The $(n \times s)$ matrix $\tilde{\beta}$ and the (n x r) matrix β constitute the cofeature and cointegrating spaces respectively. According to Vahid and Engle (1993), a trend-cycle decomposition can be obtained when the number of cointegrating and cofeature vectors adds up to the number of variables, that is $r + s = n$. When this criterion is met, then the (n x n) matrix $B = \begin{bmatrix} \tilde{\beta}\prime \\ \beta' \end{bmatrix}$ is of full rank, and thus, B^{-1} exists. Then, upon partitioning the columns of B^{-1} such that $B^{-1} = [\tilde{\beta}^{-}|\beta^{-}]$, the trend-cycle decomposition is recovered as follows:

$$x_t = B^{-1}Bx_t = \tilde{\beta}^{-}\tilde{\beta}' x_t + \beta^{-}\beta' x_t \tag{2}$$

$\beta' x_t$ is serially correlated and *I(0)*. Therefore, $\beta^{-}\beta' x_t$ represents the cyclical components. On the other hand, $\tilde{\beta}' x_t$ is a random walk and does not contain any cycles. Therefore, $\tilde{\beta}^{-}\tilde{\beta}' x_t$ represents the trend components.

4. Data and empirical results

4.1 Data

The conversations regarding crop price dynamics have shifted notably since the GFC. Before the crisis, policymakers were concerned about the consequences of high crop prices on food security, consumers were distressed about high food prices, and rising costs disquieted producers. After the crisis, declining crop prices have alleviated some of the concerns and anxieties related to high and rising crop prices. However, since mid-2020, crop prices have risen rapidly despite sluggish global growth, low energy prices, and uncertainties of the COVID-19 pandemic. The trends since the GFC are more pertinent to the contemporary realities of crop prices. Be that as it may, comparing the post-GFC crop price dynamics with those before the GFC may provide valuable insights into how the interlinkages amongst crop prices have evolved through anomalous periods marking stark turning points in global crop prices.

Thus, we analyse monthly data from January 1990 to June 2021 on the five major crop prices. The data are sourced from the International Monetary Fund database and expressed in US dollars per metric ton (FRED, 2021). For corn, US No. 2 yellow prices are used. The Thailand 5% grade and the US No. 1 hard red winter prices are used for rice and wheat respectively. The No. 2 yellow and par prices are used for soybean, and lastly, palm oil prices are based on Bursa Malaysian Derivatives Berhad. To be sure, the seasonality inherent in crop prices may mask the underlying trends and cycles in the data. In fact, in the presence of strong seasonality, the cyclical components may show recurring periodicity characteristic of seasonal fluctuations; in such cases, seasonality can be mistaken for cyclicality. Thus, it is important to derive cycles that are free of seasonal fluctuations. Accordingly, we deseasonalise the five series using the ARIMA-based X-13 seasonal adjustment method before modelling trends and cycles in crop prices.

The five crops are selected based on their significance as food crops (rice, wheat and corn), animal feed (corn, soybean and wheat) and biofuel feedstock (corn and soybean); palm oil is included due to its rising importance as an ingredient in numerous industrial, consumer and pharmaceutical products; furthermore, these crops account for a significant proportion of the global arable land (Baffes & Haniotis, 2016). In the light of these crops' common uses and tendencies to co-move to varying degrees, it is worth investigating a strong form of codependence amongst them—this is the principal aim of the present paper.

Visually inspecting the data is a useful starting point. The five series are illustrated in Figure 1. Some important trends and patterns are readily observed in the data. Before the GFC, there were two notable periods during which crop prices increased appreciably. Between 1994 and 1996, strong global demand driven by the rapid growth in East Asia and South-East Asia and low harvests in major food exporting nations led to higher crop prices. During this period, the depreciation of the US dollar also contributed to rising crop prices—they are denominated and traded in US dollars. Unsurprisingly, the Asian financial crises contributed to the reversal of these gains during 1997–1998. Then, beginning in 2000, crop prices began to increase gradually before surging at record rates during 2006 and 2007. Once again, these

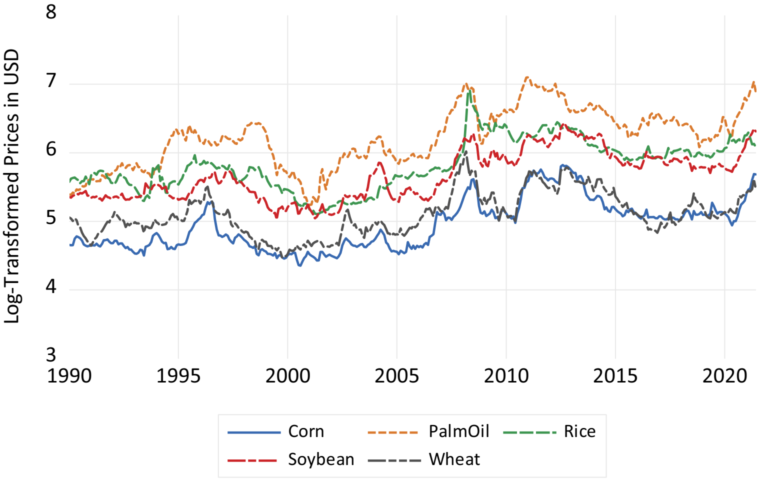

Figure 1 Log-transformed crop prices. [Colour figure can be viewed at wileyonlinelibrary.com]

increases coincided with a depreciating US dollar, strong global demand and supply shortfalls (Peters et al., 2009).

After the GFC, during the early 2010s, crop prices trended downwards. These trends started to taper around 2014–2015, from whence soybean prices flattened out, prices of wheat, corn and rice increased slightly, whereas palm oil prices behaved somewhat erratically. The spikes and falls were interspersed throughout the 2010s; for example, in 2012, palm oil and soybean prices increased dramatically, and each of the five prices declined rapidly during 2014. In addition, each of the five series shows a tendency to meander, which is characteristic of economic time series in general—none appears to be trend-stationary. Evidently, the GFC delineates two periods, on either side, characterised by strikingly different price behaviours. This has motivated a considerable body of research devoted to analysing and comparing crop price dynamics before and after the GFC (Chiou-Wei et al., 2019; Lucotte, 2016; Manera et al., 2013). Our approach follows this strand of literature.

Visual inspection is helpful; however, it is important to test the data's stationarity properties formally. To this end, we conduct unit root tests. Considering that these tests have low power, which often leads researchers to conclude incorrectly that unit roots are present, we use different specifications for unit root tests—although including unnecessary deterministic regressors reduces the power of the tests, so does incorrectly omitting them. The results presented in Table 1 indicate that the five series are non-stationary.

4.2 Common trends and common cycles analysis

The presence of common cycles is contingent upon the presence of common trends. Therefore, it is important to ascertain the number of cointegration relationships, the dual of common trends, amongst the five crop prices.

Table 1 Unit root tests

	Test	Corn	Palm Oil	Rice	Soybean	Wheat
1990–2021	$z(t_{\propto}^{-})$	−1.42	−2.06	−1.76	−1.41	−2.16
	$z(t_{\propto}^{-})$	0.66	0.79	0.29	0.68	0.16
1990–2005	$z(t_{\propto}^{-})$	−2.52	−2.13	−1.88	−2.37	−2.16
	$z(t_{\propto}^{-})$	−0.10	0.44	0.06	−0.00	−0.23
2008–2021	$z(t_{\propto}^{-})$	−1.62	−2.23	−2.52	−1.90	−2.32
	$z(t_{\propto}^{-})$	0.39	−0.02	0.04	0.23	−0.48

Note: None of the null hypotheses of a unit root being present is rejected at 5% significance level; $z(t_{\propto}^{-})$ include the intercept, whereas $z(t_{\propto}^{-})$ do not include the intercept. The lag lengths for the Phillips-Perron tests are determined by using the Schwert (1989) formula: $Int\left\{4\left(\left(\frac{T}{100}\right)^{0.25}\right)\right\}$.

Accordingly, using the full-sample period from January 1990 to June 2021, we consider two model specifications of the VEC model, one under the null hypothesis and the other under the alternative, that is.

$$H_0 : \Delta x_t = \alpha(\beta' x_{t-1}) + \sum_{i=1}^{p-1} \omega_i \Delta x_{t-i} + \in_t \tag{3}$$

$$H_A : \Delta x_t = \alpha(\beta' x_{t-1} + \delta_0) + \sum_{i=1}^{p-1} \omega_i \Delta x_{t-i} + \in_t \tag{4}$$

where $x_t = (corn_t, palmoil_t, rice_t, soybean_t, wheat_t)'$ is a (5×1) vector comprising the natural logarithmic transformations of the five crop prices; α is the vector of adjustment coefficients; ω_i represents the $(n \times n)$ coefficient matrices; δ_0 is the intercept in the cointegration relation; and $\in_t$ is the vector of innovations. Unrestricted vector autoregressions of order 12 are estimated, implying a VEC specification of order 11. The likelihood ratio (LR) test suggests that the restricted model consistent with equation (3) is suitable: the null hypothesis cannot be rejected, as the computed LR statistic, $\chi^2_{(1)} = 0.41$, has a p value of 0.75.

The λ_{trace} and λ_{max} statistics presented in Table 2 point to the presence of two significant cointegrating vectors. We are attentive to the potential of structural changes, which may lead to parameter instability in the VEC model. In such cases, it is appropriate to identify structural breaks and regime changes and estimate separate models for specific regimes of interest (Myers et al., 2014). Considering the unprecedented price behaviours leading up to,

Table 2 Cointegration tests for the full sample

Null	Eigenvalue	Trace	Max
$r = 0$	0.10	89.09*	39.56*
$r \leq 1$	0.07	49.53*	25.93*
$r \leq 2$	0.04	23.61	15.49
$r \leq 3$	0.02	8.11	7.93
$r \leq 4$	0.00	0.18	0.18

Note: *Indicates the rejection of the null hypothesis at 5% significance level.

during and after the GFC, some researchers have undertaken comparative analyses to study commodity prices during the pre-GFC period relative to the post-GFC period (Lucotte, 2016); others, emphasising the excessive volatility in commodity prices during the GFC, have modelled them while accounting for structural breaks (Chiou-Wei et al., 2019). Still others, such as Peters et al. (2009), draw attention to the anomalous price increases between 2006 and 2008—including this period may present a distorted view of the overall trends and cycles and misrepresent the commonalities amongst them over extended periods.

It bears emphasis that although there is a consensus regarding the anomalous behaviours of prices *circa* 2008, there is a lack of unanimity regarding the specific dates representing a structural shift in commodity price dynamics. Thus, bearing in mind the distinct possibility of structural breaks between 2006 and 2010, we formally analyse the stability of the parameters at different points in time using the Chow breakpoint and sample-split tests. The results reported in Table 3 indicate parameter instability between January 2006 and January 2008; no such evidence is detected during January 2009 and 2010. Thus, in the light of these results and considering the excessive price volatility and precipitous prices increases during 2006 and 2007, we analyse trends and cycles for two sub-samples: 1990–2005 (i.e. the pre-GFC period) and 2008–2021 (i.e. the post-GFC period).

First, let us consider the results for the pre-GFC period. Like in the full-sample analysis, we estimate equations (3) and (4) and conduct LR tests to ascertain the appropriate VEC specification. The LR statistic, $\chi^2_{(1)} = 0.42$ has a p value of 0.52. Thus, we select the restricted model consistent with equation (3). The λ_{trace} and λ_{max} statistics presented in the top panel of Table 4 indicate two cointegrating vectors, implying three common trends amongst the five price series. The Lagrange multiplier test for serial correlation shows that the residuals obtained from (3) are not serially correlated.

Having established the presence of three common trends, we proceed to the second stage of the decomposition framework. That is, we determine whether the five crop prices share common cycles. To this end, we test for the significance of the canonical correlations between Δx_t and

Table 3 Stability tests

Break date	Chow breakpoint test	Chow sample-split test
01/2006	505.77*	475.67*
01/2007	486.21*	461.92*
01/2008	494.76*	460.25*
01/2009	423.84	349.62
01/2010	401.23	309.70

Note: Tests of significance are based on bootstrapped p values; * denotes rejection of the null hypothesis of no structural break.

Table 4 Cointegration tests for the sub-samples

Null	Eigenvalue	Trace	Max
Panel A 1990–2005			
$r = 0$	0.23	94.84*	47.15*
$r \leq 1$	0.13	47.69*	24.99*
$r \leq 2$	0.09	22.70	17.54
$r \leq 3$	0.03	5.15	5.15
$r \leq 4$	0.00	0.00	0.00
Panel B 2008–2021			
$r = 0$	0.26	107.49*	48.15*
$r \leq 1$	0.14	59.34*	24.45
$r \leq 2$	0.11	34.89	18.76
$r \leq 3$	0.07	16.13	12.56
$r \leq 4$	0.02	3.57	3.57

Note: *Indicates the rejection of the null hypothesis at 5% significance level.

$(\beta' x_{t-1},\ \Delta x_{t-1},\ \ldots,\ \Delta x_{t-11})$. The results of the tests for common cycles are presented in Table 5. The F statistics confirm that the five crop price series have three cofeature vectors, which implies two common cycles amongst them; there are three statistically zero canonical correlations, and thus, the cofeature rank s is three. The presence of common cycles suggests short-run co-movement. Furthermore, the number of cointegrating vectors r (i.e. two) and cofeature vectors s (i.e. three) adds up to the number of the variables n (i.e. five).

We follow the same procedure to identify common trends and common cycles for the post-GFC period. The LR test for identifying the appropriate model suggests that the model consistent with the alternative hypothesis is suitable—the null is rejected, as the LR statistic is 15.31 with a p value of 0.00. In this case, however, the λ_{trace} and λ_{max} statistics presented in the bottom panel of Table 4 yield conflicting results regarding the number of significant cointegrating vectors. The former point to the presence of two significant cointegrating vectors, while the latter indicates the presence of one. However,

Table 5 Tests for common cycles

	Null	ρ_i^2	d.f.	F Stat
Panel A 1990–2005	s > 0	0.28	53	0.88
	s > 1	0.34	108	0.99
	s > 2	0.43	165	1.18
	s > 3	0.45	224	1.30*
	s > 4	0.54	285	1.48*
Panel B 2008–2021	s > 0	0.25	52	1.26
	s > 1	0.36	106	1.15
	s > 2	0.47	162	0.98
	s > 3	0.52	220	0.76
	s > 4	0.55	280	0.58*

Note: *Indicates the rejection of the null hypothesis at 5% significance level.

because the λ_{max} test has the sharper alternative hypothesis, we allow its results to take precedence (Enders, 1995). Accordingly, we conclude that $r = 1$. In other words, the five crop prices share four common trends. The Lagrange multiplier test suggests that the residuals obtained from the VEC model are not serially correlated.

The canonical correlations presented in Table 5 show four significant cofeature vectors, implying the presence of one common cycle amongst the five crop prices during the post-GFC period. Once again, the sum of the number of cointegrating vectors (i.e. one) and cofeature vectors (i.e. four) is equal to the number of variables. Therefore, following Vahid and Engle (1993), we can decompose the crop price series into their trend and cyclical components for both the pre- and post-GFC periods.

4.3 Decomposition of crop price series

The decomposition is obtained by inverting the full-rank matrix comprising the cofeature and cointegrating spaces in accordance with equation (2). To be clear, in both sub-samples, the sum of the significant cofeature and cointegrating vectors is equal to five, that is the number of variables in the model—hence, the full-rank matrices in both cases. Figure 2 shows the long-run trend components of the five series before the GFC. The trends exhibit strong co-movement throughout the pre-GFC period: between 1990 and 1996, crop prices gradually trend upward, whereas after 1996, they gradually trend downward—the trends are somewhat inconspicuous throughout the pre-GFC period. Common trends signify similar responses of the five crop prices to persistent shocks causing them to co-move in the long run; the error-correction mechanism amongst the cointegrated prices corrects any deviations from the long-run equilibrium implied by the cointegration relations.

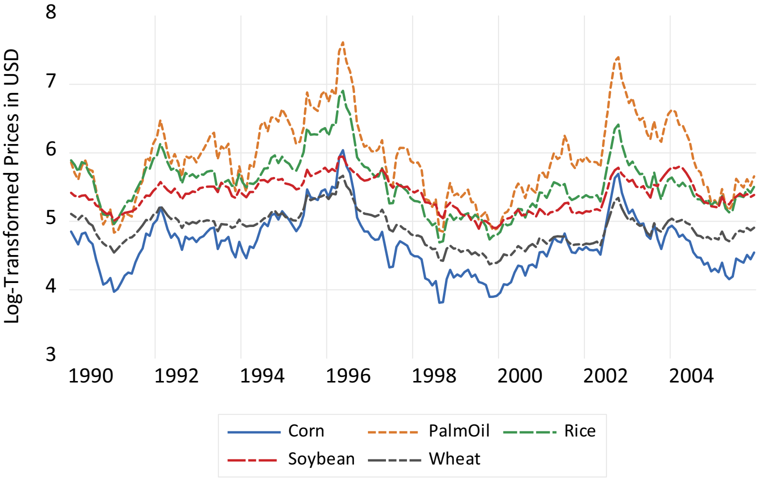

Figure 2 Pre-GFC trend components. [Colour figure can be viewed at wileyonlinelibrary.com]

The cyclical components illustrated in Figure 3 also show strong co-movement. They hover around a mean of zero, suggesting that observed prices adhere to their long-run trends. These results corroborate the findings of a recent report by the World Bank (2020). Occasionally, though, crop prices deviate from their long-run trends, causing the amplitude of the cycles to rise. This is especially noticeable during 1994–1996, a period that saw a surge in crop prices driven by robust global economic growth, especially in the newly industrialised Asian countries. The sharp increase in crop prices is captured by the trend components, indicating that the positive effects of rising global demand were persistent. Since cycles are modelled as the deviations of observed prices from their long-run trends, the cyclical components of the crop prices dipped during this period. However, the Asian financial crisis halted a period of sustained growth in crop prices, bringing the crop prices in line with their long-run trends. The cycles of palm oil, rice and wheat prices are strongly and positively correlated: their correlations are around 0.99. Soybean price cycles are strongly correlated with corn price cycles, signifying strong cyclical movement between these two crop prices. Yet, the correlations of soybean price cycles with the cycles of palm oil, rice, and wheat prices are small in comparison; nevertheless, they are still strong and positive.

Figure 4 shows the long-run trend components of the five series after the GFC. We find strong co-movement amongst corn, palm oil, soybean and wheat prices in the long run. Rice prices, on the other hand, exhibit a distinct trend. Overall, crop prices show a downward trend, confirming the notion that global commodity prices have generally declined during the 2010s.

But which factors produce persistent shocks? Productivity shocks that fundamentally change the link between inputs and outputs can lower production costs in perpetuity. The US dollar exchange rate may also have a

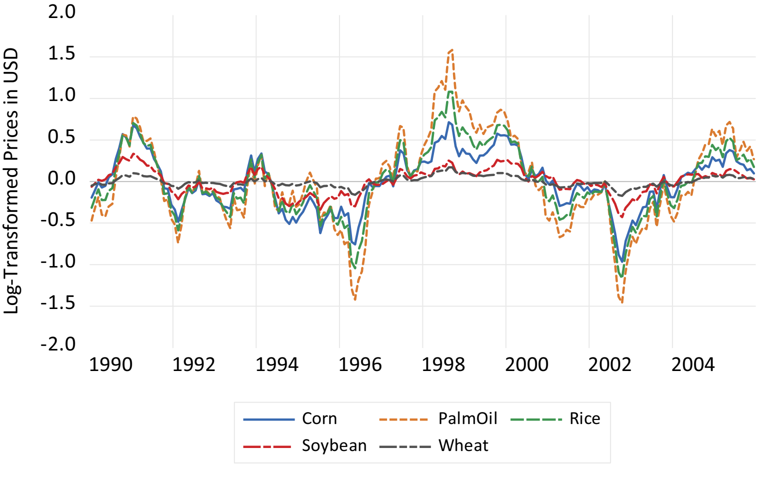

Figure 3 Pre-GFC cyclical components. [Colour figure can be viewed at wileyonlinelibrary.com]

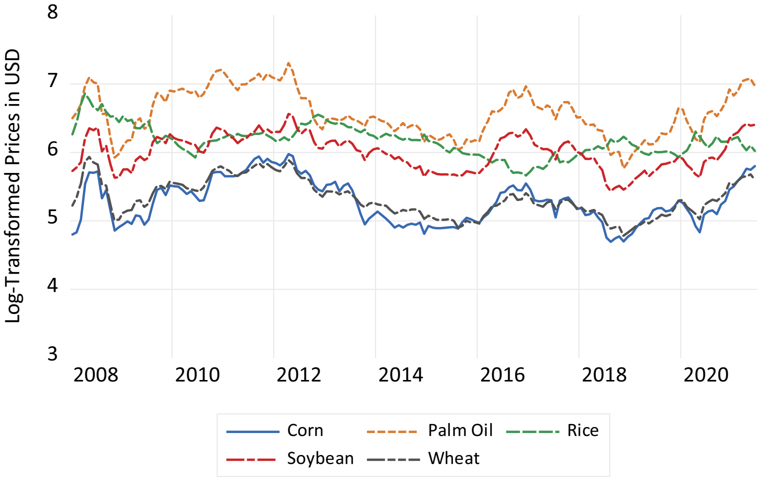

Figure 4 Post-GFC trend components. [Colour figure can be viewed at wileyonlinelibrary.com]

persistent effect on crop prices; the vast majority of global trade is conducted in US dollars; and commodities are quoted and priced in US dollars. Thus, appreciation of the US dollar contributed to the declines in commodity prices during the post-GFC period; contrastingly, leading up to the GFC, the US dollar depreciated, contributing to increases in crop prices—this reasoning is consistent with the findings of Myers et al. (2014). Energy prices may also exert a significant influence on crop prices (Baffes & Haniotis, 2016). Of course, energy prices themselves are associated with the US dollar exchange rates. A strong US dollar exerts downward pressure on energy prices and, thus, contributes to their decline (see, e.g., Baffes & Dennis, 2015; Druck et al., 2018; Gardner, 1981). Energy prices declined most conspicuously during 2008–2009; they fell notably during the latter half of 2014. Considering the currency and energy-price dynamics, it stands to reason that crop prices also fell during this period.

The cyclical components of the crop prices after the GFC are presented in Figure 5. The cyclical components of corn, palm oil, wheat and soybean prices are perfectly correlated. However, rice prices are negatively correlated with other crop prices in the short run. The pronounced upward movements in the cyclical components of corn, palm oil, soybean and wheat prices during 2012–2013 stand out. The increase is transitory; that is, the prices went above their long-run trends in the middle of 2012 and started to revert towards them in 2014.

Weather patterns may have played a significant role in transitory increases in crop prices. For example, in 2012, a drought coupled with excessive heat in the United States caused a severe deterioration of corn crops. The US Secretary of Agriculture pointed out that 78% of the corn crop was in an area designated as drought-impacted. With dwindling supply, corn prices

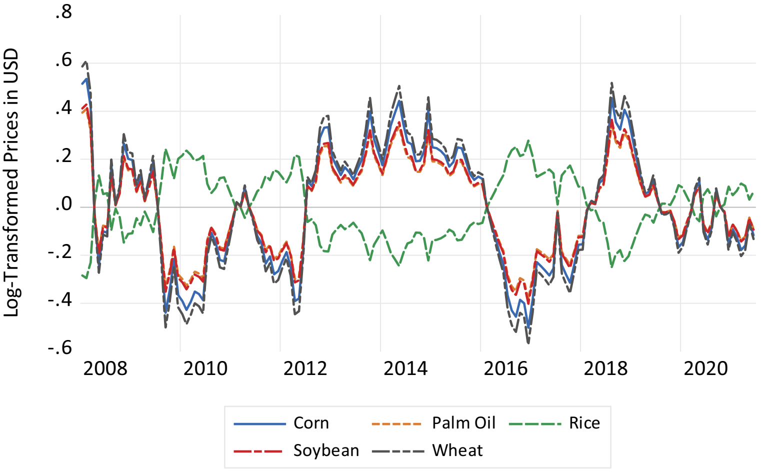

Figure 5 Post-GFC cyclical components. [Colour figure can be viewed at wileyonlinelibrary.com]

increased globally—this is unsurprising as the United States was the largest corn producer globally. The soybean crops in the United States also suffered due to sub-optimal growing conditions, which compounded the effects of reduced acreage designated to soybean crops—while Brazil has overtaken the United States as the world's largest producer of soybean, the United States was, at the time, the global leader in soybean production. Furthermore, in the wake of higher corn prices, animal feed markets sought to substitute corn with soybean, increasing its demand and price (Mondesir, 2020). The increase in the cyclical component of rice prices in 2016 also exemplifies the transitory effects of droughts in important producing regions on crop prices—in this instance, a drought afflicted the rice output in Thailand, one of the largest exporters of rice in the world. On the whole, the cycles are relatively muted after the GFC, indicating that the five crop prices are trend-dominated; the observed prices adhere closely to their long-run trends.

The decomposition underscores the importance of delineating the short- and long-run dynamics to the characterisation of stylised facts on crop price co-movement. Crop prices may co-move in the long run while departing intermittently. Thus, from an econometric standpoint, short-run co-movement should be studied in the context of long-run trends. The method used in this paper is well-suited to this endeavour. Estimating multivariate models that utilise information on all the variables simultaneously yield rich information on co-movement. Econometricians would benefit from using such frameworks instead of correlating trends and cycles derived from unrelated univariate models, such as the Hodrick-Prescott filter, the Hamilton filter and the Beveridge-Nelson decomposition framework.

The differences amongst the long- and short-run behaviours of the five crop prices suggest that policies designed with a view that food crops constitute a homogenous group may undermine the needs of stakeholders engaged in the production, marketing and trading of specific crops. To be clear, even amongst food crops such as rice and wheat, differences in price behaviours emphasise the importance of policies designed with specific crops in mind. On the other hand, the close long- and short-run associations between corn and soybean prices suggest that when crops are grown in close proximity *and* have similar uses, their prices will tend to co-move. In such cases, common policy frameworks encompassing related crops may be suitable. Finally, potentially due to the financialisation of commodity trading, prices of crops (such as palm oil) that are geographically concentrated may co-move with prices of widely produced crops. Commodity traders seeking to diversify portfolios should take note of this finding.

5. Concluding remarks

We analyse short- and long-run co-movement amongst prices of five major crops—corn, palm oil, rice, soybean and wheat—using a common-features-based multivariate trend-cycle decomposition framework. We find evidence of both common cycles (i.e. short-run co-movement) and common trends (i.e. long-run co-movement) before and after the GFC. However, crop price dynamics differ across the two periods. For example, the long-run trends of rice prices were strongly correlated with those of other crop prices before the GFC; in contrast, after the GFC, they were uncorrelated with the long-run trends of corn, palm oil and soybean prices. Furthermore, the strength of co-movement between specific crop prices may vary in the short relative to the long run—before the GFC, the short-run co-movement between palm oil and wheat prices was significantly stronger than their long-run co-movement. Thus, viewing food crops as a homogenous group or ignoring the distinction between the short and the long run can lead to incorrect conclusions. The choice of the methodological framework used in this study is driven by its aptness for analysing short- and long-run co-movement, its usefulness from the perspective of econometric modelling and a paucity of the application of multivariate decomposition frameworks to study crop price co-movement.

We coalesce two strands of the literature on commodity price co-movement: the first strand applies univariate decomposition methods to study trends and cycles in commodity prices; the second examines co-movement using multivariate models but does not distinguish between trend and cyclical co-movement. From an econometric standpoint, the approach used in this study has several desirable features: trend and cyclical components can be isolated within a single modelling framework, thereby eliminating the need to estimate separate models to study long- and short-run co-movements amongst different crop prices—cyclical patterns are identified without losing valuable information about the long run; joint treatment of variables that co-move imparts a parsimonious and more informative structure to econometric models—needless coefficients are eliminated while maintaining goodness-of-fit; last but not least, this framework allows us to understand the relative importance of trends and cycles in different time series simultaneously.

Due to the presence of three common trends and two common cycles before the GFC and four common trends and one common cycle after the GFC, we decompose the five crop prices into trend and cyclical components. The decomposition allows us to study long- and short-run price behaviours of individual crops and illuminate their differences and commonalities. It is helpful to revisit the questions posed at the outset to contextualise the following summary. Do crop prices co-move in both the short and the long run? Are there specific crops whose prices exhibit stronger co-movement relative to others? Do crop prices respond similarly to persistent and transitory shocks? Have the linkages amongst crop prices changed since the GFC?

The cyclical components show that corn and soybean prices are strongly correlated in the short run, signifying that they respond similarly to transitory shocks. This result draws attention to the role of consumption substitution (both crops are used extensively as feedstock for producing biofuels and ingredients in animal feed), production concentration (their production is concentrated in the United States, which exposes them to similar weather events) and input substitution (due to geographical concentration of production, they also use similar inputs such as land, machinery and labour) in determining cyclical movements in prices. Corn prices also co-move with wheat prices in the short run, albeit to a lesser extent. Rice prices, on the other hand, show distinct patterns; their cycles are relatively muted. The trend components show that the long-run co-movement amongst corn, soybean and wheat prices has strengthened since the GFC. To be sure, these prices co-moved even before the GFC, albeit to a lesser degree. In contrast, the co-movement of rice prices with the other crop prices has weakened during the 2010s. Overall, the cycles are relatively muted after the GFC, indicating that the five crop prices are trend-dominated.

We do not model transaction costs, causal links and transmission mechanisms underpinning the price dynamics. Nevertheless, the timing of specific changes in trends and cycles points to the role of the US dollar exchange rate, oil prices and weather events in determining crop prices. While the first two appear to have a persistent impact on food prices, the effect of weather events is transitory. In future research, these insights may inform the identification of persistent and transitory shocks in structural models to pin down the factors influencing prices over different horizons formally. This task is beyond the scope of this paper.

It bears emphasis that the decomposition of variables into trends and cycles using the above framework can be accomplished only when the number of trends and cycles equals the number of variables. Due to the specificity of this criterion, the scope of this approach in terms of time-series decomposition may be limited.

Conflict of interest

The authors have no conflict of interest to declare.

Data availability statement

The data that support the findings of this study are openly available at https://fred.stlouisfed.org.

References

Ai, C., Chatrath, A. & Song, F. (2006) On the comovement of commodity prices. *American Journal of Agricultural Economics*, 88(3), 574–588.

Allen, D.E., Chang, C., McAleer, M. & Singh, A.K. (2018) A cointegration analysis of agricultural, energy and bio-fuel spot, and futures prices. *Applied Economics*, 50(7), 804–823.

Baffes, J. & Dennis, A. (2015). Long-term drivers of food prices. Trade policy and food security: Improving access to food in developing countries in the wake of high food prices, Ch.1, in Gillson, I. & Fouad, A. (eds), *Directions in Development*. World Bank, Washington, DC, pp. 13–33.

Baffes, J. & Haniotis, T. (2016) What explains agricultural price movements? *Journal of Agricultural Economics*, 67(3), 706–721.

Beveridge, S. & Nelson, C. (1981) A new approach to decomposition of economic time series into permanent and transitory components with particular attention to measurement of the 'business cycle. *Journal of Monetary Economics*, 7, 151–174.

Camp, K.M. (2019). The relationship between crude oil prices and export prices of major agricultural commodities. Beyond the Numbers: Global Economy, vol. 8, no. 7 (U.S. Bureau of Labor Statistics, April 2019), https://www.bls.gov/opub/btn/volume-8/the-relationship-between-crude-oil-and-export-prices-of-major-agricultural-commodities.htm

Cashin, P. & McDermott, J. (2002) The long-run behavior of commodity prices: Small trends and big variability. *IMF Staff Papers*, 49, 175–199.

Chiou-Wei, S.Z., Chen, S.H. & Zhu, Z. (2019) Energy and agricultural commodity markets interaction: An analysis of crude oil, natural gas, corn, soybean, and ethanol prices. *Energy Journal*, 40, 265–296. https://doi.org/10.5547/01956574.40.2.schi

Ciaian, P. & Kancs, D. (2011) Interdependencies in the energy–bioenergy–food price systems: A cointegration analysis. *Resource and Energy Economics*, 33(1), 326–348.

Corbae, D., Ouliaris, S.S. & Phillips, P.C. (2002). Band and spectral regression with trending data. *Econometrica*, 70, 1067–1109.

Cuddington, J.T. (1992) Long-run trends in 26 primary commodity prices: A disaggregated look at the Prebisch-Singer hypothesis. *Journal of Development Economics*, 39(2), 207–227.

Cuddington, J. & Jerrett, D. (2008) Super cycles in real metals prices? *IMF Staff Papers*, 55, 541–565.

Cuddington, J. & Urzúa, C. (1989) Trends and cycles in the net barter terms of trade: A new approach. *The Economic Journal*, 99, 426–442.

Druck, P., Magud, N.E. & Mariscal, R. (2018) Collateral damage: dollar strength and emerging markets' growth. *The North American Journal of Economics and Finance*, 43, 97–117.

Enders, W. (1995) *Applied econometric time series analysis*. United States of America: John Wiley and Sons Inc.

Engle, R.F. & Granger, C.W.J. (1987) Co-Integration and error correction: Representation, estimation, and testing. *Econometrica*, 55, 251–276.

Engle, R.F. & Issler, J.V. (1993) Common trends and common cycles in Latin America. *Revista Brasileira De Economia*, 47(2), 149–176.

Engle, R.F. & Kozicki, S. (1993) Testing for common features. *Journal of Business & Economic Statistics*, 11(4), 369–380.

FRED (2021) https://FRED.stlouisfed.org/

Gardner, B. (1981) On the power of macroeconomic linkages to explain events in U.S. agriculture. *American Journal of Agricultural Economics*, 63, 871–878.

Goodwin, B.K., Holt, M.T. & Prestemon, J.P. (2021) Semi-parametric models of spatial market integration. *Empirical Economics*, 61(5), 2335–2361.

Hamilton, J.D. (2018) Why you should never use the hodrick-prescott filter. *The Review of Economics and Statistics*, 100(5), 831–843.

Hawkins, T., Ingwersen, W., Sengupta, D., Xue, X. & Smith, R. (2012) Estimating impacts across the life cycle of corn ethanol and gasoline. Presented at ISSST 2012, Boston, MA, May 16 - 18, 2012.

Hodrick, R.J. & Prescott, E.C. (1997) Postwar U.S. business cycles: An empirical investigation. *Journal of Money, Credit and Banking*, 29(1), 1–16.

Johansen, S. (1988) Statistical analysis of cointegrating vectors. *Journal of Economics Dynamics and Control*, 12(2–3), 231–254.

Johansen, S. (1996) *Likelihood-based inference in cointegrated vector autoregressive models*. Oxford: Oxford University Press.

Lence, S. & Falk, B. (2005) Cointegration, market integration, and market efficiency. *Journal of International Money and Finance*, 24(6), 873–890. https://doi.org/10.1016/j.jimonfin.2005.05.002

Lucotte, Y. (2016) Co-movements between crude oil and food prices: A post-commodity boom perspective. *Economics Letters*, 147, 142–147. https://doi.org/10.1016/j.econlet.2016.08.032

Manera, M., Nicolini, M. & Vignati, I. (2013) Financial speculation in energy and agriculture futures markets: A multivariate GARCH approach. *The Energy Journal, Cleveland*, 34(3), 55–81.

Mondesir, R. (2020) A historical look at soybean price increases: What happened since the year 2000? Beyond the Numbers: Prices & Spending, vol. 9, no. 4 (U.S. Bureau of Labor Statistics, March 2020), https://www.bls.gov/opub/btn/volume-9/a-historical-look-at-soybean-price-increases-what-happened-since-the-year-2000.htm

Myers, R.J., Johnson, S.R., Helmar, M. & Baumes, H. (2014) Long-run and short-run co-movements in energy prices and the prices of agricultural feedstocks for biofuel. *American Journal of Agricultural Economics*, 96(4), 991–1008.

Nazlioglu, S. & Soytas, U. (2012) Oil price, agricultural commodity prices, and the dollar: A panel cointegration and causality analysis. *Energy Economics*, 34(4), 1098–1104.

Peri, M. & Baldi, L. (2010) Vegetable oil market and biofuel policy: An asymmetric cointegration approach. *Energy Economics*, 32(3), 687–693.

Peters, M., Langley, S. & Westcott, P. (2009) Agricultural commodity price spikes in the 1970s and 1990s: Valuable lessons for today. *USDA Economic Research Service*, https://www.ers.usda.gov/amber-waves/2009/march/agricultural-commodity-price-spikes-in-the-1970s-and-1990s-valuable-lessons-for-today

Pindyck, R.S. & Rotemberg, J.J. (1990) The excess co-movement of commodity prices. *The Economic Journal*, 100(403), 1173. https://doi.org/10.2307/2233966

Rao, C.R. (1973) *Linear Statistical Inference and Its Applications*, 2nd edition. New York: John Wiley & Sons Inc.

Schwert, G.W. (1989) Tests for unit roots: A Monte Carlo investigation. *Journal of Business and Economic Statistics*, 7, 147–159.

Vahid, F. & Engle, R.F. (1993) Common trends and common cycles. *Journal of Applied Econometrics*, 8(4), 341–360.

World Bank (2020) Persistence of commodity shocks. http://pubdocs.worldbank.org/en/929971603211801343/CMO-October-2020-Special-Focus.pdf