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Crude oil–corn–ethanol – nexus: A contextual approach

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HIGHLIGHTS

- Strong relationship between crude oil–corn and crude oil–ethanol.
- Corn–ethanol connected through a by-pass of crude oil markets.
- Ethanol market has no direct impact on the price levels of corn.
- Corn markets became more prone to volatility due to ethanol production.

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ABSTRACT

This paper offers a holistic study on the complex relationships between crude oil, corn and ethanol during a turbulent period between 2006 and end of 2011. Through a holistic mapping of the current market situation and a contextual analytical design we show that there exists a strong relationship between crude oil and corn markets on one side, and crude oil and ethanol on the other. However, the price relationship between corn and ethanol was revealed to be less straightforward, and is driven by the US government fuel policy. Furthermore the study indicates that corn markets have became more prone to volatility due to ethanol production, especially when the demand for corn is high and/or the crude oil prices are high enough to create a competitive market for ethanol.

1. Introduction

The production of ethanol has seen a brisk increase from early 2000. Since 2006 the United States is the largest producer of ethanol with over 50% of the global production. The incentives for ethanol production were mainly driven by government support policy, such as budgetary support measures, blending or mandatory use, and trade barriers. Refraining from an in-depth analysis on the reasons behind the political decisions concerning ethanol production we may speculate that factors such as the high, and still growing demand for energy; the need for reductions of greenhouse gas (GHG) emissions; crude oil dependency – and thus a reliance on oil producing countries implying a prospective geopolitical instability – are the main drivers for the government support measures.

Current technologies to produce biofuels are mainly based on commodities such as cereals, sugar, and oilseeds. This implies that in conjunction with the growing demand for biofuels an even higher increase in demand for these crops can be expected. The limited amount of arable land and the rising global demand for food are important inhibitors for the production of first generation biofuels. Second generation biofuels are now being developed. Biofuels derived from cellulosic plant material could provide a possible means to tackle the limitations of first generation biofuels. However, there is still no large scale production of second generation biofuels, mainly due to their high production cost.

Due to the tight linkage between feedstock and first generation biofuels, the cost of production is directly dependent on the feedstock prices which, in turn, have risen due to high world market demand. However, the tale of linkage is far more intricate. The US tax credits for ethanol production are fixed and therefore do not adjust to market conditions. These fixed cash in-flows into ethanol production create a stable demand for corn and consequently (in theory) helps to stabilize corn prices. In addition, policies such as *corn-for-ethanol* magnify this effect. For an extensive analysis of this issue we refer to previous work (Natanelov et al., 2011), where we have shown that the US ethanol production, contrary to general belief, stabilized corn prices in relation to crude oil prices – until crude oil prices breach a threshold value of 75 USD/barrel.

Furthermore, when discussing the issue of price linkages it is crucial to take on a holistic view and consider certain external

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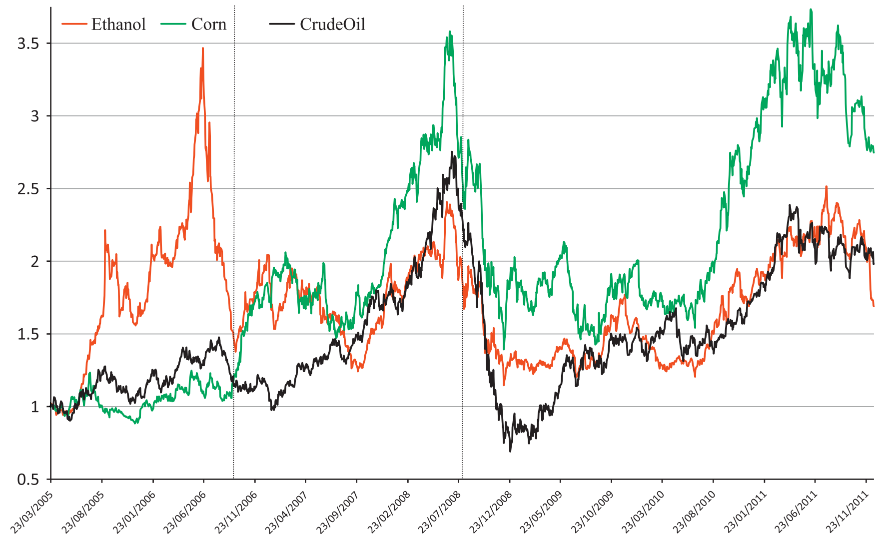

Fig. 1. Indexed price evolution between 23 March 2005 and 15 December 2011.

shocks to the markets. To exemplify, Fig. 1, clearly presents a huge peak in ethanol prices in 2006. Closer examination of adjacent markets shows that because of health concerns, due to problems with contamination of drinking water by methyl tert-butyl ether (MTBE), the US has drastically reduced its production of MTBE and banned it as a fuel additive in 2006.

In previous work (Natanelov et al., 2011) we have indicated that the linkages between energy and agricultural markets are much more intricate and nuanced than considered by most. In this paper, we analyze deeper the specific linkages between corn, ethanol and crude oil prices. We shall attempt – within a broad context – to zoom into the most recent period, which is marked by crises; unprecedented price jumps of agricultural commodities; and higher levels of volatility and speculation. Within this context, we shall analyze the dynamic relationships between corn, crude oil and ethanol prices. Through our results, logic, contextual and holistic approach we hope to be able to shed some light on the characteristics of these markets in the current environment and provide a logical and intuitive explanation for the change in relationships through time.

The paper is structured in the following manner. In the literature review an overview of previous research is presented. In the methodology section we discuss the technique used in our analysis. In the subsequent section we present and discuss the results. In the final part concluding remarks and recommendations are offered.

2. Literature review

Dynamic price relationships between commodity and energy markets have been widely discussed in recent literature. Zhang et al. (2009, 2010) support the derived demand theory for ethanol, corn, and soybean relationships with oil and gasoline. The authors highlight the role of agricultural commodity prices as market signals enabling commodity markets to restore their equilibriums after a demand or supply shock. Market shocks may in the short-run increase agricultural commodity prices, however decentralized freely operating markets, such as futures markets, will mitigate the persistence of these shocks. Furthermore, their results did not reveal long-run relationships between fuel (ethanol, oil and gasoline) prices and agricultural commodity (corn and soybean) prices. Similarly, Lewis and Tonsor (2011) analyze the impact of ethanol production on spatial corn markets in the US using cointegration. Their results suggest that spatial corn prices operated in a long-run equilibrium between 1998 and 2008 and that ethanol production has not altered these spatial price relationships. Du and Hayes (2009) analyze the impact of ethanol production on US and regional gasoline prices. Their analysis indicates that the gasoline prices are lower due to the ethanol production. The Midwest region has the highest reduction of gasoline prices due to ethanol, which is not all that surprising given the high concentration of ethanol production plants in that region. Due to its high policy relevance the authors recommend a thorough study of the linkages between the energy and agricultural sectors.

In contrast, Anderson and Coble (2010) investigate the impact of renewable fuels standard ethanol mandates on corn prices and corn production levels. The focus of the study is on the mandates' influence on market participants' expectations. Their results indicate that through the stochastic nature of supply and demand shocks, a nonbinding mandate can have substantial impact on corn prices and volumes due to the price-responsiveness of demand from the US ethanol sector instigated by the mandate. They note that the ethanol production levels are on a similar level as the mandates resulting in market participants believing that any reduction in corn supply will be met by a relatively inelastic demand – or large price – response from the ethanol sector. In a similar study, McPhail and Babcock (2012) support the results of Anderson and Coble (2010), and find that the mandates reduce price elasticity of demand for corn and gasoline, which in turn increases price variability when supply shocks hit the markets. A recent study (Serra et al., 2011) analyzed monthly prices of ethanol, corn, oil, and gasoline between 1990 and 2008. The authors indicate that the four commodity prices are related in the long run, with an especially strong link between corn and energy markets. This link between corn and energy markets is attributed to price responses in ethanol market. Gohin and Chantret (2010) measure the long-run impact of energy prices on world agricultural markets including macro-economic linkages. By incorporating a general equilibrium (GE) model they find a significant relationship. Besides identifying a positive relationship due to the cost push effect, they find that the introduction of the real income effect may imply a negative relationship between world food and energy prices. In an analogous study, Gohin and Treguer (2010) indicate that to the farmers' downside risk aversion in combination with the reduced variation of corn prices due to biofuels dampens the quantity effect of biofuels. The third column

Table 1
Summary of the literature on crude oil price effects.

Economic activity	Stock markets	Agricultural markets
Adrangi et al. (2001), Berument et al. (2010), Brown and Yücel (2001), Costantini and Martini (2010), Cunado and Perez de Gracia (2005), Fofana et al. (2009), Hamilton (2009a, 2009b), Hanabusa (2009), He et al. (2010), Hsing (2007), Huang et al. (1996), Huang and Chao (2012), Jayaraman and Choong (2009), Jiao and Ma (2006), Jones et al. (2004), Lardic and Mignon (2008), Odusami (2010), Oladosu (2009), Papapetrou (2001), Rafiq et al. (2009); Reynolds and Kolodziej (2007), Zagaglia (2010)	Basher et al. (2012), Chortareas and Noikokyris (2013), Ciner (2001), Creti et al. (2013), Ghouri (2006), Lardic and Mignon (2006), Li et al. (2012), Miller and Ratti (2009), Natanelov et al. (in press), Papapetrou (2001), Sadorsky (1999), Wang et al. (in press), Zhu et al. (2011)	Baffes (2007), Balcombe and Rapsomanikis (2008), Cha and Bae (2011), Chen et al. (2010), Ciaian and Kancs 2011), Esmaeili and Shokoohi (2011), Gohin and Treguer (2010), Ji and Fan (2012), Nazlioglu (2011), Nazlioglu and Soytas (2012), Serra et al. (2011), Trujillo-Barrera et al. (2012)

of Table 1 provides a summary of various studies indicating an linkage between crude oil prices and corn. Consequently, energy price, crude oil in particular, affects world economies and markets in many ways. The first and second column of Table 1 show an overview of studies that analyze and confirm linkages between crude oil prices and the economic activity and the stock markets respectively. This broader context indicates that price linkages between crude oil and agricultural markets should not come as a surprise. Furthermore, various studies (Ciaian and Kancs, 2011; Esmaeili and Shokoohi, 2011; Natanelov et al., 2011; Nazlioglu and Soytas, 2012) indicate a significant historic link between crude oil prices and corn before the introduction of ethanol.

The commoditization and increased popularity of agricultural markets is expressed via large increases in trades of futures contracts. The open interest of corn futures almost tripled between early 2000 and 2006 (Demirer et al., 2012). The hypothesis that ethanol markets have intensified the linkage between corn and crude oil prices seems to be a hasty conclusion, as the market situation seems to be much more complex. That being said, various studies have confirmed an increased volatility spillover effect after mid-2000. A study on speculation and volatility spillover in the crude oil, corn and wheat weekly futures prices between 1998 and 2009 (Du et al., 2011) finds evidence of volatility spillover between the markets after 2006. Similarly, Trujillo-barrera et al. (2012) show a brisk increase in volatility from 2006 in the corn markets, resulting from an increased volatility spillover from the crude oil market. Wu et al. (2011) and Ji and Fan (2012) confirm the increased volatility spillover with their results. Crude oil is the most traded commodity exceeding daily values of trillions. It is undeniable that the amount and speed of available information for markets participants have increased and improved, which might have an impact on such a relationship.

Similar to our study, Balcombe and Rapsomanikis (2008) analyze the Brazilian sugar–ethanol–oil nexus. They suggest that the long-run drivers of Brazilian sugar prices are oil prices and that there are nonlinearities in the adjustment processes of sugar and ethanol prices to oil price, but linear adjustment between ethanol and sugar prices. The nonlinear adjustment process of sugar and ethanol in contrast to the linear adjustment between ethanol and sugar prices may suggest global versus regional drivers. However, a clear differentiation between the Brazilian and the US nexus exists. The Brazilian ethanol market is far more mature that the market in US. Also, when discussing price linkages, it is essential to be aware of the characteristics of the market and price system one is analyzing. Every new commodity futures contract follows a series of steps before a viable market for that commodity occurs. As the commodity matures, the volume of traded contracts[1] will often increase as the number of agents that buy and sell the commodity contracts increases, thus providing liquidity to the market. The US ethanol futures market is relatively new compared to the well-established futures markets for corn, wheat, and soybeans. Ethanol futures trading were only introduced at the Chicago Board of Trade (CBOT) in May 2005. Ethanol futures can certainly be considered as a thinly traded futures market. Thin markets are typically characterized by problems associated with imperfect competition, price inaccuracy and market inefficiency (Bessler, 1980; Gray, 1960; Hayenga et al., 1978; Schrader, 1984; Sporleder, 1984). Market makers in thinly traded futures markets often require large bid-ask spreads which results in higher transaction costs (Frino et al., 2007). Furthermore, Chordia et al. (2008) provides strong empirical evidence to support the notion that market liquidity promotes market efficiency. However, in case of ethanol futures, market efficiency[2] may be attributed to its strong linkage to over-the-counter (OTC) ethanol swaps market. An exchange-for-risk provision allows highly liquid OTC swap products to be traded for ethanol futures, and in so doing has the effect of tying the two derivatives markets together (Berry, 2009). Dahlgran (2009) also notes that because ethanol futures positions can be exchanged for ethanol swaps, and that the swap market is very liquid, the thinness of the ethanol futures market is not an issue in terms of its ability to provide effective risk management. In this sense price discovery and hedging through ethanol futures is aided by the OTC ethanol swaps market which is actively traded side by side with ethanol futures. Cavalcanti et al. (2012), among others indicate even that a variation in the Brent spot price does not automatically cause a variation in gasoline prices in Brazil. Furthermore, the different market characteristics of sugar and corn may induce different dynamics in linkages. The intricate global trade system furthers complicates matters. To illustrate more in detail, the historic high sugar prices in 2011 resulted in extensive exports by Brazil, causing an input shortage for ethanol production. In turn, this resulted in corn imports from the US to meet the demand.

Due to the complexity of inter-relations between crude oil and various commodities and the whole economy (Oladosu, 2009), traders might excessively transfer price movements from one market to the other, especially in the futures markets. That being said, trading behavior might change in different economic environments. Furthermore, concepts such as volatility or speculation are relative terms and need to be considered as such. Since speculators are the main market actors who transfer information into price movements, it seems evident that speculators are more active in volatile periods, implying that cause and effect are practically indistinguishable. Furthermore, Chortareas and Noikokyris

[1] We make use of the price discovery role of futures markets through which supply and demand shocks and price spillovers between markets can be accurately determined.

[2] Following McKenzie and Holt (2002) we have conducted market efficiency analysis with results indicating that the ethanol futures market is both efficient and unbiased in the long and short-run. To refrain from discombobulating the reader due to similar methodologies yet different context, we do not include the analysis in this paper. The analysis and results; however, are available upon request.

(in press) note that the news component about real economic activity impacts the position of traders. Similarly, Reboredo (2011) indicates that the oil market is 'one great pool' in contrast to a more regionalized perspective, implying that the global news component is prominent. Given the intrinsic nature of futures markets, in parallel with the digitalization of the global markets information systems, yields a situation where market connections are easily established and broken up by market participants.

The main goal of this paper is to analyze price movements of the crude oil, corn and ethanol and attempt to understand their dynamic relationship and what is behind the changes it undergoes in a broad economic context.

3. Methodology

The maximum likelihood (ML) method and inference on cointegration developed by Johansen (Johansen, 1988, 1991; Johansen and Juselius, 1990) has been widely used in various academic fields. A swift search of the three papers, on which the cointegration method is based, indicates almost twenty thousand citations combined. However, given the relatively complex mathematics behind the method, a non-expert may find it difficult to develop an intuitive understanding of the logic behind the methodology. To aid in this understanding we present an intuitive explanation of the technique in appendix 1, where we show the calculations used to implement the method in terms of simple mathematic transformations. We believe it essential for the reader to go beyond understanding the methodology and to develop a certain level of *fingerspitzengefühl* with its application.

3.1. Data

The data used in the empirical analysis comprises daily futures prices of crude oil, corn, and ethanol from 23 March 2005 until 15 December 2011. Daily prices for the nearest futures contracts[3] are analyzed. To account for the problem of comparing disparate price units, the data is indexed based on the price of 23 March 2005 for each commodity respectively. Fig. 1 depicts a graphical representation of the data.

3.2. Johansen co-integration

In the case of non-stationary time-series, cointegration provides appropriate statistical techniques to investigate if there is an economically significant long-run relationship between prices. Therefore we test the price series for stationarity in levels and in first differences. In time series econometrics, prices that are integrated of order one are denoted by $P_t \sim I(1)$ and prices that are integrated of order zero by $\Delta P_t \sim I(0)$. When price series are found to be non-stationary in levels but stationary in first differences, cointegration techniques may be applied. The cointegration procedure is based upon an unrestricted vector autoregressive (VAR) model specified in error-correction form (Johansen (1988) and Johansen and Juselius (1990)):

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Phi D_t + v_t \tag{1}$$

where X_t includes all n variables of the model which are $\sim I(1)$, the Π, Γ_i and Φ are parameter matrices to be estimated, D_t is a vector with deterministic elements (constant, trend and dummy) and v_t is a vector of random errors which follow a Gaussian white noise process. Eq. (1) implies that there can never be any relationship between a variable with a stochastic trend, $I(1)$ and a variable without a stochastic trend, $I(0)$. So, if $\Delta P_t \sim I(0)$, then Π will be a matrix of zeros, except when a linear combination of the variables in P_t is stationary. The Johansen test for cointegration evaluates the rank (r) of the matrix Π. If $r=0$, all variables are $I(1)$ and thus not cointegrated. In case $0<r<N$, there exist r cointegrating vectors. In the third case, if $r=N$ all the variables are $I(0)$ and thus stationary, and any combination of stationary variables will be stationary. Π represents the long response matrix and is defined as the product of two matrices: α and β', of dimension $(g \times r)$ and $(r \times g)$ respectively. The β matrix contains the long-run coefficients of the cointegrating vectors; α is known as the adjustment parameter matrix and is similar to an error correction term. The linear combination(s) $\beta' x_{t-k}$ of this matrix will be $I(0)$ in the case where the times series are cointegrated. In other words, if rank of $\Pi = r = K$, the variables in levels are stationary meaning that no integration exist; if rank $\Pi = r = 0$, denoting that all the elements in the adjustment matrix have zero value. Therefore, none of the linear combinations are stationary. According to the Granger representation theorem (Engle and Granger, 1987), when $K>0$ and rank of Π $(r)<K$, there are r cointegrating vectors or r stationary linear combinations of the variables. The Johansen cointegration method estimates the Π matrix through an unrestricted VAR and tests whether one can reject the restriction implied by the reduced rank of Π. Two methods of testing for reduced rank of Π are the trace test and the maximum eigenvalue, respectively:

$$\lambda_{\text{trace}} = -T \sum_{i=r+1}^{n} \ln(1-\hat{\lambda}_i^2) \tag{2}$$

$$\lambda_{\max}(r,\ r+1) = -T \ln(1-\lambda_{r+1}) \tag{3}$$

where, λ_i is the estimated values of the ordered eigenvalues obtained from the estimated matrix and T is the number of the observations after the lag adjustment. The trace statistics test the null hypothesis that the number of distinct cointegrating vectors (r) is less than or equal to r against a general alternative. The maximal eigenvalue tests the null that the number of cointegrating vectors is r against the alternative of $r+1$ cointegrating vectors.

3.3. Causality from vector error correction model (VECM)

The existence of cointegration in the bi-variate relationship implies Granger causality at least in one direction which under certain restrictions can be tested within the framework of Johansen cointegration by the Wald test (Dolado and Lütkepohl, 1996; Mosconi and Giannini, 1992). If α matrix in the cointegration matrix (Π) has a complete column of zeros, no casual relationship exists since no cointegrating vector appears in that particular block. Pair wise causal relationship can be represented through the following equation:

$$\begin{bmatrix} \Delta X_{1,t} \\ \Delta X_{2,\ t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} (X_{1,\ t-1} - \beta X_{2,\ \ t-1}) + A_1 \begin{bmatrix} \Delta X_{1,\ \ t-1} \\ \Delta X_{2,\ \ t-1} \end{bmatrix} + \ldots A_k \begin{bmatrix} \Delta X_{1,\ \ t-k} \\ \Delta X_{2,\ \ t-k} \end{bmatrix} + \begin{bmatrix} v_{1t} \\ v_{2t} \end{bmatrix} \tag{4}$$

Parameters contained in matrices A_k measure the short run causality relationship, while β is the cointegrating parameter that characterizes the long run equilibrium relationship between the series. Through Eq. (4), three possibilities for long-run causality may be identified, (i) $\alpha_1 \neq 0$, $\alpha_2 \neq 0$; (ii) $\alpha_1 = 0$, $\alpha_2 \neq 0$, and (iii) $\alpha_1 \neq 0$, $\alpha_2 = 0$. The first case indicates bi-directional causality, while the second and third imply uni-directional causality.

To analyze for short-run causality we apply the Wald test with the null hypothesis that the joint contribution of the lags of

[3] Crude Oil (Brent), – *Intercontinental Exchange* (*ICE*). Corn (No. 2 Yellow); Ethanol (AC) – *Chicago Board of Trade (CBOT)* part of *CME Group*.

Table 2
Tri-variate (crude oil–corn–ethanol) Johansen cointegration rank test.

	Test statistics	Critical values ($\lambda_{0.95}$)	Decision
(March 2005–December 2011) ($k=1$; Criteria: AIC)		**Model 3**	
λ_{trace}			
$H_0: r=0$ vs. $H_1: r\geq 1$	19.41	29.80	Not rejected
$H_0: r\leq 1$ vs. $H_1: r\geq 2$	–	–	
$H_0: r\leq 2$ vs. $H_1: r\geq 3$	–	–	
λ_{max}			
$H_0: r=0$ vs. $H_1: r\geq 1$	12.02	21.13	Not rejected
$H_0: r\leq 1$ vs. $H_1: r\geq 2$	–	–	
$H_0: r\leq 2$ vs. $H_1: r\geq 3$	–	–	
(March 2005–August 2008) ($k=3$; Criteria: AIC)		**Model 3**	
λ_{trace}			
$H_0: r=0$ vs. $H_1: r\geq 1$	13.08	29.80	Not rejected
$H_0: r\leq 1$ vs.$H_1: r\geq 2$	–	–	
$H_0: r\leq 2$ vs. $H_1: r\geq 3$	–	–	
λ_{max}			
$H_0: r=0$ vs. $H_1: r\geq 1$	7.78	21.13	Not rejected
$H_0: r\leq 1$ vs. $H_1: r\geq 2$	–	–	
$H_0: r\leq 2$ vs. $H_1: r\geq 3$	–	–	
(August 2008–December 2011) ($k=0$; Criteria: AIC)		**Model 4**	
λ_{trace}			
$H_0: r=0$ vs. $H_1: r\geq 1$	43.11	42.92	Rejected
$H_0: r\leq 1$ vs. $H_1: r\geq 2$	16.18	25.87	Not rejected
$H_0: r\leq 2$ vs. $H_1: r\geq 3$	5.35	12.52	Not rejected
λ_{max}			
$H_0: r=0$ vs. $H_1: r\geq 1$	26.94	25.82	Rejected
$H_0: r\leq 1$ vs. $H_1: r\geq 2$	10.83	19.39	Not rejected
$H_0: r\leq 2$ vs. $H_1: r\geq 3$	5.35	12.52	Not rejected

Model 3 – linear deterministic trend.
Model 4 – allows linear trend in the cointegrating space.

endogenous variables is equal to zero. If the null cannot be rejected it implies that the respective endogenous variables can be treated as exogenous in the system. In case of bi-variate models, the Johansen cointegration Eq. (1) can be rewritten as:

$$\Delta X_{1,\,t} = \mu_1 + \sum_{i=1}^{k1} \beta_i \Delta X_{1,\,t-i} + \sum_{j=1}^{k2} \beta_j \Delta X_{2,t-j} + \alpha_1 \mathrm{ECT}_{\,t-1} + \varepsilon_{t,1} \tag{5}$$

$$\Delta X_{2,\,t} = \mu_2 + \sum_{i=1}^{k1} \beta_i \Delta X_{1,\,t-i} + \sum_{j=1}^{k2} \beta_j \Delta X_{2,t-j} + \alpha_2 \mathrm{ECT}_{\,t-1} + \varepsilon_{t,1} \tag{6}$$

where, $X_{1,t}$ and $X_{2,t}$ are time series (of prices) and ECT is the error correction term. We test the short run causality through Eqs. (5) and (6), by examining the significance of all lagged dynamic terms.

4. Results and discussion

First let us turn to Fig. 1, which graphs evolution of ethanol, corn and crude oil prices from March 2005 through December 2011. As mentioned in the first section, the ethanol peak of 2006 immediately catches the eye. Next, we notice the spike in all three price series which occurred in 2008. In addition, a noticeable jump in corn prices occurred during the 2010–2011 period. Besides these unmistakable price movements, we also notice over this period, that the prices clearly exhibit a structural change in their relationships. Furthermore, as indicated in the literature review various studies have indicated this change. The sample period to the left of the dotted line (in Fig. 1) indicates the period where corn prices resumed their conventional market movement in the wake of the crude oil price hike. This large increase in crude oil prices breached a threshold level making ethanol competitive with crude oil and thus generating *normal* market conditions in the corn market (Natanelov et al., 2011). To continue, we break down our analysis into 2 dimensions: (i) we apply a trivariate and a bivariate cointegration model; and (ii) we break down our sample into 2 distinct periods, as denoted by the dotted line in Fig. 1.

To determine whether the price series are stationary, the Augmented Dickey–Fuller (ADF) test and the Phillips–Perron (PP) test are carried out. For all prices the tests point to the existence of a single unit root $I(1)$ in levels[4]. In contrast, each series is stationary in first differences. Since the price series are integrated of the same order, cointegration techniques may be applied to determine whether a stable long-run relationship exists between the time series. Johansen's tests for cointegration are performed. The VAR specification is estimated by applying one to 20 lags. The Akaike's information criterion (AIC) was utilized to select optimal lag length.

Initially a tri-variate model of crude oil, corn, and ethanol was analyzed, detailed results to be found in Table 2. The results are broken down into three parts: where initially we analyze the whole sample period; subsequently we analyze the period between March 2005 and August 2008; and finally we analyze the period between August 2008 and December 2011.

Our tri-variate results with respect to the whole sample period show no cointegrating long-run relationship exists between the prices. In the case of the 2005–2008 sample period, again we find no evidence of cointegration. Thus these initial results indicate that the respective prices appeared to evolve independently and were not bound together by underlying economic forces. In the context of our holistic approach, our results are unsurprising. The evolution of the ethanol price peak of 2006 due to the MTBE issue, and the shift in the corn–crude oil price relationship in late 2006, as mentioned above, clearly disrupted any co-movement among the price series. Interestingly, with respect to the 2008–2011 sample period we find the price series to be cointegrated. Trujillo-Barrera et al. (2012) have indicated a peak in volatility

[4] Detailed results can be found in Appendix B.

spill over in that period between crude oil and corn markets. In addition, a combination of increasing volumes corn-for-ethanol flow and steady corn exports could have added to a closer relationship between the markets.

Since the results of the trivariate model fail to indicate specific relationships between identified time series we repeat the analysis for 3 bivariate systems, namely: crude oil–corn; crude oil–ethanol; and corn–ethanol. Tables 3 through 5 show the bivariate results for: the full sample period; the March 2005–July 2008 sample period; and the August 2008–December 2011 sample period. Tables 3 and 4 show that for each bivariate system, over the full sample period and over the 2005–2008 sample period, we find no evidence of cointegration. Closer scrutiny of the design of the analysis may elucidate the rationale behind it. First, we note that per time period 3 different bivariate systems may be constructed, allowing for more detailed model specifications. Various permutations allow each analysis (i.e. specific market interactions) to be optimized according to specific model specifications. Finally,

Table 3
Bi-variate Johansen cointegration rank test (March 2005–December 2011).

	Model 2			**Model 3**		
	Test statistics	Critical values ($\lambda_{0.95}$)	Decision	Test statistics	Critical values ($\lambda_{0.95}$)	Decision
Crude oil–corn ($k=12$; Criteria: AIC)						
λ_{trace}						
$H_0: r=0$ vs. $H_1: r\geq 1$	10.24	20.26	Not rejected	9.32	15.49	Not rejected
$H_0: r\leq 1$ vs. $H_1: r\geq 2$	–	–	–	–	–	–
λ_{max}						
$H_0: r=0$ vs. $H_1: r=1$	7.47	15.89	Not rejected	7.45	14.26	Not rejected
$H_0: r\leq 1$ vs. $H_1: r=2$	–	–	–	–	–	–
Crude oil–ethanol ($k=1$; Criteria: AIC)						
$\lambda_{trace\ statistics}$						
$H_0: r=0$ vs. $H_1: r\geq 1$	10.52	20.26	Not rejected	9.92	15.49	Not rejected
$H_0: r\leq 1$ vs. $H_1: r\geq 2$	–	–	–	–	–	–
$\lambda_{max\ statistics}$						
$H_0: r=0$ vs. $H_1: r=1$	7.60	15.89	Not rejected	7.58	14.26	not rejected
$H_0: r\leq 1$ vs. $H_1: r=2$	–	–	–	–	–	–
Corn–ethanol ($k=1$; Criteria: AIC)						
λ_{trace}						
$H_0: r=0$ vs. $H_1: r\geq 1$	9.22	20.26	Not rejected	8.38	15.49	Not rejected
$H_0: r\leq 1$ vs. $H_1: r\geq 2$	–	–	–	–	–	–
λ_{max}						
$H_0: r=0$ vs. $H_1: r=1$	7.41	15.89	Not rejected	7.12	14.26	Not rejected
$H_0: r\leq 1$ vs. $H_1: r=2$	–	–	–	–	–	–

Model 2 – no deterministic trend (restricted constant).
Model 3 – linear deterministic trend.

Table 4
Bi-variate Johansen cointegration rank test (March 2005–July 2008).

	Model 2			**Model 3**		
	Test statistics	Critical values ($\lambda_{0.95}$)	Decision	Test statistics	Critical values ($\lambda_{0.95}$)	Decision
Crude oil–corn ($k=12$; Criteria: AIC)						
λ_{trace}						
$H_0: r=0$ vs. $H_1: r\geq 1$	9.54	20.26	Not rejected	5.40	15.49	Not rejected
$H_0: r\leq 1$ vs. $H_1: r\geq 2$	–	–	–	–	–	–
λ_{max}						
$H_0: r=0$ vs. $H_1: r=1$	5.57	15.89	Not rejected	5.24	14.26	Not rejected
$H_0: r\leq 1$ vs. $H_1: r=2$	–	–	–	–	–	–
Crude oil–ethanol ($k=1$; Criteria: AIC)						
$\lambda_{trace\ statistics}$						
$H_0: r=0$ vs. $H_1: r\geq 1$	8.59	20.26	Not rejected	5.36	15.49	Not rejected
$H_0: r\leq 1$ vs. $H_1: r\geq 2$	–	–	–	–	–	–
$\lambda_{max\ statistics}$						
$H_0: r=0$ vs. $H_1: r=1$	6.20	15.89	Not rejected	5.23	14.26	not rejected
$H_0: r\leq 1$ vs. $H_1: r=2$	–	–	–	–	–	–
Corn–ethanol ($k=5$; Criteria: AIC)						
λ_{trace}						
$H_0: r=0$ vs. $H_1: r\geq 1$	8.29	20.26	Not rejected	6.06	15.49	Not rejected
$H_0: r\leq 1$ vs. $H_1: r\geq 2$	–	–	–	–	–	–
λ_{max}						
$H_0: r=0$ vs. $H_1: r=1$	6.69	15.89	Not rejected	6.00	14.26	Not rejected
$H_0: r\leq 1$ vs. $H_1: r=2$	–	–	–	–	–	–

Model 2 – no deterministic trend (restricted constant).
Model 3 – linear deterministic trend model.

Table 5
Bi-variate Johansen cointegration rank test (August 2008–December 2011).

	Test statistics	Critical values ($\lambda_{0.95}$)	Decision	Test statistics	Critical values ($\lambda_{0.95}$)	Decision
Crude oil–corn ($k=0$; Criteria: AIC)		**Model 1**			**Model 4**	
λ_{trace}						
$H_0: r=0$ vs. $H_1: r \geq 1$	11.66	10.47[a]	Rejected	31.32	25.87	Rejected
$H_0: r \leq 1$ vs. $H_1: r \geq 2$	0.13	2.98[a]	Not rejected	4.96	12.52	Not rejected
λ_{max}						
$H_0: r=0$ vs. $H_1: r=1$	11.53	11.22[a]	Rejected	26.39	19.39	Rejected
$H_0: r \leq 1$ vs. $H_1: r=2$	0.13	4.13[a]	Not rejected	4.96	12.52	Not rejected
Crude oil–ethanol ($k=0$; Criteria: AIC)		**Model 3**				
λ_{trace} statistics						
$H_0: r=0$ vs. $H_1: r \geq 1$	12.47	15.49	Not rejected	30.72	25.87	Rejected
$H_0: r \leq 1$ vs. $H_1: r \geq 2$	–	–	–	6.00	12.52	Not rejected
λ_{max} statistics						
$H_0: r=0$ vs. $H_1: r=1$	10.07	14.26	Not rejected	24.72	19.39	Rejected
$H_0: r \leq 1$ vs. $H_1: r=2$	–	–	–	6.00	12.52	Not rejected
Corn–ethanol ($k=5$; Criteria: AIC)		**Model 3**				
λ_{trace}						
$H_0: r=0$ vs. $H_1: r \geq 1$	14.10	13.43[a]	Rejected	22.82	25.87	Not rejected
$H_0: r \leq 1$ vs. $H_1: r \geq 2$	1.74	2.71[a]	Not rejected	–	–	–
λ_{max}						
$H_0: r=0$ vs. $H_1: r=1$	12.36	12.30[a]	Not rejected	15.23	19.39	Not rejected
$H_0: r \leq 1$ vs. $H_1: r=2$	1.74	2.71[a]	Rejected	–	–	–

Model 1 – no intercept and no deterministic trend.
Model 3 – linear deterministic trend.
Model 4 – allows linear trend in the cointegrating space.
[a] Indicates the 10% probability level.

Table 6
Summary of the Johansen cointegration rank tests.

Trivariate model			
Crude oil–corn–ethanol		**March 2005–December 2011**	
$r=1$		Rejected	
Crude oil–corn–ethanol	**March 2005–July 2008**		**August 2008–December 2011**
$r=1$	Rejected		*Not rejected*
$r=2$	Rejected		Rejected
Bivariate model			
Crude oil–corn		**March 2005–December 2011**	
$r=1$		Rejected	
	March 2005–July 2008		**August 2008–December 2011**
$r=1$	Rejected		*Not rejected*
Crude oil–ethanol		**March 2005–December 2011**	
$r=1$		Rejected	
	March 2005–July 2008		**August 2008–December 2011**
$r=1$	Rejected		*Not rejected*
Corn–ethanol		**March 2005–December 2011**	
$r=1$		Rejected	
	March 2005–July 2008		**August 2008–December 2011**
$r=1$	Rejected		*Not rejected*

Complete results can be found in Tables 2 through 5.

Table 5 shows that for each bivariate system we find a cointegrating relationship during the 2008–2011 sample period. Our results illustrate the importance of accounting for economic events/factors that change the data generating process of the time series under consideration. The results in Table 5 indicate that there is a linear relationship between crude oil–corn markets, and crude oil–ethanol markets. However, with respect to the corn–ethanol pairing, we only find evidence of cointegration at 10% significance level, suggesting a weaker long-run relationship exists between these two markets. Table 6 shows a summary of the cointegration tests.

Once cointegration between time series is established it is of interest to analyze for causality of each cointegrating pair. Causality from the estimated Johansen VECM is analyzed through a likelihood ratio (LR) test by restricting the disequilibrium error term. Table 7 presents the results of these tests. The results indicate that crude oil granger causes corn and ethanol. In case of corn–ethanol relationship we find that corn precedes ethanol.

To further elaborate on our results consider Fig. 2, which graphically represents the crude oil–corn–ethanol nexus as discussed in the previous sections. The thick black arrows symbolize the supply and demand in each market. Here we note that in the case of the ethanol market, the demand is government mandated and thus no arrow is shown as demand is in effect *fixed*. The highlighted part of Fig. 2 indicates the so called *corn-for-ethanol*[5],

[5] Next to the implications of government policy, we have to consider the daily management practices of farmers where forward contracting – especially in the

Table 7
Causality from Johansen VECM (weak exogeneity test).

Models	Causality test		Causality decision
	A	B	
Crude oil–corn[b]	3.78 (0.02)	0.36 (0.70)	Crude oil → corn
Crude oil–ethanol[b]	3.38 (0.03)	0.09 (0.91)	Crude oil → ethanol
Corn–ethanol[a]	0.82 (0.57)	1.09 (0.36)	Corn → ethanol

A indicates $H_0 : \alpha_1 = 0$ vs. $H_1 : \alpha_1 \neq 0$.
B indicates $H_0 : \alpha_2 = 0$ vs. $H_1 : \alpha_2 \neq 0$.
Parentheses indicate the probability level.
→ indicates unidirectional causality.
[a,b] Indicates that the results are derived from models 1, 3, 4 respectively.

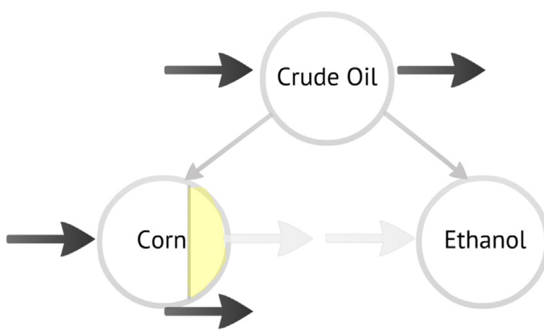

Fig. 2. Graphic representation of crude oil–corn–ethanol linkages.

which addresses the inelastic demand response – to corn supply side shocks – by the ethanol industry. This *corn-for-ethanol* interaction means corn market is relatively more sensitive to corn supply (production) shocks and demand shocks emanating from sources other than the ethanol sector. In other words, the policy driven ethanol market has no direct impact on the price level of corn through its own demand needs, but ethanol policy indirectly makes the corn markets more prone to supply and non-ethanol induced demand shocks, and as a result increases overall corn price volatility. The gray lines indicate the price relationships between crude oil–corn and crude oil–ethanol. This indirect policy induced link between corn and ethanol markets explains our weaker cointegration results and implies that prices in the two markets are not as tightly linked as prices are between corn and crude oil markets; or between ethanol and crude oil markets.

5. Concluding remarks

The policy driven increased production of ethanol – mainly reliant on first generation technologies – combined with a turbulent period in the global (commodities) markets created a complex dynamic scenario of market linkages. This paper offers a holistic study on the complex relationships between crude oil; corn; and ethanol during a turbulent period between 2006 and end of 2011. Using futures prices as our data source, we are able to capture all potential market linkages, either based on physical (production) linkages or macroeconomic linkages reflected in information based trade. After considering a holistic mapping of market situations over our sample period we put considerable effort into building a contextual design for the analysis. Through the use of the widely accepted Johansen cointegration methodology – for which we offer an intuitive primer – we were able to discern interesting and unique results. Namely, we have shown that there exists a strong relationship between crude oil and corn markets on one side, and crude oil and ethanol on the other. The relationship between corn and ethanol was revealed to be less straightforward, as it is driven more by government policy than the marketplace. With this in mind we argue that ethanol and corn market prices – contrary to common belief – are not strongly bound by a long-run cointegrating relationship. Instead we argue that price transmission between the two sectors is determined by the government mandated levels of ethanol use in gasoline production. Furthermore, while discussing market relationships a broader perspective needs to be taken into account. Various factors played an important part in the dynamics of price interaction between crude oil, corn and ethanol markets, such as: The Energy Policy Act of 2005; abolition of MTBE in 2006; crude oil price level surpassing the threshold of 75 USD/barrel; steady corn export; financial crisis of 2008; and the commoditization of agricultural markets. In addition considering the inherent nature of futures markets, where the news component plays a crucial role (i.e. information is rapidly incorporated on a global scale), results in a scenario of various forces pulling the markets in different directions in function of present-day market conditions.

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Appendix A. Representation of the Johansen maximum likelihood (ML) estimator

The ML cointegration method is based on a simple vector autoregressive (VAR(k)) model with Gaussian errors in the error correction form

$$\Delta y_t = \mu + \Gamma_1 \Delta y_{t-1} + \ldots + \Gamma_{k-1} \Delta y_{t-k+1} + \Pi y_{t-k} + \varepsilon_t \qquad (1)$$

where ε_t ($t=1, \ldots, T$) are independent p-dimensional Gaussian variables with mean zero and variance matrix Λ. The $(n \times 1)$ variables y_t are integrated of order one – $I(1)$, and thus Δy_t is $I(0)$. The arguments $\Gamma_1, \ldots, \Gamma_{k-1}$, μ and Λ may vary without restrictions. In case the coefficient matrix Π has reduced rank $(r < n)$ there are $(n \times r)$ α and β matrices with rank r so that $\beta' y_t$ is stationary and $\Pi = \alpha \beta'$. Under the assumption of cointegration of order r

$$\Delta y_t = \mu + \Gamma_1 \Delta y_{t-1} + \ldots + \Gamma_{k-1} \Delta y_{t-k+1} + \alpha \beta' y_{t-k} + \varepsilon_t \qquad (2)$$

where α and β both have dimensions $p \times k$. The number of parameters in the unrestricted model is $p + kp^2 + p(p+1)/2$. The elements of α are the adjustment parameters in the VECM while each column of β represents a cointegrating relationship.

Johansen introduces two different likelihood ration tests of the reduced rank of the Π matrix: the trace test (3) and the maximum

(*footnote continued*)
case of corn production for ethanol – is a common practice, in continuum with Anderson and Coble (2010) indicating that the ethanol production levels are on a similar level as the mandates resulting in market participants inferring that any reduction in corn supply will be met by a relatively inelastic demand response from the ethanol sector, as already mentioned in the literature review.

eigenvalue test (4).

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} \ln(1-\hat{\lambda}_i^2) \tag{3}$$

$$\lambda_{\max}(r,\ r+1) = -T\ln(1-\hat{\lambda}_{r+1}) \tag{4}$$

In Eq. (2) the first k data points are assumed to be fixed and the calculation of the likelihood function is based on their values. Let $Z_{0t} = \Delta y_t \wedge Z_{1t} = (\Delta y'_{t-1},\ \ldots, \Delta y'_{t-k+1}\ ,\ 1) \wedge Z_{kt} = y_{t-k}$ and define the moment matrices

$$M_{ij} = T^{-1} \sum_{t=1}^{T} Z_{it} Z'_{jt} \quad (i,\ j = 0,\ 1,\ k)$$

We regress Z_{it}, $i=0,\ k$ on Z_{1t} and get residuals R_{it}, $i=0,\ k$. Denote the residual sum of squares from regressing Z_0 and Z_k on Z_1 as S_{ij}; $i,\ j=0,\ k$. Define the sample covariance matrices.

$$S_{ij} = T^{-1} \sum_{t=1}^{T} R_{it} R'_{jt} \tag{5}$$

The maximum likelihood estimator of α and β is a function of these residuals (Johansen, 1988; Johansen, 1991). Computing the eigenvalues and eigenvectors of $S_{10}S_{00}^{-1}S_{01}$ with respect to S_{11} amounts to solving the eigenvalue problem.

$$|\lambda S_{11} - S_{10}S_{00}^{-1}S_{01}| = 0 \tag{6}$$

The maximum likelihood estimation is in function of the deterministic term and the stationary effects. In other words we consider the following multivariate linear regressions:

$$\Delta \boldsymbol{y}_t = \gamma_0 + \Omega_1 \Delta y_{t-1} + \ldots + \Omega_{k-1} \Delta y_{t-k+1} + \boldsymbol{u}_t \tag{7}$$

$$\boldsymbol{y}_{t-1} = \gamma_1 + \Phi_1 \Delta y_{t-1} + \ldots + \Phi_{k-1} \Delta y_{t-k+1} + \boldsymbol{v}_t \tag{8}$$

The sample covariance matrices can be written as

$$S_{00} = \frac{1}{T-k} \sum_{t=k+1}^{T} \hat{u}_t \hat{u}'_t\ , \quad S_{01} = \frac{1}{T-k} \sum_{t=k+1}^{T} \hat{u}_t \hat{v}'_t,$$

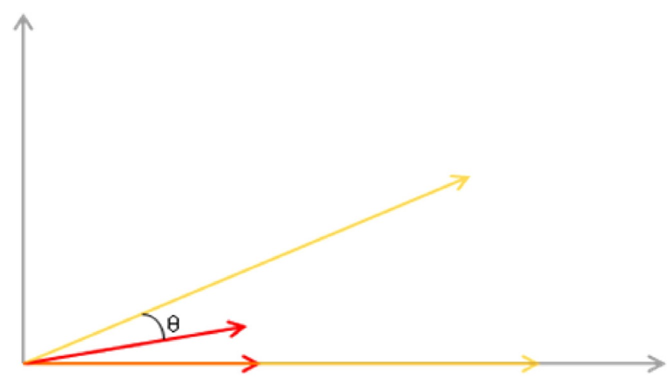
$$S_{11} = \frac{1}{T-k} \sum_{t=k+1}^{T} \hat{v}_t \hat{v}'_t$$

For sake of clarity of the algebraic interpretation of the sample covariance matrices we will briefly continue in a 2-dimensional space. Considering 2 time series $y_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix}$ we can specify the residuals from the auxiliary regressions (7) and (8) with corresponding residual matrices $\boldsymbol{u}_t = \begin{bmatrix} u_{1,t} & u_{2,t} \end{bmatrix}$ and $\boldsymbol{v}_t = \begin{bmatrix} v_{1,t} & v_{2,t} \end{bmatrix}$.

$S_{00} = \frac{1}{T-k}\Sigma_{t=k+1}^{T}(u_{1,t}^2 + u_{2,t}^2)$ mean (t) squared magnitude of $\boldsymbol{u} \rightarrow \overline{||\boldsymbol{u}||^2}$
$S_{01} = S_{10} = \frac{1}{T-k}\Sigma_{t=k+1}^{T}(u_{1,t}v_{1,t} + u_{2,t}v_{2,t})$ mean (t) *of* $\langle u, v \rangle$
$S_{11} = \frac{1}{T-k}\Sigma_{t=k+1}^{T}(v_{1,t}^2 + v_{2,t}^2)$ mean (t) squared magnitude of $v \rightarrow \overline{||\boldsymbol{v}||^2}$

It is evident that the algebraic representation is valid for an n-dimensional space and thus the eigenvalue problem specified in (6) can be transformed to the following form:

$$\left| \lambda\, \overline{\boldsymbol{v}^2} - \frac{\langle \boldsymbol{u}, \boldsymbol{v} \rangle^2}{||\boldsymbol{u}||^2} \right| = 0 \tag{9}$$



From Eq. (9) we can deduct that:

$$\hat{\lambda} = \frac{\langle \boldsymbol{u},\ \boldsymbol{v} \rangle^2}{||\boldsymbol{u}||^2 ||\boldsymbol{v}||^2} = (\cos\ \theta)^2 \tag{10}$$

Furthermore, the Cauchy–Schwarz inequality states that $\boldsymbol{u}, \boldsymbol{v}^2 \leq \overline{\boldsymbol{u}^2}\ \overline{\boldsymbol{v}^2}$ which implies that $\hat{\lambda} \leq 1$. Looking back at (3) and (4) we can state that Johansen cointegration test, in a very intuitive way, may be characterized by the (mean(t)) angle between the vectors of residuals in Eqs. (7) and (8).

Appendix B. Unit root tests using the augmented Dickey–Fuller & Phillips–Perron

See Table B1.

Table B1
Unit root tests using the augmented Dickey–Fuller and Phillips–Perron.

	1989–2010 Period			
	Augmented Dickey–Fuller		Phillips–Perron	
Variable (price)	Drift	Trend	Drift	Trend
Crude oil	−1.59	−1.90	−1.53	−1.86
Δ Crude oil		−42.91®		−42.93®
Corn	−1.68	−2.00	−1.43	−2.06
Δ Corn		−39.57®		−39.57®
ethanol	−2.57	−2.53	−2.78	−2.73
Δ Ethanol		−38.16®		−35.52®

Lag length for ADF tests are based on AIC.
Maximum bandwidth for PP tests is decided based on Newey and West (1994).
Critical values are −2.89 (5%), −3.49 (1%) with drift only and; −3.45 (5%), and −3.49 (1%) for a model with constant and trend; −1.94 (5%), and −2.58 (1%) for a pure random walk model (Mackinnon, 1996).
® indicates the pure random walk model.

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