STRUCTURAL CHANGE IN THE RELATIONSHIP BETWEEN ENERGY AND FOOD PRICES

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Abstract.

High fuel prices combined with legislative policies have increased biofuel production causing high food prices and establishing a link between energy and agricultural markets. This paper examines price relationships between agricultural food and energy commodities over the recent decade. A structural change analysis on weekly prices of crude oil, gasoline, ethanol, corn and wheat is conducted. The presence and the nature of structural breaks are empirically tested on single prices and on the price relationships. A cointegration analysis is conducted accounting for the presence of structural breaks. We find that commodity prices have experienced structural changes both at price levels and in the price relationships. The energy and food commodity prices exhibit long run relationships when structural breaks are considered. The break dates identified are in line with biofuel policy interventions and changes in policy regimes in the United States.

Keywords: commodity prices, energy prices, structural breaks, co-breaking cointegration, policies.

JEL codes: C10, C32, Q10, Q18, Q28, Q42,Q48

1. Introduction

Agricultural commodities experienced substantial increases in prices over the most recent decade with major surges in both 2007-08 and again in 2010-11. The prices of food commodities such as maize, rice and wheat increased dramatically from late 2006 through to mid-2008, reaching their highest levels in nearly thirty years. In the second half of 2008, the price upswing decelerated and prices of commodities decreased sharply in the midst of the financial and economic crisis. A similar price pattern emerged in early 2009 when the food commodity price index slowly began to climb. After June 2010, prices shot up, and by January 2011, the index of most commodities exceeded the previous 2008 price peak These price movements coincided with sharp rises in energy prices, in particular crude oil.

Several authors have discussed the factors lying behind the recent sharp increases though no consensus has been reached on the cause of these phenomena. Rapid economic growth in China and other Asian emerging economies, decades of underinvestment in agriculture, low inventory levels, poor harvests, depreciation of the U.S. dollar, and financializiation and speculative influences are among the factors cited as leading to high levels of commodity prices (Abbot et al, 2008, Cooke and Robles, 2009; Gilbert, 2010; Wright, 2011).

The diversion of food crops as biofuels stands out as an important and new factor that many have seen as accounting for the recent food price spikes (Mitchell, 2008). Global biofuel production has increased rapidly over the last twenty years (Wright, 2014). In the United States biofuel production began to rise rapidly in 2003 while in the European Union it accelerated from 2005 (USDA, 2008). Ethanol production (mainly in the United States and Brazil) tripled from 4.9 billion gallons to almost 15.9 billion gallons between 2001 and 2007. In the U.S., corn production used for ethanol production increased from 12.4 percent in the 2004/05 crop year to over 38.5 percent in the 2010/11 crop year (USDA, 2011). Over the same period, biodiesel production, mainly in the European Union and deriving from vegetable oils, rose almost ten-fold, to about 2.4 billion gallons.

This expansion in biofuels production has been driven by a number of economic and environmental factors. High crude oil prices and keenness to promote non-petroleum energy sources to reduce dependence on oil imports have been important policy drivers in the United States, Brazil, and the European Union. Environmental concerns over greenhouse gas emissions and the urge to slow down global warming due to fossil fuel emissions have also contributed to this expansion. In Brazil, the presence of large areas of poorly utilized land allowed rapid growth of the sugar cane production for use as the biofuel feedstock. Debate remains on whether the increase in biofuels production was primarily market or policy-driven. Some authors believe that the boom was mainly driven by the increase in crude oil prices. Others sustain that the boom resulted from government policies, such as mandates and tax credits in the U.S. aimed at increasing energy self-sufficiency and, in Europe, environmental pressures to reduce emissions (DeGorter and Just, 2009; Abbot, 2013; Peri and Baldi, 2013).

It has been argued that increased biofuel production has contributed to the increases in the prices of the main food commodities by increasing the demand for grains and oil seeds used as feedstocks (Rosegrant et al., 2008). According to FAO (2008), the demand for cereals for industrial use, including biofuels, rose by 25 percent from 2000 to 2008 against a 5 percent increase in global food consumption. The IMF estimated that by 2008, the increased demand for biofuels accounted for 70 per cent of the increase in maize prices and 40 per cent of the increase in soybean prices. Increased international food commodity prices were in large measure transmitted back to domestic markets in developing countries where poor households, particularly those in urban areas, spend a large proportion of their incomes on food (World Bank, 2008). It is argued that this rightward shift in the demand function for grains and vegetable oils has put upward pressure on the entire range of food prices (Tyner, 2010; Serra, 2011a).

We investigate the claim that the advent of biofuels has altered the nature of the relationship between energy and agricultural markets – see Taheripuor and Tyner (2008) and Gilbert and Mugera (2012). In the past, this relationship largely reflected cost factors. Crude oil enters the aggregate production function of most primary commodities through the use of various energy-intensive inputs such as fertilizers, heating, pesticides as well as through costs of transportation.

Baffes (2007) estimated the pass-through of oil prices into agricultural commodity prices as 17 per cent. Mitchell (2008) estimated that energy and transport costs amount of between 15 per cent and 20 per cent of overall agricultural production costs in the U.S. (Gilbert, 2010) concurred with these estimates and argued that there was little reason to believe that this proportion had increased significantly over recent years.

Increased biofuel production and consumption over the recent decade may have created a new demand side link between energy markets and food commodities by making the demand for grains and vegetable oils sensitive to the price of crude oil. A number of authors have documents the increased co-movement and correlation between crude oil prices and food commodity prices over the most recent decade (Tyner, 2010; Serra et al., 2011c; Gilbert and Mugera, 2013). This increase in co-movement appears to have commenced at around the same time as biofuels production took off. In particular, July 2005 marked the beginning of what Abbot (2013) termed as the "ethanol gold rush." Moreover, in 2005, the Renewables Fuels Standards was enacted (U.S. Congress, 2005). In 2007 then followed the Energy Policy Act which significantly increased the mandated RFS minimum levels of ethanol production (U.S. Congress, 2007). Tyner (2010) confirms that the correlation between energy and agricultural markets has been strong since the 2006 start of the ethanol boom. He highlights the summer of 2008 as the period where these two markets were closely linked. As the crude oil price increased so did the price of corn and other agricultural commodities.

Other commentators claim that the increased comovement with oil prices is not confined to food commodities and attribute these changes to financialization which affects all those commodities which are traded on liquid futures markets. According to this view, food commodities have come to be seen as part of the "commodity asset class". Financial flows into commodity futures, including those for food commodities result from calculations of likely returns on commodities, generally considered as a group, relative to those on equities and bonds. The consequence is that there is now a new set of demand shocks common to the entire range of traded commodity futures. (Büyükşahin, Haigh and Robe, 2010; Tang and Xiong, 2010; Bicchetti and Maystre, 2012).

Increases in energy prices, the boom in biofuel production and government policy interventions have led to questions in relation to the stability in the long run relationships between food and energy commodity prices. The main hypothesis of this research is that recent market and policy events may have induced changes in the relationship between food and energy markets. We ask whether there have been any structural changes in relationships between energy and commodity prices and if so, whether any such breaks may be modelled as shifts in the mean of the food price processes. We test for the presence of multiple structural breaks in the single price series of crude oil, gasoline, ethanol corn, and wheat without pre-specifying the dates of any such breaks. We also examine the evolution of the price relationships over the recent decade. Our main focus is the United States. This choice is driven by several factors. Firstly, the United States is one of the largest producers and exporters of grains and oilseeds. Secondly, the United States is the world's largest producer and consumer of biofuels. Thirdly, in the recent decade, the United States has experienced a large number of policy and regulatory changes that may have affected both the energy and food commodity markets and their inter-relationship.

The structure of the paper is as follows. Section 2 documents the relationship between food and energy markets. Section 3 provides details of U.S. biofuels policy. Section 4 examines the structural break methodology. Section 5 defines our data. Section 6 reports the results from univariate tests and section 7 reports multivariate (cointegration) results. Section 8 provides conclusions.

2. The relationship between food and energy commodities

Evidence on the relationship between food and energy markets is mixed. A number of authors conclude that the linkage is weak or absent (Dillon and Barrett, 2013; Zilberman et al., 2012; Zhang et. al., 2010). Others have argued that there is support for the hypothesis that energy prices are an important driver of long-run world food price levels (Secchi and Babcock, 2007, Tokgoz et al., 2007 Ciaian and Kanks, 2011; Natalenov et al., 2011). Most econometric studies are based around the existence or non-existence of cointegration between grains and energy prices. Cointegration results when it is possible to find a stationary linear combination of two or more series each of which is non-stationary.

Cointegration results when it is possible to find a stationary linear combination of two or more series each of which is non stationary. The presence of cointegration also indicates that a long-run equilibrium relationship exists between these series which therefore must adjust to ensure the elimination over time of departures from the long run relationship (Engel and Granger, 1987). The results we report in section 7 stand in this tradition.

Serra et al., (2011b) evaluate price linkages and transmission patterns in the U.S. ethanol industry from 1990 to 2008, a period that saw significant changes in U.S. ethanol and related markets. Their study concentrates on the relationships between ethanol, corn, crude oil and gasoline prices. They found that the four prices are related in the long run through two cointegrating relationships: one between corn and ethanol representing the equilibrium within the ethanol industry and second one between crude, oil and gasoline, representing the equilibrium in the oil-refining industry. The ethanol market provides the link between corn and energy markets, and the price of ethanol increases as the prices of both corn and gasoline increase, with the price of corn being the dominant factor when it is relatively high.

Biofuels production has also been important in Brazil which is currently the leading worldwide producer of ethanol from sugarcane. Strong ethanol demand and less attractive sugar prices have led the Brazilian industry to divert increasing quantities of sugar cane to ethanol production. In the 2007/08 marketing year, the use of sugarcane for alcohol production (55%) slightly exceeded the use for sugar production (45%). Brazilian ethanol production in the 2007/08 marketing year was 22.4 billion liters, while Brazilian ethanol exports were around 3.6 billion liters with the U.S. and Europe being the main destinations (USDA, 2008). In a study on Brazil, Serra (2011c) uses nonparametric corrections to time series estimations to provide support for the presence of a long-run linkage between ethanol and sugar-cane prices. The paper confirms the role of both crude oil and sugarcane prices in as drivers of Brazilian ethanol prices. Balcombe and Rapsomanikis (2008) used ethanol, sugar and crude oil prices to investigate price inter-relationships in the Brazilian ethanol market. They adopt a generalized bivariate error correction models that allow for cointegration between sugar, ethanol, and oil prices, where dynamic adjustments are potentially nonlinear functions of the disequilibrium errors. They find evidence of cointegration between sugar, crude oil and ethanol prices.

Using weekly prices of corn, sorghum, soybeans, soybean oil, palm oil, world sugar and crude oil prices from 2003 to 2007 Campiche et al. (2007) find corn and soybean prices to be cointegrated with crude oil prices in the period subsequent to the boom in biofuels, with crude prices driving feedstock prices. Saghaian (2010) also find evidence for cointegration between crude oil, ethanol, wheat, corn and soybean prices in the US for monthly crude oil, ethanol, wheat, corn, and soybeans prices between December 1996 and December 2008. He finds that crude oil as a driver of corn, soybean, wheat and ethanol prices, while ethanol affects long-run corn prices. Ciaian and Kanks (2011) find cointegration between crude oil and a range of weekly food commodity prices between January 1994 and December 2008. Using weekly German diesel, biodiesel, rapeseed oil and soy oil prices from 2002 to 2007, Busse et al. (2007) conclude that equilibrium feedstock prices of biodiesel are influenced by energy prices (Busse et al., 2009).

A separate strand of research has relied on computable partial and general equilibrium (CGE) models in order to examine the impact of policies on the energy-food commodity relationship (Janda et al., 2012). CGE models focus on equilibrium relationships more than short-run price dynamics. They are well-suited to the examination of the medium and long term impacts of policy changes which can be accurately reflected in the model structure. However, they are less well suited to the explanation of short term price movements in periods of high price volatility where prices may differ substantially from their equilibrium values (Beckman et al., 2011). In that sense, CGE models may be seen as complementing the more data-based models which emerge from the time series econometric approach. We review that CGE literature on U.S. biofuels policy in section 3.

3. U.S. biofuels policies

The United States began subsidizing biofuels in 1978 with the passage of the National Energy Policy Conservation Act of 1978 (Tyner, 2008; U.S. Congress, 1978). However, it is only in the most recent decade that U.S. production of biofuels increased dramatically. In 1983, ethanol production was 375 million gallons, growing to almost three billion gallons by 2000 and by 2010 it had reached 13 billion gallons. Key policy measures aimed at encouraging biofuel production included the Renewable Fuels Standard (RFS), subsidies to ethanol blenders, the blend wall, regulations on gasoline chemistry and import tariffs. Many believe that these interventions helped to create this new, persistent demand for corn and contributed to incentives to create the capacity to produce ethanol and to use corn for fuel rather than food (DeGorter and Just, 2009; Abbot, 2013).

RFS Mandates

2005 saw the enactment of significant changes in the legislation governing ethanol production (Tyner, 2008). The Renewable Fuels Standard (RFS), which mandated minimum production levels for future years for ethanol, was passed (U.S. Congress, 2005). This legislation also included continued subsidization of ethanol production which initiated in 2004. Gasoline blenders were offered a tax credit of $0.51 per gallon referred to as the Volumetric Ethanol Exercise Tax Credit – (VEETC), and import tariffs of $0.45 per gallon plus 2.5% of imported value were imposed on imported ethanol, to insure foreign producers did not get the subsidy. In December 2007, the U.S. Congress passed a major new energy legislation mandating widespread improvements in energy efficiency (U.S. Congress, 2007). The Energy Policy Act (EPA) of 2007 substantially increased RFS mandated minimum ethanol production levels for the future. The VEETC tax credit was later reduced to $0.45 per gallon in 2007-08 food crises, and expired in December 2011. Moreover, the import tariffs on ethanol for fuel were cut in January 2012.

The Blend Wall

EPA regulations also imposed a limit on the amount of ethanol used in reformulated gasoline produced and sold by blenders. This is because ethanol is corrosive and may damage older engines or engines that have not been designed to tolerate high concentrations of ethanol. Modern flex-fuel vehicles use blends including up to 85% ethanol while many vehicles with conventional engines tolerate between 10 and 20 per cent without being damaged. The EPA thus set a limit at 10% (E10) for gasoline not explicitly marketed as E85, and permitted up to 15% of ethanol (E15) to be blended for newer vehicles. Tyner and Viteri (2009) analyze how this affects ethanol and gasoline markets, and refer to this limitation as the “blend wall”. This constraint is imposed on gasoline blenders, generating a ceiling on ethanol demand for fuel use. The effects of this ceiling are felt all along the ethanol supply chain. The blend wall restricts ethanol use and therefore reduces demand for corn for ethanol.

The blend wall thus affected the link between crude oil and corn prices. The effect of the blend wall was more influential at high crude oil prices, where ethanol production was limited by the wall level thereby limiting the impact on corn prices. The blend wall was thus an effective constraint on demand, so an increase in the wall limit affected the linkage between crude oil and corn (Tyner, 2010).

MTBE/Oxygenate Substitution

In the early 1990s, the Clean Air Act required additives to reduce carbon monoxide emissions and reduce atmospheric pollution by including either a fuel oxygenator Methyl Tert-Butyl Ether (MTBE) or ethanol. It was subsequently discovered that MTBE was carcinogenic implying a possible threat to drinking water safety (EIA, 2000). Gasoline blenders, who were using MTBE to meet clean air regulations, sought waivers from liability but in 2006 it became clear that such waivers would not be granted. By mid-2006, 25 states had banned the use of MTBE in gasoline. This encouraged blenders to use ethanol rather than face the potential liability costs from MTBE. This contributed to the rapid expansion of ethanol production after 2005 (Hertel and Beckman, 2012).

The timing of the policy changes in regime switches is crucial as they may have led to changes in the relationship between energy and food commodity prices (Abbot, 2013). Key policy intervention dates are reported in the Table1. The econometric analysis which we report in section 6 of the paper has the aim of relating these policy changes to changes in the relationship between grains and energy prices.

As discussed in section 2, CGE analysis is well-suited to the analysis of the impact of policy changes. Adopting the CGE approach, Elobeid and Tokgoz (2008) estimate the effects of a hypothetical removal of federal tax credit and trade liberalization on the U.S. ethanol industry.

According to their results, U.S. ethanol prices would have been substantially higher in the absence of these credits. DeGorter and Just (2009a) find that the combined impact of tax credits and the blend mandate effectively subsidize fuel in the U.S. In DeGorter and Just (2009b), the same authors conclude that ethanol would not be commercially viable without government intervention. In DeGorter and Just (2010), they argue that U.S. biofuels mandates have increased the retail prices of gasoline and generate transfers to ethanol producers. Feng and Babcock (2010) analyze land use changes induced by the expansion of ethanol production taking into account acreage allocations. They concluded that elasticities of crop demand are crucial in determining the eventual impacts of yield increases. Hertel and Beckman (2011) argue that the binding U.S. Renewable Fuels Standard has increased the inherent volatility in U.S. coarse grains prices by about one quarter. Jingbo et al., (2011) construct a simplified general equilibrium (multimarket) model of the United States and the rest-of-the-world economies that link the agricultural and energy sectors to each other and to the world markets. Their results show that the largest economic gains to the United States from policy intervention come from the impact of policies on U.S. terms of trade, particularly on the price of oil imports.

This body of literature demonstrates that U.S. biofuels policy has had the potential to substantially raise corn prices and to change the relationship between grains and energy prices. There is less comparable work on the impact of European policy on vegetable oils but the same types of impact may be foreseen. In what follows we show that these changes in U.S. biofuels policy have induced breaks in the time series properties of important grains price series and the relationship of these prices to energy prices.

4. Structural break analysis

As outlined in section 3, there have been major changes in U.S. biofuels policy since the start of the new century. Policy changes have the potential to induce structural breaks both in univariate relationships characterizing the time series property of a price and in multivariate relationships linking different prices. A number of empirical analyses demonstrate that failure to account for structural breaks may lead to incorrect policy implications and predictions. In analyzing the U.S. post-war quarterly real GNP series (1947:1-1986:III), Perron (1989) finds that only two policy-driven events had a permanent effect on the macroeconomic variables. First, the 1929 Great Crash generated a dramatic drop in the mean of most aggregate variables. Second, the 1973 oil price shock was followed by a change in the slope of the trend for most aggregates such as a slowdown in growth. Hansen (2001) finds evidence on a structural break in labour productivity in U.S. manufacturing and durables sectors between 1992 and 1996. Analysing the market response of interest rates to discount rates Bai (1997) finds that the response is consistent with the policy interventions by the Federal Reserve Board on its operating procedures. Garcia and Perron (1996) examine the time series behaviour of the U.S. real interest rate from 1961 to 1986 by allowing three possible regimes affecting both the mean and variance. They find that the average interest rate value experienced occasional jumps caused by important structural events. One such jump is associated with the sudden rise in the oil price in 1973 while the mid-1981 second jump is more in line with a federal budget deficit explanation than with the change of monetary policy that occurred in the end of 1979.

Defining Structural Breaks

Breaks can be defined as events which change the structure of the econometric model under consideration. Consider the most simple univariate representation, the first-order autoregression:

$$y_t = \alpha + \rho y_{t-1} + u_t$$
$$E u_t^2 = \sigma^2 \tag{1}$$

where u_t is a time series of serially uncorrelated shocks $\alpha, \rho, and\ \sigma^2$ are the parameters with -1 $\leq \rho \leq 1$. Stationarity requires that these parameters be constant over time (Hansen, 2001). We say that a *structural break* has occurred if at least one of these parameters changes at some date - the *break date* - in the sample period. A structural break may affect either or both of the parameters α and ρ. Changes in the autoregressive parameter ρ reflect changes in the serial correlation in y_t while the intercept α controls the mean of y_t through the relationship $E(y_t) = \alpha/(1-\rho)$. In the general case, neither the timing nor the magnitude of these breaks will be known

Over the past fifteen years, there have been important contributions to the structural breaks literature. These include tests for the presence of structural breaks when the break date is unknown and the subsequent estimation of the break dates when any such changes occur. In addition to this, work has been reported on the nature of the breaks. The simplest form of break is that of a sharp jump to new parameter values at the break date (Chow, 1960; Andrews and Ploberger, 1994; Bai and Perron, 1998; Perron, 1989; Bai and Perron, 2003). Sharp breaks may be induced if there is an unanticipated change in government or administration policy is announced. In section 6, we follow this approach in relating breaks in grains price representations to changes in U.S. biofuels policy. The alternative approach is to allow breaks to be smooth or fuzzy (Gallant, 1984; Becker, Enders and Hurn, 2004, 2006; González and Teräsvirta, 2008; Enders and Holt, 2012). In this framework breaks are seen as slowly evolving changes in parameters which take place around a break date.

Moving to a multivariate context, one may be interested in whether related series have common break dates. In that case, we can describe the series as co-breaking. In section 7 we show that grains prices co-break in that the relationship between the prices is unaffected by breaks in their respective univariate representations.

Consider the equations

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} \mu_y \\ \mu_x \end{pmatrix} + \begin{pmatrix} u_{yt} \\ u_{xt} \end{pmatrix} \tag{2}$$

with $$\begin{pmatrix} u_{yt} \\ u_{xt} \end{pmatrix} \sim NI\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_y{}^2 & \rho\sigma_x\sigma_y \\ \rho\sigma_x\sigma_y & \sigma_x{}^2 \end{pmatrix}\right].$$

The implied line of regression linking y_t to x_t is

$$y_t = \alpha + \beta x_t + u_t \tag{3}$$

where $\beta = \dfrac{\rho\sigma_y}{\sigma_x}$ and $\alpha = \mu_y - \beta\mu_x$. A change in μ_x to m_x will induce a corresponding change in α to $\mu_y - \beta m_x$. We say that the series x and y are co-breaking if μ_y also changes, say to m_y such that $\alpha = m_y - \beta m_x$ remains invariant (Hendry and Massman, 2007). In that case, the line of regression (3) continues to hold despite the structural breaks in both the x and y processes.

This argument generalizes in a straight forward manner if the relationships (2) become autoregressive or contain exogenous regressors.

Testing for Structural Breaks

One-time structural change when the break-date is known

The classical test for structural change at a known date is due to Chow (1960). This procedure splits the sample into two sub-periods, estimates the parameters for each sub-period, and then uses a Wald F test to ask whether the two sets of parameters are equal. The Chow test is performed splitting the sample at the known break-date (Chow, 1960; Enders, 2010). In the model

$$y_t = \beta_1' x_t I(t \leq t_0) + \beta_2' x_t I(t > t_0) + u_t \tag{4}$$

where $u_t \sim iid\ \mathcal{N}(0, \sigma^2)$ and $I(x)$ is the indicator function the Chow test sets the null hypothesis $\mathrm{H}_0\colon \beta_1 = \beta_2$ against the alternative hypothesis $\mathrm{H}_1\colon \beta_1 \neq \beta_2$. This is an F-test with n and T-2n degrees of freedom (Teräsvirta, et al., 2010).

The Chow test requires the potential break-date $t_0 = \pi_0 T$ to be known. A researcher who does not know the break date in advance would be obliged either to pick an arbitrary candidate break-date or to choose a break-date based on some feature of the data. In the first case, the Chow test may be uninformative and imprecise, as the true break-date may be missed. In the second case, the Chow test can be misleading, as the candidate break-date is correlated with the data and thus lead to a pre-test selection bias of the data (Hansen, 2001).

Testing for a single structural change when the break date is unknown

In practice, we seldom have precise knowledge on potential break dates. Quandt (1960) suggested taking the largest Chow statistic over all possible break-dates. He proposed to split the sample at a break-date and estimate the model parameters separately on each subsample. If the parameters are constant, the subsample estimates should be the same across candidate break-dates, subject to estimation error. On the other hand, if there is a structural break, then the subsample estimates will vary systematically across candidate break-dates, and this will be reflected in the Chow test sequence. However, the Quandt statistic was seldom implemented because critical values were unavailable. Andrews (1993) and Andrews and Ploberger (1994) proposed a solution to this problem. They derive optimal tests for structural change with an unknown change point. Their procedure involves searching for a break-date by performing the Chow test for every possible date. As in Quandt's (1960) procedure, the break date is identified as the date at which the Chow statistic attains its maximum (or supremum) value.

Consider a model indexed by parameter β_t for t = 1,2,...., T, where T is the sample size. The null hypothesis of parameter stability and thus of no structural change is given by:

$H_0: \beta_t = \beta_0$ for all $t \geq 1$ for some value of β_0.

The alternative hypothesis of interest may take a number of different forms. In the case of a one-time structural change alternative with change point $\pi \in (0,1)$ the alternative with change point π is given by

$$H_{1T}(\pi): \beta_t = \beta_1 I(\pi \leq \pi_0) + \beta_2 I(\pi > \pi_0) \tag{5}$$

where β_1 and $\beta_2 \neq \beta_1$ are parameters to be estimated, πT is the break date, and $\pi \in (0,1)$ is referred to as the break point. This test procedure falls outside the standard testing framework because the parameter π only appears under the alternative hypothesis and not under the null. Consequently, Wald, LM, and LR-like tests constructed with π treated as a parameter do not possess their standard large sample asymptotic distributions. Critical values are obtained by simulation.

Some restrictions need to be imposed on the break point π to ensure that there is an adequate number of observations in each of the two subsamples. This requires that the break date neither not occurs near the very beginning (t_0) nor near the end of the sample ($T - t_0$). In particular, Andrews (1993) showed that if no restrictions are imposed on π for instance then the test diverges to infinity under the null hypothesis. This indicates that critical values grow and the power of the test decreases as π gets smaller. Hence, the range over which one searches for a maximum must be small enough for the critical values not to be too large and for the test to retain decent power, yet big enough to include potential break dates.

Andrews (1993) recommended restriction of the break-date π to an interval such as [0.15, 0.85] and this restriction has now become standard practice.

Testing for multiple unknown break dates

Allowance for multiple breaks at unknown dates are a natural extension to the Andrews (1993) and Andrews and Ploberger (1994) procedure. Bai and Perron (1998; 2003) extended Andrews and Ploberger's (1994) supremum test for a one-time break to allow for $k \geq 1$ possible break dates. In their earlier work Bai and Perron (1998) the build a theoretical model on the limiting distribution of estimators and the statistics in linear regression models with structural breaks. In particular, they examined the properties of the estimators such as the nature of the break dates and their respective tests. In their subsequent research, they proposed a dynamic programming algorithm that enables the investigator to obtain the global minimizers of the sum or squared residuals. They also discuss estimation of the number of break dates and the construction of confidence intervals for the break dates given different conditions on the structure of the data and error terms across subsamples and (Bai and Perron, 2003).

The procedure is based on sequentially applied least squares. The initial step is to test for a single structural break. If the test rejects the null hypothesis that there is no structural break, the sample is split in two and the test is reapplied to each subsample. This sequence continues until each subsample test fails to find evidence of a break. In the presence of multiple structural breaks, the sum of squared errors which is a function of the break date can have a local minimum near each break date. The sample is then split at the break date estimate, and analysis continues on the subsamples. In the context of the regression model with up to *k* breaks:

$$y_t = \beta_j{}' x_t + u_t \quad \left(t = \pi_{j-1}T + 1, \ldots, \pi_j T\right) \tag{6}$$

Relative to the *k*-partition, $\left(\pi_1, ..., \pi_k\right)$, parameter estimates are obtained by minimizing the sum of squared residuals:

$$\sum_{i=1}^{k+1} \sum_{t=\pi_{j-1}T+1}^{\pi_j T} \left(y_t - \beta_j{}' x_t\right)^2 \tag{7}$$

where $\pi_0 = 0$ and $\pi_{k+1} = 1$.Substituting these estimates in the objective function and denoting the sum of squared residuals as $S_T(\pi_1, ..., \pi_k)$, the estimated break points $(\hat{\pi}_1, \ldots, \hat{\pi}_k)$ are such that

$$(\hat{\pi}_1, \ldots, \hat{\pi}_k) = \arg\min_{\pi_1, \ldots, \pi_k} S_T(\pi_1, \ldots, \pi_k) \qquad (8)$$

where the minimization is taken over all partitions $\pi_1, \ldots, \pi_k$ .Thus the break-point estimates are global minimizers of the sum of squared residuals of the objective function. Given the sample size T, the global sum of squared residuals for the *k*-partition $(\pi_1, ..., \pi_k)$ for any value of *k* would be a linear combination of the $\frac{1}{2}T(T+1)$ sums of squared residuals and the estimates of the break points $(\hat{\pi}_1, \ldots, \hat{\pi}_k)$ correspond to the minimum value of this linear combination. The dynamic programming algorithm compares all the combinations corresponding to the *k*-partitions in order to minimize the global sum of squared residuals.[1]

In the application of their model Bai and Perron (2003) consider a number of different cases. In particular, the test statistic for the null hypothesis H_0 of no structural break *k=0* versus the alternative hypothesis H_1 that there are *k=v* breaks for some fixed number of breaks is a *supF* type test. The preferred choice for number *k* of breaks can result by reference to the Schwartz Bayesian Information Criterion (BIC) or the modified Schwartz information criteria proposed by Liu et al. (1997).

Testing for a structural change in cointegrating relationships with unknown break-date

Our interest is in the relationship between grains and energy prices. The stability of long-run equilibrium relationships of variables has always been open to question. In particular, there is vast literature on the stability of the money demand equation, some of which include works of Lucas (1988) and Stock and Watson (1993). Perron (1989) argued that if there is a break in the deterministic trend then the conclusion of the presence of a unit root is misleading. Models with constant coefficients have been found to perform poorly in terms of their ability to examine the

[1] Becker, Enders and Hurn (2004) model multiple breaks as smooth or fuzzy. They use a trigonometric expansion to approximate the known functional form of the time-varying regression coefficient. González and Teräsvirta (2008) propose a different and simpler specification which can accommodate both sharp and smooth shifts in the mean giving what they term a time-varying autoregressive (TV-AR) process.

effects of policy changes or forecasting in the context of oil price shocks and other major regime changes. These issues can be addressed within the cointegration framework.

Standard tests for cointegration are either residual-based or VAR-based. Residual-based tests are appropriate if it is known that the variables under investigation are linked by at most a single cointegrating relationship. The Engel and Granger (1987) test consists of application of the ADF test to the residuals from the supposed cointegrating regression estimated by OLS. The critical values are given by Mackinnon (1991) In the more general case in which there may be multiple cointegrating relationships, the Johansen (1988) reduced rank VAR procedure is employed. Consider a VAR(k) in m variables denoted by the vector y which may be written as

$$\Delta y_t = \kappa + \sum_{j=1}^{k-1} \Theta_j \Delta y_{t-j} + \alpha\beta' y_{t-1} + u_t \qquad (9)$$

column of β gives the weights of the variables in the relevant cointegrating vector and each column of α gives the reaction of the n variables to departures of this vector from its equilibrium value. The number of cointegrating vectors ***(r)*** can be obtained by verifying the significance of the characteristic roots of Π. If the variables in y_t are not cointegrated then the rank of Π equals zero and the characteristic roots will be equal to zero. Johansen suggested two tests for determining the cointegrating vectors:

In the context of the grains-energy nexus, the changes in U.S. biofuels policy listed in Table 1 may have resulted in structural breaks which in turn may have affected the cointegration properties of these prices. The stability of long-run relationships can be statistically assessed by testing for structural change of the cointegrating vector between the variables. The standard tests for cointegration are not appropriate, since they suppose that under the alternative hypothesis the cointegrating vector is time-invariant (Gregory and Hansen, 1996). Tests will therefore fail to reject the null hypothesis of no cointegration. They propose a test for cointegration that allows for a single shift in either the intercept alone or the entire coefficient vector with an unknown break date.

The Gregory and Hansen (1996) null hypothesis is no cointegration against the alternative hypothesis of cointegration with a single unknown break-date. This extends the Engel and Granger (1987) test but continues to suppose a single and known candidate cointegrating vector

$$\left[\beta_1 I\left(\pi \le \pi_0\right) + \beta_2 I\left(\pi > \pi_0\right)\right]' y_{\pi T} \tag{10}$$

Their procedure computes the ADF test statistic for each possible break-date and takes the smallest value (the largest negative value) across all the possible break dates. The test statistic is $ADF^* = \inf_{\pi\in(0,1)} ADF\left(\pi\right)$. They report critical values for up to four regressors.

5. Data

We analyze the logarithms of nominal average weekly cash prices of corn, wheat, crude oil, and gasoline from 2000 to 2012 and ethanol prices from January 2003 to December 2012 giving a total of 678 observations (and 475 observations for ethanol prices observations prior to the construction of lags. [2] We choose spot rather than futures prices since we are keen to represent transactions prices[3] and because we have only a very limited history for ethanol prices, where weekly U.S. ethanol cash prices are only available from November 2003. Data sources are as follows:

Corn (CBOT and US), crude oil and wheat cash prices: USDA and Chicago Mercantile Exchange. Ethanol cash price: Illinois Department of Agriculture.Gasoline cash price: U.S. Energy Information Administration (EIA).[4]

Table 2 reports the non-stationarity tests. The ADF tests fail to reject the null hypothesis of the presence of a unit root at the 5% level for crude oil, gasoline, corn and wheat but not got ethanol. We also report the Phillips-Perron (1988) test, which may be more robust to the equation specification. The results are similar but this test now marginally fails to reject non-stationarity for ethanol at then 5% level. In summary, these results clearly demonstrate non-stationarity of the crude oil, gasoline, corn and wheat prices but indicate that it may be problematic to regard

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[2] In an earlier draft of the paper, we also included the soybeans price.

[3] Irwin et al. (2009) document convergence problems in the U.S, wheat futures market. This may imply additional noise in the wheat cash prices around that time.

[4] Corn, wheat crude oil prices:www.bloomberg.com; ethanol prices: www.agr.state.il.us; gasoline prices: www.eia.gov.

the ethanol price appear to be stationary. It is possible the difference in the results for ethanol and the other four commodities is a consequence of the relatively short sample that we have available for ethanol prices.

6. Univariate test results

The discussion in section 3 underlined that there have been a large number of policy changes affecting the U.S. biofuels market. These changes were summarized in Table 1. Other developments may have also affected energy and grains prices in both energy and grains markets. These may include rapid economic growth in China and other Asian emerging economies, depreciation of the U.S. dollar, decades of underinvestment in agriculture, low inventory levels, poor harvests, financializiation and speculative forces – see the discussion in section 3. Any of these changes may have resulted in structural breaks in the time series representations of these series. The initial step of our analysis is to look for breaks in the autoregressive representations of these prices.

We implement the Bai and Perron procedure (2003) to test for the presence of multiple breaks in each of these price series setting the maximum of breaks to be five. The *sup-F* test rejects this null hypothesis of no breaks against the alternative of five breaks. We use the BIC to select the preferred number of breaks for each of the prices. The BIC selects five breaks for crude oil gasoline, corn and wheat and four breaks for ethanol. The results, reported in Table 3, confirm that each of the series saw multiple breaks over the sample period.

Table 4 reports the month in which the Bai and Perron (2003) tests identify breaks. There is considerable commonality in the break dates. The first set of breaks occurs in the summer of 2002 with a common break month for corn and wheat. This may be associated with the U.S. Farm Bill provisions on Farm Security and Rural Investment which was passed on and become effective in May 2002 – see Table 1. This act directed the increase agricultural subsidies by about 16.5 billion dollars resulting in a probable increase in the production of grains such as corn and wheat as well as the oil seeds.

The second set of breaks occurs in the summer of 2004 and appears common across both the two energy commodities and the two grain. The breaks in the summer may be associated with the introduction of the tax credit in the beginning of 2004 that was given to blenders for each gallon of ethanol mixed with gasoline – see Table 1. The August 2005 break in the ethanol series follows closely after the July 2005 enactment of the RFS1 standard – see section Table 1.

The third set of breaks, which occurs in the fall of 2006, and which is again common to the two grains as well as crude oil, comes shortly after the June 2006 MTBE ban and hence may reflect biofuels developments – see section Table 1.

The fourth group of breaks occurs in the fall of 2008. It seems likely that these reflect the effects of two important acts that were both passed in 2008, the Food, Conservation, and Energy Act, and The Energy Improvement and Extension Act of 2008 – see Table 1. The former was a 288 billion dollar, five-year agricultural policy bill and was a continuation of the 2002 Farm Bill. It included agricultural subsidy as well as pursuing areas such as energy, conservation, nutrition, and rural development. The latter extended existing tax credits for renewable energy initiatives, including cellulosic ethanol and biodiesel development, and wind, solar, geothermal and hydro-electric power.

The final set of breaks occurs in 2010 after EPA. These breaks are seen as coming after the finalization of the National Renewable Fuel Standard Program (RFS2) for 2010 and beyond in February 2010. Among its interventions, it increased the required renewable fuel volume to be achieved by 2022 see Table 1 and the discussion in section 3.

In summary, the univariate structural break analysis shows that the price series under study to have been subject to multiple breaks over the sample period. Inference on the origin of these breaks within a univariate framework is necessarily casual and based on temporal coincidence. However, these estimates do suggest that biofuels-related legislation in 2006 may have been the key event that impacted both the crude oil and the grains markets.

7. Multivariate test results

The multivariate methodology set out in section 4 requires that the price series are non-stationary. This is unclear for ethanol. Inclusion of ethanol in the cointegration-based analysis is therefore problematic both because it would force use of a shorter sample and because the analysis throws up the ethanol price itself as a trivial cointegrating vector. We therefore, reluctantly, drop the ethanol price from the remainder of the analysis.

We have established that the remaining four price time series under consideration are non-stationary and have shown that they experienced structural breaks over the period under consideration. We are interested in the long run relationships, if any, between these series. We consider three questions:

a) Can we consider the two grains series (corn and wheat) as moving together over the long run? Since they are both non-stationary this requires that they should be cointegrated. Since they experience breaks, these breaks must be common, i.e. they must co-break. If these conditions are satisfied, we can think of a common long run grains price.
b) Can we consider the two energy series (crude oil and gasoline) as moving together over the long run? The same considerations apply as with corn and wheat. If these conditions are satisfied, we can think of a common long run energy price.
c) Supposing an affirmative answer to the first two questions, is there any long run relationship between the grains prices and energy prices? If not, can we identify such a relationship once we allow for structural breaks?

Table 5 reports the Johansen (1989) cointegration tests for the four-vector of prices. We fail to reject the null hypothesis that the $\alpha\beta'$ matrix in equation (9) is of rank 1 or less at the 10 per cent level and at rank 0 at the 5 per cent level. This suggests that the four prices are related by one or two stationary combinations of cointegrating vectors.

The hypotheses set out at the start of this section indicate that there may be two such vectors, the first linking crude oil and gasoline and the second corn and wheat. The first two columns of Table 6 therefore report the results of two bivariate reduced rank tests which confirm the presence of both energy and a grains cointegrating vector. We conclude that the weaker evidence in Table 5 arises out of the lower power associated with implementation of the test with four price series.

The cointegration of corn and wheat implies that these two series must co-break. Any structural breaks in one of the two series must correspond with breaks in the other series since otherwise cointegration would fail – see the discussion in section 5. Taking the grains cointegrating relationship, we can test for co-breaking by imposing the estimated break dates reported for wheat in Table 4 on the corn price series. Regarding these dates as known, we perform a set of Chow tests for five structural breaks. We perform these tests sequentially. Denote the five estimated corn break dates as $\pi_1 T$, $\pi_2 T$ …, $\pi_5 T$. We first consider the sub-sample [1: $\pi_2 T$] and test for a break at $\pi_1 T$. We then consider the sub-sample [$\pi_1 T$+1: $\pi_3 T$] and test for a break at $\pi_2 T$ and so forth to the sub-sample [$\pi_4 T$+1: T] and test for a break at $\pi_5 T$. We follow the same procedure for crude oil and gasoline using the estimated gasoline break dates from the same table.

Table 7 reports the Chow test for wheat breaks on corn prices. The test statistic shows that we reject the null hypothesis of no structural breaks for all the five break dates. This results confirms that corn and wheat co-break. Similar results are obtained when we impose gasoline breaks dates on crude oil prices implying that also crude oil and gasoline co-break. The results are reported in Table 8.

Returning to Table 6, the final column repeats the Johansen bivariate cointegration exercise for crude oil and corn where we fail to reject the null hypothesis that the $\alpha\beta$' matrix is of rank zero implying no cointegration. The same conclusion results from the other three possible bivariate combinations (gasoline-corn; gasoline-wheat and crude oil-wheat) since if both the two energy prices and the two grains price are cointegrated but crude oil and corn are not cointegrated, no other energy-grain combination can be cointegrated. These results allow us to take the crude oil – corn relationship as representing the entire energy-grains link for the remainder of this analysis.

The absence of cointegration between the grains and energy prices leads us to the third question posed at the start of this section, namely whether cointegration results if we allow for structural breaks in the cointegrating relationship. As above, we look at the crude oil – corn relationship and report results from the Gregory and Hansen (1996) test for cointegration in the presence of a structural break over the sample (weekly, 7 January 2000 to 28 December 2012) and using a lag length of nine lags selected using the AIC. We run this test in GAUSS. The modified ADF test given by equation 15 is -5.1639 which is to be compared with the 5 per cent critical value provided by Gregory and Hansen (1996) of -4.61. We reject the null hypothesis of no cointegration in the corn-crude oil price relationship once allowance is made for structural a break. This allows us to conclude that corn and crude oil are cointegrated in the presence of one break.. Given the presence of multiple breaks in both corn and crude oil, it seems possible that there could be more than one break date in the corn crude oil cointegrating vector.

We conduct a Bai and Perron (2003) multiple break date analysis on the corn-crude oil cointegrating vector. As in the corresponding univariate tests reported in section 6, we set a maximum of five breaks and select an actual number using the BIC criteria. The procedure selects four as the ideal number of break dates. The break dates in the cointegrated vector are reported in the final column of Table 4 (see section 6). The 2008 break is therefore the sole instance of co-breaking in that relationship while the remaining four breaks define five energy-grains price regimes. The identified break dates are similar to the ones we identified in the single price series confirming that corn and crude oil do co-break. Moreover, the break dates stay in line with policy interventions in the agricultural and energy markets. The 2006 break date occurs after the RFS1 was enacted and the MTBE band became effective. Both these two factors contributed to the increase in ethanol production which in turn increased the demand for corn and its price thus affecting its relationship with crude oil prices. The VEETC tax credit is reduced and the blend limit becomes eminent in January 2010. The combination of these two factors induced a reduction in biofuel production and this imposes a break in the corn-crude oil price relationship. Importantly, one of the regime changes is coincident with the introduction of the MTBE ban in June 2006 – see section 3.

These results imply that the cointegrating vector linking crude oil and corn should be stationary within each of the five regimes defined by the break points listed in the final column of Table 4. In Table 8, as a robustness check, we report the ADF and Phillips-Perron tests for non-stationarity within these regimes. Both the ADF and PP tests reject the null hypothesis of the presence of a unit root. On the basis of these results, we conclude that there has been a relationship between energy and grains prices over the period we have investigated but that this relationship has been subject to regime changes. We can relate one of these changes, that which is identified as having taken place in the fall of 2006, with a prior change in U.S. biofuels policy, namely the June 2006 introduction of the MTBE ban.

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8. Conclusions

Food commodities prices increased over the recent decade attracting the attention of market participants and policy makers. Biofuels have been identified as one of the main drivers of high food prices over the most recent decade. High fuel prices combined with legislative policies have been accused of increasing biofuel production causing high food prices and establishing a link between energy and agricultural prices. There has been a huge controversy on the food versus fuel debate and the role of biofuels as well as biofuel policies. The United States has undergone major policy changes over the recent decade, changes that have affected both the energy and agricultural sector. The June 2002 Farm Bill, the two RFS Energy Acts in 2005 and 2007, the 2006 MTBE Ban and the Energy Improvement and Extension Act are some of the policy interventions that the US implemented in the recent decade.

We conduct a rigorous econometric analysis to verify whether there has been a structural change in both the prices and price relationships of grains and energy commodities. We are motivated by the fact that prices and price relationships react to both market factors and policy regimes. These factors are not static over time and may change in response to policy and market developments. In addition, the failure to detect and consider breaks induces misspecification which may adversely affect the inference procedure leading to poor forecasting. In particular, ignoring existing breaks in the prices would lead to a biased rejection of the null hypothesis of stationarity in the series. Our multiple structural breaks analysis on both food energy commodity prices show that the commodities experienced the breaks in line with the policy interventions. In particular, the 2006 break date common in the commodities analyzed marks the "ethanol gold rush" which was induced by the 2006 MTBE ban and the 2005 RFS1 Energy Act.

Our analysis also provides evidence of long-run cointegrating relationship between corn and wheat on the one hand and crude and gasoline on the other. Cointegration implies that the series co-break. We find that corn and wheat do co-break, and crude and gasoline co-break. We however find that corn and crude are not cointegrated and thus do not co-break. Given this last result we attempt to verify whether corn and crude are cointegrated if we incorporate structural breaks. We find that corn and crude are cointegrated when we allow for two break dates. The first break date in June 2006 matches the MTBE ban while the January 2009 break date appears after the Energy Improvement and Extension Act. Our results show that US biofuel policy and policy regimes have both played a major role in defining the relationship between food and energy markets in the recent decade. In particular, it has enforced the link between energy and grain prices. Our results have strong policy considerations as we show that in order to have a sensible food policy it is necessary to de-link food and energy prices.

Tables and Figures

Table 1
Policy Interventions

Date	Policy Intervention
June 2002	US Farm Bill-Farm Security and Rural Investment
May2004	VEETC introduced for ethanol blending with gasoline
July 2005	Renewable Fuels Standard (RFS1) - Energy Act
June 2006	MTBE ban became effective - liability waivers not granted
December 2007	Renewable Fuels Standard (RFS2) - Energy Act
May 2008	The Food Conservation and Energy Act
October 2008	The Energy Improvement and Extension Act
January 2009	VEETC credit tax reduced to $0.45 per gallon
February 2010	EPA finalizes RFS Program for 2010 and beyond
December 2011	The VEETC tax credit expired
January 2012	Import tariffs on ethanol for fuel were cut

Table 2
Stationarity tests

	Lag length	ADF	Phillips-Perron	1% c.v	5% c.v
Crude oil	4	-1.146	-1.290	-3.430	-2.860
Gasoline	1	-1.640	-1.748		
Corn	3	-0.935	-0.899		
Wheat	2	-1.528	-1.592		
Ethanol	3	-3.270	-2.836	-3.442	-2.871

The table reports the ADF and Phillips-Perron test statistics for non-stationarity and the associated critical values. Lag lengths were selected using AIC and SC criteria.
Sample (crude oil, gasoline, corn and wheat) : weekly, 7 January 2000 to 28 December 2012 (678 observations).
Sample: (ethanol): weekly, 28 November 2003 to 28 December 2012 (475 observations)

Table 3
Bai and Perron (date) sup *F* break tests

Crude oil	47.42***	Corn	108.13***
Gasoline	51.83***	Wheat	20.40***
Ethanol	6.11***		

The table reports the Bai and Perron (date) sup F test for structural breaks using a maximum of 5 structural breaks.
Critical values: 1% 4.91; 5% 3.91; 10% 3.4700
*** significant at the 1% level, ** at the 5% level, *at the 10% level
Sample (crude oil, gasoline, corn and wheat) : weekly, 7 January 2000 to 28 December 2012 (678 observations);.
Sample: (ethanol): weekly, 28 November 2003 to 28 December 2012 (475 observations)
The BIC selects 5 breaks for crude oil, gasoline, corn and wheat; 4 breaks for ethanol.

Table 4
Estimated break dates

	Crude Oil	**Gasoline**	**Corn**	**Wheat**	**Ethanol**	**Crude oil - corn**
2002	August	May	June	June	pre-sample	July
2004	July	April	September	July		September
2005					August	
2006	November	March	October	September		September
2007					January	
2008	October	October	October	August	October	
2010	October	November	October	August	September	September

The first five columns of the table reports the month and year in which each of the five breaks identified by the Bai and Perron (2003) procedure occurs. The final column of the table reports the four break dates identified by the Bai and Perron (2003) procedure for the cointegrating vector linking crude oil and corn – see section 7.
Ethanol sample starts in November 2003 precluding of any break prior to this date.

Table 5
Multivariate Johansen (1988) cointegration tests

	χ^2 statistic	p-value
rank ≤ 0	81.21**	0.000
rank ≤ 1	28.44*	0.072
rank ≤ 2	9.709	0.309
rank ≤ 3	1.452	0.228

The table results of the Johansen (1989) reduced rank tests and the associated tail probabilities for the VAR(4) linking the prices of crude oil, gasoline, corn and wheat. The VAR length was chosen using AIC.
Sample: weekly, 7 January 2000 to 28 December 2012 (678 observations)
** significant at the 5% level, * at the 10% level.

Table 6
Bivariate Johansen (1989) cointegration tests

	crude oil – gasoline	**corn – wheat**	**crude oil – corn**
VAR length	5	2	4
rank = 0	49.56** [0.000]	21.41** [0.005]	8.613 [0.410]
rank ≤ 1	1.171 [0.297]	1.674 [0.196]	0.660 [0.416]

The table results of three pairs of bivariate Johansen (1989) reduced rank tests. Tail probabilities are given in parentheses. The VAR length was chosen using AIC.
Sample: weekly, 7 January 2000 to 28 December 2012 (678 observations)
** significant at the 5% level, * at the 10% level.

Table 7
Test for co-breaking: corn and wheat

Break date	Sample	Statistic	1% c.v.	5% c.v.	10% c.v.
28-Jun-2002	07-Jan-2000 – 16-Jul-2004	4.913^{***}	3.100	2.253	1.873
16-Jul-2004	05-Jul-2002 – 22-Sep-2006	4.486^{***}	3.104	2.256	1.875
22-Sep-2006	23-Jul-2004 – 29-Aug-2008	5.789^{***}	3.107	2.258	1.875
29-Aug-2008	29-Sep-2006 – 06-Aug-2010	10.334^{***}	3.113	2.261	1.878
06-Aug-2010	05-Sep-2008 – 28-Dec-2012	19.344^{***}	3.102	2.255	1.874

The table reports the results of a sequence of Chow tests for corn prices based on the wheat break dates reported in Table4.
*** significant at the 1% level, ** at the 5% level, *at the 10% level.

Table 8
Test for co-breaking: crude oil and gasoline

Break date	Sample	Statistic	1% c.v.	5% c.v.	10% c.v.
10-May-2002	07-Jan-2000 – 16-Apr-2004	4.902^{***}	3.100	2.254	1.873
16-Apr-2004	17-May-2002 – 24-Mar-2006	6.083^{***}	3.109	2.259	1.876
24-Mar-2006	23-Apr-2004 – 17-Oct-2008	3.523^{***}	3.096	2.252	1.872
17-Oct-2008	31-Mar-2006 – 05-Nov-2010	6.966^{***}	3.094	2.251	1.871
05-Nov-2010	24-Oct-2008 – 28-Dec-2012	5.639^{***}	3.102	2.255	1.874

The table reports the results of a sequence of Chow tests for crude oil prices based on the gasoline break dates reported in Table4.
*** significant at the 1% level, ** at the 5% level, *at the 10% level.

Table 9 Piecewise stationarity tests							
Regime	Initial date	Final date	Lag length	ADF	PP	5% c.v.	10% c.v.
1	07-jan-2000	12-Jul-2002	3	-2.878*	-2.702*	-2.888	-2.578
2	19-Jul-2002	17-Sep-2004	10	-2.750*	-2.618*	-2.889	-2.579
3	24-Sep-2004	22-Sep-2006	4	-3.011**	-2.623*	-2.890	-2.580
4	06-Oct-2006	10-Sep-2010	3	-2.621*	-2.723*	-2.883	-2.573
5	17-Sep-2010	28-Dic-2012	3	-3.177**	-3.528**	-2.889	-2.579
The table reports the ADF and Phillips-Perron test statistics for non-stationarity and the associated critical values for the cointegrating vector linking crude oil and corn prices for the five regimes defined in the final column of Table 4. Lag lengths were selected using SC.							

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