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Agricultural commodity prices and oil prices: mutual causation

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Abstract

The world market price of many commodities including US corn (maize) peaked sharply in 2008. The US Energy Policy Act (2005) led to a rapid rise in demand for corn ethanol as a partial substitute for gasoline in the USA. In this paper we report analysis of weekly prices of corn, wheat, sugar and crude oil, together with monthly series derived from those and other weekly prices, for two consecutive seven year periods: 1999-2005 and 2006-2012. We find strong evidence of cointegration between prices in both series, but only weak evidence of causation. We conclude that the normal stimulus to production of agricultural commodities given by a price increase is sufficient to restore equilibrium in supply and demand within a period of about a year.

Keywords: Crops, biofuel, sustainability.

Introduction

The impact of oil price shocks on various aspects of the world economy has been assessed in numerous publications. Many investigators have reported findings of correlation between prices of oil and other widely traded commodities. For example, Blanchard and Riggi (2009) estimated vector autoregressions (VARs) before and after 1984 in six variables: GDP, employment, wages in USA, the GDP deflator, the US CPI, and the nominal price of oil; they noted two changes which modified the transmission mechanism of the oil shock: vanishing wage indexation and an improvement in the credibility of monetary policy. By treating oil price shocks as exogenous (perhaps arising from arbitrary supply manipulation) some investigators have found causality traceable to oil price. Nazlioglu and Soytas (2012) confirmed the influence of world oil prices on prices of several agricultural commodities. Wang *et al* (2013) reported that oil price shocks affect stock markets differently depending on whether or not the stock market is located in an oil exporting country. There is also evidence of causality in other directions; Barsky and Kilian (2004) assessed the role of exogenous political events in influencing the oil market, and found some reverse causality from macroeconomic variables to oil prices. Baumeister and Peersman (2008), in a Bayesian VAR framework, distinguished supply from demand oil price shocks, and found that oil supply shocks accounted for a smaller fraction of the variability of the real price of oil, implying a greater role for oil demand shocks. Beckmann and Czudaj (2013a) analysed the time-varying causality from nominal dollar exchange rates to nominal oil prices using a vector error correction model (VECM), and using the same model they that changes in nominal oil prices are responsible for ambiguous real exchange rate effects (Beckmann and Czudaj, 2013b).

Peaks in world oil price, coupled with concern about carbon emissions contributing to global warming, have stimulated demand for biofuel as a substitute motor fuel, resulting in government mandates and directives to expand the use of biofuel. In the USA, the Energy Policy Act of August 2005 specified the amount of biofuel to be mixed with gasoline sold to be 4 billion US gallons in 2006, increasing to 6.1 billion by 2009 and to 7.5 billion US gallons by 2012. In the EU, the Renewable Energy Directive (Directive 2009/28/EC) established the target of 10 per cent of energy in road transport coming from renewable sources in each of the EU Member States by 2020. Zhang *et al* (2010) found that demand for ethanol influences short-run agricultural commodity prices, while Ciaian and Kancs (2011) quantified interdependencies in the energy-bioenergy-food price system. The diversion of crops from food use to biofuel production threatens to place further strain on world food supply already facing the implications of climate change (Knox, Morris and Hess, 2010), with impact potentially greatest on poorer farmers (Wheeler and Kaye, 2010).

In this paper we investigate the effect on food prices of the rapid increase in demand for corn ethanol following the US Energy Policy Act (2005). We test a data set of weekly agricultural commodity prices, and also a derived dataset of monthly estimates of cost of subsistence; we examine the price relationships in the seven year period (1999-2005) in comparison with relationships in the following seven year period (2006-2012).

Data

As proxy for the price of oil we use the monthly average of the ICE Brent Crude Futures Contract (Front Month) (www.theice.com/products/219) in US$/barrel. Figure 1 shows the weekly oil price sequence and the prices of three agricultural commodities, corn (maize), wheat and refined sugar. A gradual rise in the price of oil from 2003 is reflected in the price of sugar, but not in the prices of corn and wheat. The corn and wheat prices peaked jointly in 2004, independently of the oil price. The co-movement between oil and sugar during this period relates to the large quantities of Brazilian sugar used for biofuel between 2004 and 2005. Figure 2 depicts the continuation of the same four sequences on the same scale. The prices of corn and wheat increased with the price of oil in 2009, and again in 2011. The price of sugar declined during 2012, reflecting the capacity of agricultural production to respond quite rapidly to a demand shock.

As proxy for cost of subsistence, we use the data in the Biclab tables (www.biclab.com) which provide a calculation derived from commodity price data series weighted in proportion to the actual annual consumption of each commodity, scaled to provide a food calorie intake of 2800 kcal/day/cap, with other individual consumption scaled correspondingly. This calculation has four components representing the daily cost per capita of food, electrical power, fuel and materials averaged for each calendar month (McFarlane, 2012), seasonally adjusted and compensated for inflation using the GDP dollar deflator to reflect real goods prices (http://data.worldbank.org/indicator/NY.GDP.DEFL.KD.ZG). Figure 3 shows that the real price of a basket of food items weighted in proportion to actual household consumption remained almost constant, at about 45 US cents per capita per day, while the total cost of subsistence, which takes account of actual household consumption of energy, housing and apparel as well as food, increased from about 70 cents to about $1.30 per capita per day towards the end of this period, reflecting the significance of oil price in the household cost of subsistence. Figure 4 shows the continuation of the same three sequences on the same scale. The oil price peak in 2008 is reflected in a temporary increase in real cost of subsistence to above $2 per capita per day (in US$'2000). The sustained increase in oil price in 2011 and 2012 is reflected in the rise in real price of household food to about 80 cents and of subsistence to about $1.60 per capita per day during 2011 and 2012.

Statistical analysis

It is well known that commodity price series tend to be cointegrated (two or more time series are said to be *cointegrated* if they share a common stochastic drift), and that it is helpful to remove the effect of unit roots (i.e. the persistent drift in value, which is characteristic of a *non-stationary* variable) by using first-difference of logarithms of the variables (Brown and Cronin, 2010). Tables 1and 2 show the descriptive statistics of the four sets of sequences. Tables 3 and 4 shows the results of augmented Dickey-Fuller (ADF) unit root tests on each sequence before and after taking the first-difference of the logarithms. Tables 3 and 4 demonstrate that all the original series in all 4 datasets have unit roots, and all the unit roots are eliminated by taking the first difference of the logarithms. Tables 5 and 6 show results of Johansen (1992) tests for cointegration within the datasets. From visual appraisal of the series shown in Figures 1 to 4 it appears likely that there is cointegration among the variables. Tables 5 and 6 list the results of formal tests. In Table 5, results are shown for corn, crude oil and wheat in the two time periods, and in Table 6 results for crude oil with either food or cost of subsistence. From the results for all tests, we see that the null hypothesis of no cointegrating vector is the most probable.

Tables 7 and 8 show estimated VAR coefficients and *t*-values. Additional information about the relationship between the variables is obtained by estimating a vector autoregression (VAR) for each set, VAR being appropriate for situations in which causation may be in either direction, which is the case here (as indicated in the introduction). Table 7 shows that the weekly values of wheat and corn are not continually affected by previous oil price in the period 1999-2005, and and Table 8 indicates only mild effect in the 2006-12 period. Tables 7 and 8 show that the food price and cost of subsistence are mildly influenced by oil price in both periods.

Discussion

The diversion of quantities of corn from food use to ethanol production in 2006 caused consternation in some special interest groups, for example Farm Econ (www.farmecon.com), and anxiety in the United Nations Food and Agriculture Organisation and in the United States Congress, as reported by Bullis (2011) and by Carducci (2013). Baffes and Dennis (2013) confirmed that, of the factors affecting food price, it was crude oil prices that mattered the most during the peak period in food prices. Zilbermann *et al* (2012) noted that, while oil prices influence gasoline prices, which, in turn, influence ethanol prices, fuel prices do not significantly affect food prices; they found that the introduction of biofuel had a lower impact on food commodity prices when biofuel production was not competing with food crops for resources, such as land and water. Thus, the expansion of sugarcane ethanol in Brazil and second-generation biofuels grown on non-agricultural lands were likely to have a much smaller impact on food prices than the expansion of corn ethanol.

The statistical analysis reported in this paper, while being limited to a small selection of agricultural commodities, tends to confirm that there is linkage between the world price of crude oil and the price of internationally traded corn.

Zhang *et al* (2010), referred to above, further concluded that their results supported the effect of agricultural commodity prices as market signals, leading to markets reverting rapidly to equilibrium after a demand or supply shock. The analysis in this paper is consistent with Zhang *et al* in confirming this effect, i.e. that prices of agricultural goods revert to levels set by equilibrium of supply and demand within about a year. As mentioned above, it has been shown elsewhere that the oil price both affects and is affected by other factors such as currency exchange rates, as well as by supply and demand for a range of commodities. This analysis could therefore be strengthened by extending the datasets to include commodity production and consumption quantities, and quantities of year-end stocks. This data is to some extent obtainable from public sources.

Conclusion

In this paper we have analysed two related sets of data spanning seven years before and after US legislation was passed in 2005 which had the effect of diverting some US corn production from food to biofuel. This US law played some part in a demand-led food price increase, but the increase led to only minor and temporary disruption of food supply, and agricultural markets for cereal grains rapidly returned to equilibrium. During 2008 there was a general peak in world prices of most traded commodities, which briefly took a cost of subsistence indicator above US$2 per capita per day. The subsistence indicator has since then remained consistently below $2 in real terms.

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Figure 1 - Nominal weekly world commodity prices 1999-2005

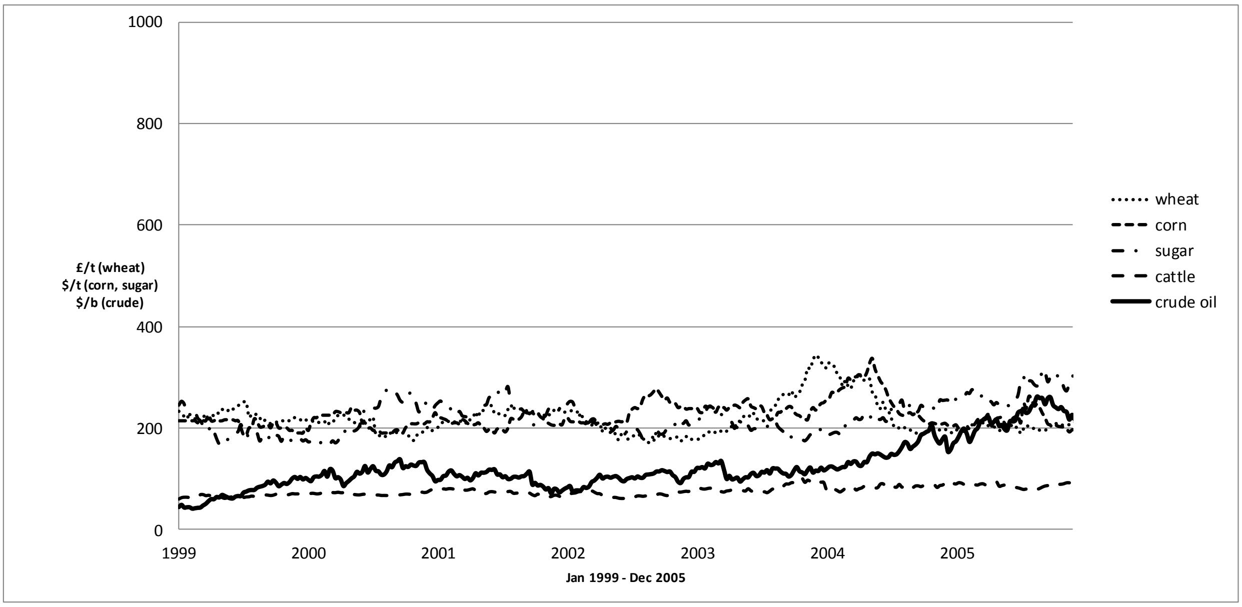

Figure 2 - Nominal weekly world commodity prices 2006-2012

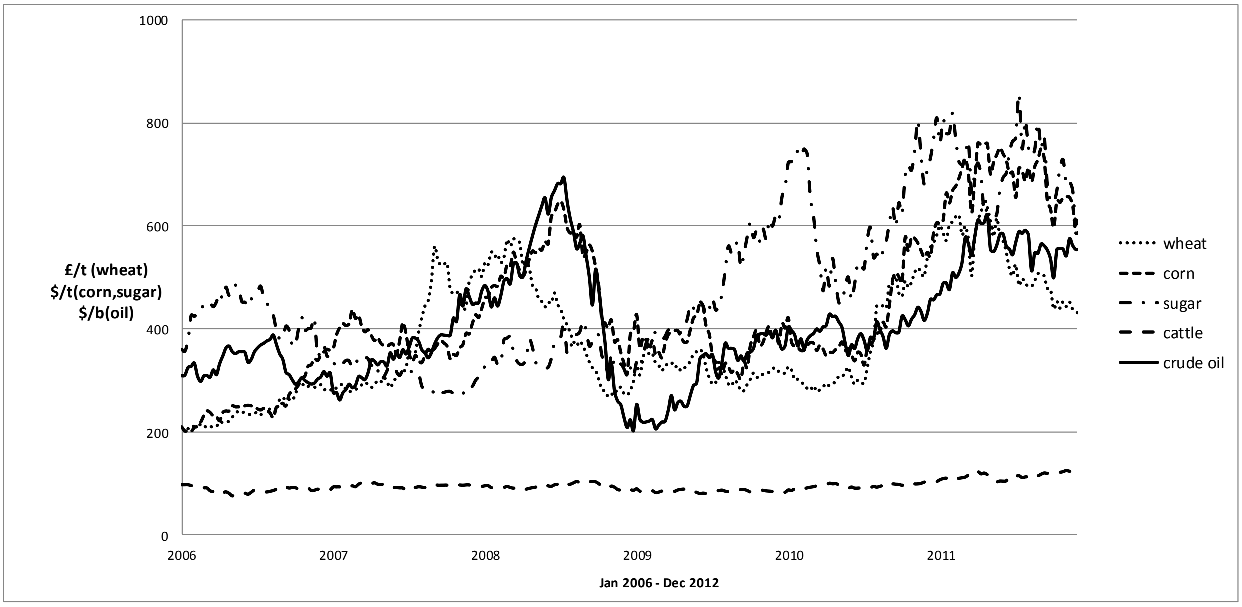

Figure 3 – monthly cost of subsistence vs oil price 1999-2005
(adjusted for inflation to US$'2000)

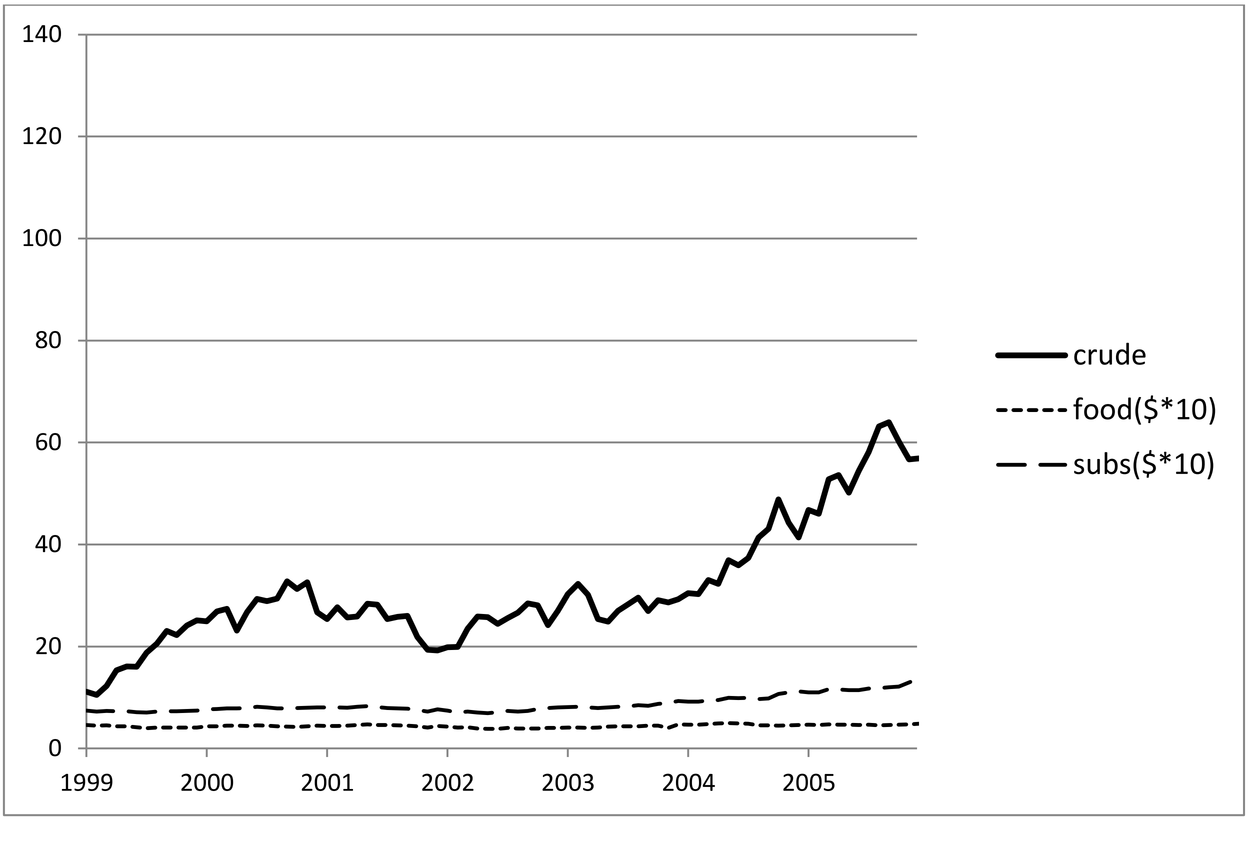

Figure 4 – monthly cost of subsistence vs oil price 2006-2012
(adjusted for inflation to US$'2000)

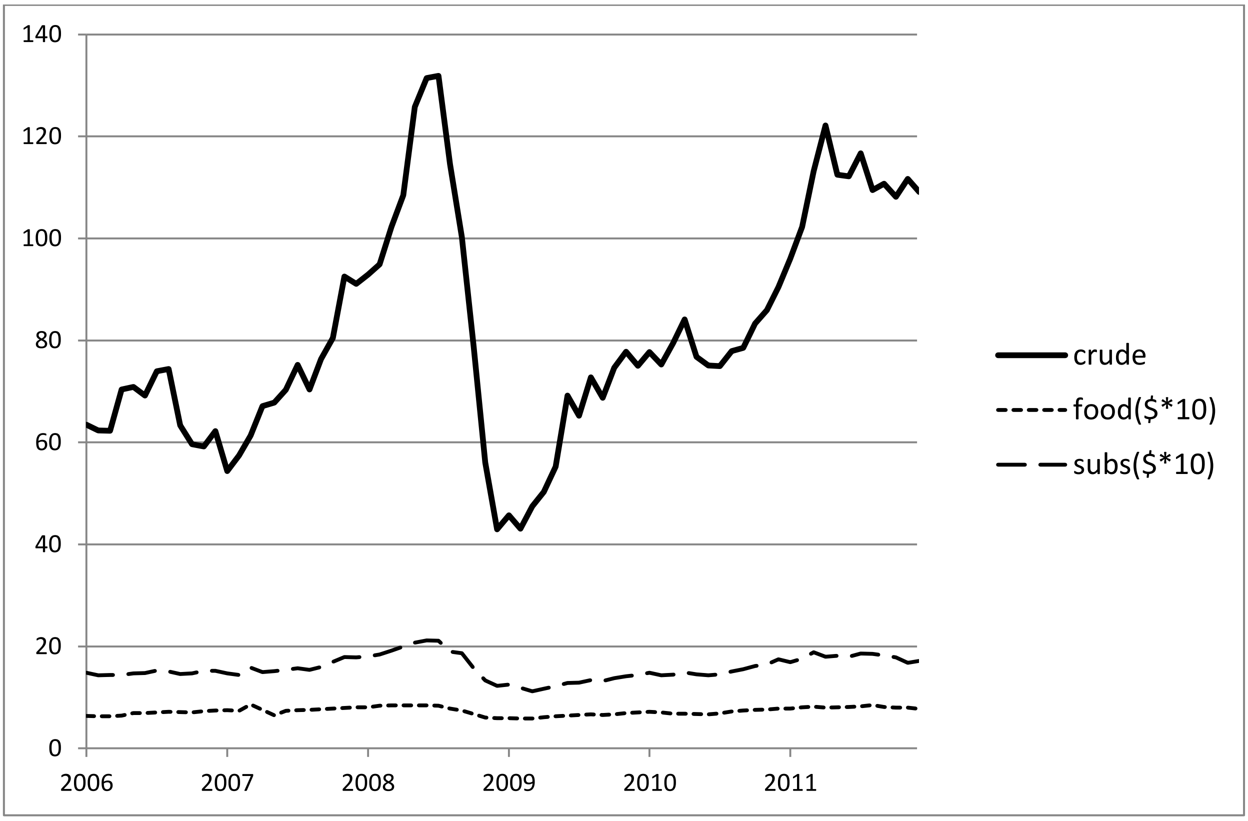

Table 1 – Descriptive statistics of weekly data series

Sources: corn – CBOT($/t), crude oil – Brent IPE ($/b), refined sugar – LIFFE ($/t), wheat – LIFFE (£/t)

1999 Jan - 2005 Dec (N=336)				
variable	mean	min	max	std.dev
corn	223.7	186.0	337.0	25.9
crude_oil	31.1	10.2	65.4	12.1
sugar	223.6	166.4	340.0	35.3
wheat	72.7	57.0	114.6	11.1
corn_log_d1	0.000	-0.098	0.166	0.029
crude_oil_log_d1	0.005	-0.254	0.133	0.053
sugar_log_d1	0.001	-0.127	0.099	0.035
wheat_log_d1	0.000	-0.169	0.094	0.028

2006 Jan - 2012 Dec (N=336)				
variable	mean	min	max	std.dev
corn	474.4	200	830.6	162.87
crude_oil	85.8	40.36	138.75	23.4
sugar	496.8	268.5	857	151.12
wheat	135.0	68.5	217.25	42.26
corn_log_d1	0.004	-0.165	0.221	0.047
crude_oil_log_d1	0.002	-0.212	0.225	0.050
sugar_log_d1	0.001	-0.188	0.131	0.049
wheat_log_d1	0.003	-0.134	0.166	0.039

Table 2 – Descriptive statistics of monthly data series

(all monthly data seasonally adjusted and compensated for inflation)

Sources: crude oil - (as above), food and subsistence - Biclab tables www.biclab.com

Units: crude - $’2000/barrel, food – {$’2000/cap/d}*10, subsistence – {$’2000/cap/d}*10

1999 Jan - 2005 Dec (N=84)				
variable	mean	min	max	std.dev
crude	31.1	10.5	64.0	12.0
food	4.4	3.8	5.0	0.3
subs	8.7	7.0	13.8	1.6
crude_log_d1	0.020	-0.200	0.226	0.085
food_log_d1	0.001	-0.111	0.161	0.033
subs_log_d1	0.007	-0.051	0.089	0.025

2006 Jan - 2012 Dec (N=84)				
variable	mean	min	max	std.dev
crude	85.8	43.0	131.9	23.2
food	7.4	5.9	8.9	0.8
subs	16.0	11.2	21.2	2.2
crude_log_d1	0.007	-0.339	0.225	0.089
food_log_d1	0.003	-0.153	0.159	0.045
subs_log_d1	0.002	-0.170	0.098	0.044

Table 3 – Unit root testing of weekly data series

Unit root test with 3 lagged differences

Significance thresholds: 10% -1.62, 5% -1.94, 1% -2.56

	corn	corn_log_d1	crude_oil	crude_oil_log_d1	sugar	sugar_log_d1	wheat	wheat_log_d1
sample range: 1999 Jan, 2005 Dec, T = 332								
test statistic:	-0.36	-8.33	1.12	-9.37	0.62	-8.86	-0.45	-8.38
sample range: 2006 Jan, 2012 Dec, T = 332								
test statistic:	0.77	-8.85	0.16	-8.18	-0.33	-8.92	0.72	-7.84

Table 4 – Unit root tests of monthly data series

Unit root test with 3 lagged differences

Significance thresholds: 10% -1.62, 5% -1.94, 1% -2.56

	crude	crude_log_d1	food	food_log_d1	subsistence	subsistence_log_d1
sample range: 1999 Jan, 2005 Dec, T = 80						
test statistic:	1.88	-4.40	0.32	-4.16	2.69	-2.50
sample range: 2006 Jan, 2012 Dec, T = 80						
test statistic:	-0.14	-3.87	0.20	-3.98	-0.12	-3.11

Table 5 – Johansen cointegration test of weekly data series

The table includes the probability value (pval), and the probability test levels for the likelihood ratio (LR) for each rank

Johansen Trace Test for: corn / crude_oil / wheat

included lags (levels): 2 trend and intercept included

r0	LR	pval	90%	95%	99%
sample range:		1999 Jan, 2005 Dec, T = 334			
0	31.28	0.434	39.73	42.77	48.87
1	10.92	0.874	23.32	25.73	30.67
2	3.53	0.803	10.68	12.45	16.22
sample range:		2006 Jan, 2012 Dec, T = 333			
0	39.66	0.101	39.73	42.77	48.87
1	15.41	0.548	23.32	25.73	30.67
2	6.82	0.374	10.68	12.45	16.22

Table 6 – Johansen cointegration test of weekly data series

The table includes the probability value (pval), and the probability test levels for the likelihood ratio (LR) for each rank

Johansen Trace Test for: crude / food

r0	LR	pval	90%	95%	99%
sample range:	1999 Jan, 2005 Dec, T = 83				
included lags (levels):	1	trend and intercept included			
0	13.3	0.717	23.32	25.73	30.67
1	2.4	0.925	10.68	12.45	16.22
sample range:	1999 Jan, 2005 Dec,, T = 82				
included lags (levels):	2	trend and intercept included			
0	24.58	0.070	23.32	25.73	30.67
1	6.65	0.393	10.68	12.45	16.22

Johansen Trace Test for: crude / subsistence

r0	LR	Pval	90%	95%	99%
sample range:	1999 Jan, 2005 Dec, T = 82				
included lags (levels):	2	trend and intercept included			
0	24.91*	0.064	23.32	25.73	30.67
1	5.5	0.536	10.68	12.45	16.22
sample range:	2006 Jan, 2012 Dec, T = 82				
included lags (levels):	2	trend and intercept included			
0	19.68	0.247	23.32	25.73	30.67
1	4.39	0.687	10.68	12.45	16.22

Number of included lags determined by Akaike Information Criterion (AIC)

Table 7 – VAR estimation results for weekly series

t-distribution values in square brackets

endogenous variables: corn_log_d1, crude_oil_log_d1, sugar_log_d1, wheat_log_d1

sample range: 1999 Jan, 2005 Dec, T = 331

endogenous lags: 4

		corn_log_d1	crude_oil_log_d1	sugar_log_d1	wheat_log_d1
corn_log_d1	(t-1)	0.041	-0.067	-0.04	-0.011
		[0.724]	[-0.653]	[-0.607]	[-0.205]
crude_oil_log_d1	(t-1)	-0.015	-0.035	0.012	-0.04
		[-0.510]	[-0.631]	[0.342]	[-1.328]
sugar_log_d1	(t-1)	0.003	-0.078	0.074	-0.012
		[0.058]	[-0.880]	[1.303]	[-0.256]
wheat_log_d1	(t-1)	0.062	0.024	-0.143	0.02
		[1.074]	[0.225]	[-2.090]**	[0.351]
corn_log_d1	(t-2)	0.078	0.048	-0.003	-0.048
		[1.404]	[0.465]	[-0.050]	[-0.877]
crude_oil_log_d1	(t-2)	-0.01	0.022	-0.078	-0.006
		[-0.317]	[0.396]	[-2.172]**	[-0.207]
sugar_log_d1	(t-2)	-0.021	0.056	-0.051	0.067
		[-0.434]	[0.638]	[-0.895]	[1.435]
wheat_log_d1	(t-2)	0.034	0.018	-0.065	0.089
		[0.584]	[0.168]	[-0.936]	[1.556]
corn_log_d1	(t-3)	-0.02	0.004	-0.088	0.016
		[-0.356]	[0.034]	[-1.343]	[0.299]
crude_oil_log_d1	(t-3)	-0.06	0.117	0.02	0.012
		[-1.976]*	[2.111]**	[0.566]	[0.387]
sugar_log_d1	(t-3)	0.018	-0.008	0.023	0.008
		[0.379]	[-0.089]	[0.406]	[0.163]
wheat_log_d1	(t-3)	0	-0.005	-0.031	0.028
		[0.005]	[-0.049]	[-0.457]	[0.496]
corn_log_d1	(t-4)	0.03	0.079	-0.075	0.059
		[0.530]	[0.766]	[-1.141]	[1.083]
crude_oil_log_d1	(t-4)	-0.001	-0.127	-0.014	0.01
		[-0.035]	[-2.254]**	[-0.384]	[0.329]
sugar_log_d1	(t-4)	-0.009	0.106	0.01	-0.002
		[-0.196]	[1.221]	[0.174]	[-0.040]
wheat_log_d1	(t-4)	0.155	-0.22	0.039	0.013
		[2.674]***	[-2.075]**	[0.565]	[0.225]

sample range: 2006 Jan, 2012 Dec, T = 333
endogenous lags: 2

		corn_log_d1	crude_oil_log_d1	sugar_log_d1	wheat_log_d1
corn_log_d1	(t-1)	-0.011	0.087	0.001	0.128
		[-0.183]	[1.379]	[0.022]	[2.538]**
crude_oil_log_d1	(t-1)	-0.09	-0.106	-0.06	-0.152
		[-1.601]*	[-1.838]*	[-1.019]	[-3.28]***
sugar_log_d1	(t-1)	-0.041	0.04	-0.06	-0.052
		[-0.741]	[0.709]	[-1.042]	[-1.132]
wheat_log_d1	(t-1)	0.06	0.065	0.068	0.082
		[0.847]	[0.893]	[0.912]	[1.405]
corn_log_d1	(t-2)	0.077	0.249	0.089	0.023
		[1.239]	[3.921]***	[1.378]	[0.449]
crude_oil_log_d1	(t-2)	-0.048	0.067	-0.12	-0.002
		[-0.848]	[1.149]	[-2.022]**	[-0.052]
sugar_log_d1	(t-2)	0.065	-0.037	0.038	0.033
		[1.174]	[-0.642]	[0.651]	[0.722]
wheat_log_d1	(t-2)	0.08	-0.026	-0.145	0.059
		[1.139]	[-0.358]	[-1.989]**	[1.027]

Table 8 – VAR estimation results for monthly series

t-distribution values in square brackets

endogenous variables: crude_log_d1, food_log_d1, subs_log_d1

		crude_log_d1	food_log_d1	subsistence_log_d1
sample range:	1999 Jan, 2005 Dec, T = 81			
endogenous lags:	2			
crude_log_d1	(t-1)	0.176	-0.098	-0.068
		[1.428]	[-2.246]**	[-1.896]*
food_log_d1	(t-1)	0.145	-0.487	-0.315
		[0.389]	[-3.689]***	[-2.913]
subs_log_d1	(t-1)	-0.436	0.378	0.455
		[-0.874]	[2.151]**	[3.156]***
crude_log_d1	(t-2)	-0.131	-0.046	0.012
		[-1.002]	[-1.004]	[0.328]
food_log_d1	(t-2)	-0.283	-0.192	-0.05
		[-0.703]	[-1.350]	[-0.429]
subs_log_d1	(t-2)	0.114	0.329	-0.057
		[0.203]	[1.666]*	[-0.350]
sample range:	2006 Jan, 2012 Dec, T = 80			
endogenous lags:	3			
crude_log_d1	(t-1)	0.035	0.132	0.147
		[0.227]	[1.422]	[1.691]*
food_log_d1	(t-1)	0.415	-0.109	0.253
		[1.603]	[-0.702]	[1.728]*
subs_log_d1	(t-1)	0.578	0.136	-0.103
		[1.656]	[0.650]	[-0.524]
crude_log_d1	(t-2)	0.262	-0.013	0.047
		[1.662]	[-0.136]	[0.526]
food_log_d1	(t-2)	0.297	-0.198	0.221
		[1.123]	[-1.245]	[1.480]
subs_log_d1	(t-2)	-0.385	-0.173	-0.248
		[-1.054]	[-0.787]	[-1.203]
crude_log_d1	(t-3)	0.169	0.021	0.102
		[1.189]	[0.241]	[1.279]
food_log_d1	(t-3)	0.756	0.149	0.291
		[2.763]***	[0.906]	[1.882]*
subs_log_d1	(t-3)	-0.985	0.075	-0.192
		[-2.797]***	[0.354]	[-0.966]