Crude oil and agricultural futures: an analysis of correlation dynamics

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Abstract

Correlations between oil and agricultural commodity markets have varied dramatically over the past two decades, impacted by renewable fuels policy and turbulent economic conditions. Using weekly futures returns, we estimate smooth transition conditional correlation models for 12 agricultural commodities and WTI crude oil. Analysis shows markedly increased and more variable correlation between oil and most agricultural commodities futures returns. While a clear structural change in conditional correlation occurred at the time of the introduction of biofuel policy, oil and food price levels are also key influences. High correlation between biofuel feedstocks and oil is more likely to occur when both food price levels and oil price levels are high. Correlation with the oil returns is stronger for biofuel feedstocks and negligible for many other agricultural futures, suggesting that contagion from energy markets to food has been limited.

Key words: Smooth transition conditional correlation; Structural breaks; Return comovement; Biofuel; Commodity futures

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1 INTRODUCTION

Renewable fuel policies have changed the degree of integration between agricultural and energy markets, making the work of futures traders more challenging.[1] Energy and agricultural prices have long been connected on the production side, where natural gas and petroleum contribute a large part of agricultural input costs (Hertel and Beckman, 2011; Du and McPhail, 2012). However, subsidies, quotas and biofuel infrastructure development, aimed at reducing greenhouse gases, promoting energy security or renewable fuel industry development, now connect energy and agricultural prices on the consumption side as well (Hochman et al., 2010b). Increased integration between energy and agricultural futures markets over the past decade shows up in correlation dynamics.

Hedgers, speculators and investors in agricultural commodity futures will prefer contracts that offer counter-cyclical profits, paying off when other assets do not. Returns to commodity derivatives usually have low correlations with financial assets and have been attracting the interest of investors looking for diversification (Gorton and Rouwenhorst, 2006, Kat and Oomen, 2007, Chong and Miffre, 2010).[2] However any closer connections between traditional agricultural and energy commodities make the set of common state variables underlying stochastic discount factors larger. News coming out of energy markets can spillover into biofuel feedstock trading, and then into otherwise unrelated commodity markets if commodities are treated as a single asset class by investors or if there is contagion into food markets (Tang and Xiong, 2012).[3] Furthermore, macroeconomic shocks to consumer demand and business investment will transmit more readily to agricultural commodity returns via oil price shocks (Kilian, 2008). Correlation is a critical measure of financial market integration and contagion, and successful trading depends on understanding it (Pericoli and Sbracia, 2003; Forbes and Rigobon, 2002).

We apply recent advances in conditional correlation modelling to give new insights into the dynamics of correlation between returns to WTI crude oil and 12 agricultural commodity futures, including the main biofuel feedstocks, in the period covering the introduction of biofuel

[1] For an extensive survey of time series literature on biofuels, see Serra and Zilberman (2013).

[2] For an evaluation of the arguments for and against commodities as an investor asset class see Skiadopoulos (2013).

[3] Research into the excess co-movement of commodity prices began with Pindyck and Rotemberg (1990), was disputed by Deb et al. (1996), Cashin et al. (1999) and Ai et al. (2006), and has be re-examined recently by Chong and Miffre (2010) and Büyüksahin and Robe (2014) among others.

policies in the mid-2000s, sharp increases in oil and food prices in 2008 and 2010 and the financial crisis. Using time, oil prices and food prices as state variables, we track state-contingent changes in conditional correlations in this period where the variation in market and policy settings makes modelling especially informative. Up to now, most research has used multivariate GARCH (MGARCH) or dynamic conditional correlation (DCC) models to study the transmission of shocks between energy, biofuel and agricultural markets (e.g., Busse et al., 2010, Du and McPhail, 2012 and Ji and Fan, 2012).[4] The Double Smooth Transition Conditional Correlation models (DSTCC–GARCH) we estimate have some advantages over conventional DCC and MGARCH estimations that we exploit to untangle the oil-agriculture correlation dynamics (Silvennoinen and Teräsvirta, 2009a; Silvennoinen and Thorp, 2013; Koch, 2014). Our study makes four main contributions.

First, over the time period we study, renewable fuel mandates are introduced, modified and escalated, at various times and in different countries, causing a series of sudden and/or gradual structural changes in the data-generating process. While a DCC model can be adjusted for standard data breaks (Du and McPhail, 2012), the unknown timing and duration of responses to regulation makes identifying both sudden breaks and gradual changes in correlations important (Enders and Holt, 2012; Koch, 2014). Unless structural breaks are modelled, DCC or MGARCH can be dominated by local and past dynamics and over-estimate persistence.[5] Here we estimate both sharp and gradual breaks in correlation regimes and thus more clearly identify significant changes, especially those related to incremental and /or anticipated changes to policy.

Second, unlike DCC and rolling correlation models that are entirely dependent on past returns, DSTCC–GARCH helps interpret correlation dynamics. Correlations can jump or transition smoothly between a few regimes where the movement depends on latent or observable state variables. We introduce oil prices and food prices as separate transition variables, comparing their relative impact on correlation states. We use time as a proxy for latent factors such as renewable fuel policy changes or variation in macroeconomic conditions, and by including both time and oil or food prices in transition functions, we can separate out underlying macroeconomic changes from energy price effects or food price effects alone. In this way, our

[4]For a survey of volatility models, see Serra.

[5]See Koch (2014) for a comparison between DCC and DSTCC–GARCH in the closely related context of energy and carbon prices.

study complements and extends the results of Peñaranda and Rupérez Micola (2009). We find a significant role for time, oil and food prices, and their interactions, in oil-agricultural correlation dynamics.

Third, regulatory and technical constraints on biofuel production and usage mean that regime changes in correlations might be related to price thresholds (O'Connell, 2007; Doornbosch and Steenblik, 2007; Tyner, 2010). DSTCC–GARCH makes estimates of threshold parameters in the smooth transition function that identify levels effects in latent factors, such as price levels where blend walls or minimum fuel standards become binding. Our modelling adds to the threshold co-integration analysis of Natanelov et al. (2011) by searching for oil and food price levels which mark changes in correlation regimes.

Fourth, our study adds to the literature on the spillover effects of renewable energy policy on agricultural prices. The question of how much of recent swings in food prices might be linked to demand for biofuels has generated a very large body of research. Roberts and Schlenker (2010) estimate demand and supply elasticities for key food crops and attribute about 30% of the 2008 rises to biofuel demand. Hochman et al. (2010a), allowing for supply responses from OPEC, reach a lower estimate, concluding that demand factors, including concerns for food security, rather than biofuel policies, were the main drivers of the 2003–2008 commodities boom, with about 15% of food price rises in 2007 being attributable to biofuels. Carter et al. (2013) use inventories to estimate corn price increases and conclude that biofuel mandates accounted for an increase around 30% in the long run.[6] However the view that the nexus between food prices and oil prices has permanently changed is widespread (Headey et al., Ciaian and Kancs, 2011, Ajanovic, 2011, and Saghaian, 2010). Our model shows the extent to which commodities that are not used directly in renewable fuel production have been subject to the same correlation dynamics as those agricultural commodities that are. We do this by identifying and estimating the role of several common factors in the co-trending of oil and agricultural commodities.

Our results show markedly increased and more variable correlation between oil and most of the agricultural commodities futures returns we model. While a significant structural change in conditional correlation is evident at the time of the introduction of biofuel policy, price

[6] The part played by commodity index investment in linking agricultural and oil futures markets is also debated. See, for example, Tang and Xiong (2012), Hamilton and Wu (2012) and Peñaranda and Rupérez Micola (2009).

levels in oil and food markets are also important influences. Our modelling shows that very high correlation between biofuel feedstocks and oil mainly occurs at times when both food price levels and oil price are high. Integration with energy markets is stronger for biofuel feedstocks and negligible for many other agricultural futures, suggesting that contagion from energy markets to food in general has so far been limited.

In section 2 we describe biofuel policy and its potential connection with food and agricultural markets. Next we set up the econometric model and its properties, and describe the data, pricing, volatility factors and state variables used in estimation, including a discussion of the state variables used to drive correlation dynamics. Section 4 presents results for conditional volatility and correlation estimations and section 5 concludes.

2 BACKGROUND

First generation biofuels are manufactured directly from oils and starches: biodiesel is made from vegetable oils such as palm oil, soybeans, canola and rapeseed,[7] and ethanol is distilled from starchy crops including sugar, corn, wheat, and barley. Most of the biofuel used in transportation comes from ethanol (Doornbosch and Steenblik, 2007), and although still a small percentage of global transportation fuel, consumption is set to increase as the regulated minimum use of renewable fuels rises (Ciaian and Kancs, 2011). Biofuels are the third largest renewable energy source in the OECD (IEA, 2013), and while they are a very small share of total energy supply, they can take a large share of feedstock production, making the transmission of shocks from fossil fuel markets to agricultural markets very likely.

2.1 Renewable fuel policy

The U.S. gives regulatory support to biofuel production by tariff protection, subsidies or tax credits, and mandatory usage levels (Doornbosch and Steenblik, 2007).[8] The Renewable Fuel Standard (RFS), was first enacted in 2005 and later expanded under the Energy Independence

[7]Cotton seeds are also used to produce biodiesel and coffee beans are a potential source. Dutch firm Essent began using Brazilian coffee husks in electricity generation in 2007: `http://www.essent.eu/content/about_essent/news/archive/green_electricity_from_coffee_husks.html`

[8]Tax credits on ethanol to U.S. gasoline blenders were reduced in 2007–2008 and then removed at the end of 2011. They apply through most of the sample studied here.

and Security Act (EISA) of 2007 (Schnepf, 2011). The revised RFS specifies minimum quantities of biofuel usage annually, rising from 9 billion gallons in 2008 to at least 36 billion gallons in 2022.[9]

Other countries also stipulate targets for the share or blend of renewable fuel in petrol or diesel. Most targets were set in the mid-late 2000s but Brazil introduced mandatory ethanol blending as early as 1977. The European Union (EU) introduced the Biofuels Directive in 2003, aiming to have renewable sources contributing 2% of energy use in 2005 and 5.75% by 2010. But response from member countries was poor with only Sweden and Germany meeting targets by 2005 and biofuels still at only 1.4% of total EU energy use in 2006.[10] In 2007, the Commission recommended a 10% share for biofuels by 2020 (Sundström, 2008). The European Union, Australia and Canada stipulate blends of 10% (Doornbosch and Steenblik, 2007). The EU and other leading OECD producers of biofuel also protect local biofuel producers with tariffs, and subsidises production via lower excises than fossil fuels.

2.2 Regulatory and technological limits to co-movement

Freely adjusting energy markets should generate positive price correlation between biofuel and fossil fuel substitutes, but if mandatory consumption levels or other technological constraints bind, price co-movement and hence correlation may break down. At very low oil prices, for example, biofuels become uneconomic to produce and use as fuel (O'Connell, 2007; Doornbosch and Steenblik, 2007). While renewable usage targets are substantial, mandatory usage levels are still relatively low, and probably have not forced the production and use of biofuels at uneconomic prices very often. One indicator of whether the RFS is a binding constraint is the market for Renewable Identification Numbers (RIN) in the U.S. (Thompson et al., 2009).[11]

[9]The EISA prescribes volume requirements on four nested sub-categories of biofuels, creates standards for greenhouse gas emission reduction and prescribes that biofuels must be made from 'renewable biomass'. This last set of regulations was designed to prevent the possible worsening of greenhouse gas emissions if the RFS encouraged land clearing to grow biofuel feedstocks or substitutes. The result was that the 'feedstocks' used to make biofuels must not be produced on virgin land cleared or cultivated after December 2007 either domestically or overseas (Schnepf, 2011).

[10]After some shocks to gas supplies in 2006 when the Russian supplier Gazprom refused to export to the Ukraine, with spillover effects on several other European countries reliant on Russian gas supplies, the Heads of State and Government meeting in Brussels in March 2006 planned to increase biofuel use in transport to 8% by 2015 and renewable energy generally to 15%. Large increases in bioethanol and biodiesel production capacity were planned.

[11]Evidence of compliance with the production and blending rules set by RFS is established by the issuance of a Renewable Identification Number for each gallon of renewable fuel. RINs are good for two years compliance

While Schnepf (2011) argues that RIN values have been low because the minimum blending requirements have not been binding, Tyner (2010) notes that the price of RINs doubled in the fourth quarter of 2008 after a dramatic decline in oil prices which coincided with a reduction in ethanol production capacity, so that blenders had difficulty meeting the regulatory minimums. Normal correlations might have broken down when the RFS was a binding constraint.

Another potential boundary on biofuel-fossil fuel correlation is the 'blend wall', that is the technical or regulatory limit on the amount of biofuel that can be added to gasoline. If the blend wall is binding and biofuels cannot easily be moved to markets where blends are more flexible, in periods of high oil prices there may be an excess supply of biofuels. Tyner (2010) observes that the blend wall became a binding constraint on the ethanol market in the summer of 2009 when ethanol appeared to be in oversupply, and prices were driven by the price of corn, rather than by the demand side pressure of energy prices. Furthermore, in a detailed review of the various constraints on the US ethanol market from 2005-2012, Abbott (2014) argues that production capacity for ethanol was more important than the RFS and blend wall to short-run pricing for most of the period.

The state of binding and non-binding constraints depends on the interaction between the rising RFS, the technical constraints of the blend wall, production capacity, corn stocks and prices for other fuels. The correlation between biofuel commodity prices and oil prices is likely to be weaker if and when mandatory usage, production or blending constraints are binding.

3 MODEL

We model the direct link between crude oil and 12 heterogenous agricultural commodities. By including biofuel feedstocks and other agricultural products, we can find differences in the size and variation in integration between agricultural commodities at different distances from energy markets. The models also identify the timing, direction and strength of correlation regime changes and the relative importance of state variables to the regimes. We are specifically looking for sharp or gradual breaks during the 2005-2009 period when policies changed the most, for

obligations and a firm can meet up to 20% of its current obligations from last year's RINs. In addition, blending companies that more than meet the regulatory standards can sell their excess RINs to blenders who are under the regulated volume, so that RINs are substitutes for purchases of biofuels (Schnepf, 2011).

switches to low correlation when either the RFS or blend wall become binding, and also looking for threshold levels of oil or food prices at which those switches might occur.

We estimate the model in three stages. First, we de-mean returns, accounting for systematic and idiosyncratic pricing factors, seasonality and time dependence. Next we investigate the impact of several exogenous factors on the volatility of each commodity return. Once these effects have been accounted for, we examine the co-movements between the commodity returns, linking them to observable indicators such as oil prices and food prices. Adequately clearing the mean and volatility is necessary for reliable estimates of the correlations.

3.1 Returns

We compute returns to WTI oil and 12 agricultural commodity futures, including grains and oilseeds, meat and livestock, and food and fibre from 2 May 1990 to 9 March 2011. We take the average of the collateralized weekly log commodity i futures return on the two most active contracts at time t, $y_{it,F}$:

$$y_{it,F} = \frac{1}{2}\sum_{k=1}^{2} \tilde{r}_{i,t,\tau_k} + r_{f,t}, \tag{1}$$

where $\tilde{r}_{i,t,\tau_k}$ is the log return to future contract with maturity τ_k and $r_{f,t}$ is the weekly T-bill rate.[12] The Appendix reports all data sources.

3.2 Conditional mean

The conditional mean is a function of common and idiosyncratic pricing factors, $x_{ip}, p = 1, ..., P$, and ARMA terms to capture seasonality and time dependence (Silvennoinen and Thorp, 2013), so that

$$y_{it} = \delta_{i0} + \sum_{p=1}^{P} \phi_{ip} x_{ip,t-1} + \sum_{j=1}^{J} \delta_{ij} y_{i,t-j} + \sum_{m=1}^{M} \delta_{im} \varepsilon_{i,t-m} + \varepsilon_{it}. \tag{2}$$

Common systematic factors are the short rate (3-month US Treasury Bill) and the corporate yield spread (Moody's AAA Corporate Bonds and the T-bill) and these are included in all mean

[12] Returns are computed from Wednesday–Wednesday closing prices or the closing price from the preceding Tuesday where Wednesdays are missing. The daily futures price data are continuous and we compute the return by closing out on the last Wednesday of the month before expiry and then "purchasing" the next nearest futures contract. Collateralizing is equivalent to viewing the investor as holding a risk-free investment equal in value to a long position in the futures contract.

equations, along with changes in USD exchange rates where relevant. Inventory conditions (convenience yields) for each commodity are proxied by the interest-adjusted basis (the log difference in the future and spot price for the commodity), and autoregressive terms filter seasonal effects.

3.3 Conditional volatility

Conditional variances of the futures returns are a function of price components, movements in exogenous factors, and the recent history of the commodity volatility. We incorporate the past volatility in an autoregressive manner using the first-order GJR–GARCH model of Glosten et al. (1993). Specifically, the conditional variance of commodity i follows the process

$$h_{it} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \delta_i I^-(\varepsilon_{i,t-1})\varepsilon_{i,t-1}^2 + \sum_{j=1}^{J} \phi_{i,j} f_{j,t-1}^{(c)} + \sum_{k=1}^{K} \psi_{i,k} f_{k,t-1}^{(s)} + \beta_i h_{i,t-1}, \tag{3}$$

where $I^-(\cdot)$ is equal to one whenever the argument is negative, otherwise it takes on the value zero, $f_j^{(c)}$, $j = 1, \ldots, J$ are the exogenous factors common to all commodities, and $f_k^{(s)}$, $k = 1, \ldots, K$ are the factors specific to particular commodity i.

Studies of commodity markets show the importance of spillovers and asymmetries in volatility models (Serra; Tang and Xiong, 2012; Silvennoinen and Thorp, 2013). Here, each volatility equation includes the common systematic factors yield spread, short rate and the commodity basis. Equity market conditions and investor sentiments are proxied by weekly lagged levels of the CBOE volatility index, VIX (Bekaert et al., 2011; Coudert and Gex, 2008; Cheng et al., 2012). Exchange rate variation is modelled via the lagged change in the DXY U.S. dollar futures index (giving the value of the USD against six major world currencies). Food market conditions are included via the lagged weekly value of the Food and Agriculture Organization (FAO) price index, and energy market conditions via the implied volatility of NYMEX crude oil futures options to capture volatility spillovers from energy markets (Serra).[13] The interest of non-commercial traders such as financial investors, hedge funds, money managers or speculators in agricultural commodity futures is measured by the lagged percentage of long open interest (OI), where available, and the lagged difference between (percentage) long and short open interest by non-commercial traders divided by total percentage non-commercial interest (DOI), $DOI_t =$

[13]Implied volatility data are available from the authors on request.

$(long\%_t - short\%_t)/(long\%_t + short\%_t + spread\%_t)$ (Gorton et al., 2013; Silvennoinen and Thorp, 2013).

3.4 Conditional co-movement

We want to test whether co-movements in oil and agricultural commodity returns can be linked to specific observable indicators, and if so, how the strength of the co-movement is affected by the changes in levels of any given indicator. We also want to see if the timing of changes coincides with changes to biofuel regulations or market conditions. Co-movements are easiest to interpret when analyzed as conditional correlations. To achieve the most accurate insights possible, we focus only on bivariate relationships.

We incorporate observable indicators, or transition variables, through the Smooth Transition Conditional Correlation (STCC) GARCH modelling framework, as set out in Silvennoinen and Teräsvirta (2009, 2013). In the STCC GARCH model, the oil-agricultural commodity correlation is allowed to move between two extreme values that we define below and label as $P_{(i)}, i = 1, 2$. At any point in time, the conditional correlation P_t is a convex combination of the two extreme correlation values, where the share of each is given by a logistic transition function. The transition function depends on an observable state variable (in this case, time, oil prices or food prices). As the state variable passes through a threshold, the logistic function switches on or off, moving the correlation from P_1 to P_2 or the reverse. Another parameter in the transition function decides the speed of the switch. Slow transition speeds make P_t an intermediate combination the extreme correlations for a period of time. Fast transition speeds mean that P_t goes from one correlation extreme to the other in one step. The DSTCC–GARCH model allows for up to two transition variables simultaneously being linked to time-varying correlations.

We test for the number of extreme correlation states and related transition functions by starting with a constant level, then testing to see if the dynamics are better fit to two (STCC) or four (DSTCC) extremes. We begin by estimating the Constant Conditional Correlation (CCC) GARCH model of Bollerslev (1990), $P_t = P$, where P_t is the conditional correlation matrix of the filtered returns ε_{it} and ε_{jt} of commodities i and j. Then, we test the transition variables for relevance in indicating correlation movements. This is done individually and jointly. (See Silvennoinen and Teräsvirta (2009, 2013) for details.) Failing to reject the null hypothesis of irrelevance of the transition variable(s) will maintain the simple model whereas a rejection will allow us to estimate a model incorporating the test variable(s).

3.4.1 DSTCC–GARCH structure

In the original STCC–GARCH model of Silvennoinen and Teräsvirta (2015), the conditional correlations are modelled as:

$$P_t = (1 - G_t)\, P_{(1)} + G_t P_{(2)} \tag{4}$$

where $P_{(1)}$ and $P_{(2)}$ are constant correlation matrices defining the extreme levels between which the time-varying correlation matrix P_t moves according to the transition function $G_t \in (0, 1)$. G_t is the logistic function:

$$G_t = G(s_t; c, \gamma) = \frac{1}{1 + exp(-\gamma(s_t - c))} \tag{5}$$

where s_t is a transition variable, c defines the location of the transition, and γ is the speed of the transition. We abbreviate this model by STCC(s_t). It then follows that, when $s_t << c$, the transition function G_t is approximately zero, thus moving the conditional correlation matrix P_t towards the extreme state $P_{(1)}$. When $s_t >> c$, G_t is approximately one, and P_t approaches the extreme state $P_{(2)}$.

The smoothness of the path between the extreme states is governed by the parameter γ: the larger the value, the more abrupt the change in P_t. As $\gamma \to \infty$, the smooth transition becomes a threshold. The extension to the double transition (DSTCC–GARCH) model is natural and discussed in detail in Silvennoinen and Teräsvirta (2009a). In the DSTCC(s_{1t},s_{2t}) model, the conditional correlations are now modelled as

$$P_t = (1 - G_{2t})\,[(1 - G_{1t})\, P_{(11)} + G_{1t}P_{(21)}] + G_{2t}[(1 - G_{1t})\, P_{(12)} + G_{1t}P_{(22)}] \tag{6}$$

where the conditional correlations move between four extreme states according to two transition functions G_{it}, $i = 1, 2$ each governed by a transition variable s_{it}, $i = 1, 2$, and parameters c_i and γ_i, $i = 1, 2$.

In three of the DSTCC models here, we set the second transition to depend on a linear time trend. In this way we allow for the possibility that other (possibly unobservable) factors approximated by the time trend can affect the correlations and change the way the correlations are linked to the first transition variable. The relationship between the conditional correlations and s_{1t} can thus change over time: at the early stages of the sample, the first transition function moves the conditional correlations between the extreme states $P_{(11)}$ and $P_{(21)}$, whereas towards the end of the sample those two extreme states are $P_{(12)}$ and $P_{(22)}$. In another model, we allow the other state variables to interact to produce the transitions. This model can give evidence on whether both state variables must exceed a threshold level to create stronger co-movement or whether only one state variable is driving the correlation.

3.5 Transition factors

We introduce three variables to capture changing relations between oil and agricultural commodities. First, time proxies for global growth and changes in macroeconomic conditions, tracking both the expansion leading up to, and sharp contraction that followed, the financial crisis. Correlation between returns to energy and agricultural commodities could be expected to be influenced by the growth cycle, as captured by time. Further, biofuel policies typically have increasing targets for the substitution of biofuels for fossil fuels. Other things being equal, if these targets imply that agricultural products are increasingly used as fuelstocks, then correlation between energy and agricultural futures returns may increase over time, being driven by common trends. A linear time trend t/T, where T is the sample size, serves as a proxy for such accumulated effects. This model lets us formally test whether the correlation between futures returns for crude oil and a particular agricultural commodity is adequately described as a constant level, or whether that level changed over time and whether the STCC(t/T) or DSTCC(t/T,t/T) models is better. The resulting estimated correlations can now informally be interpreted as time-varying unconditional level shifts, driven by aggregate effects.

Second, the spot (WTI) oil price level, denoted OP_t, by contrast, may exhibit zones of high and low correlation with agricultural commodities. On the supply side, high oil prices increase production costs for agricultural commodities. High oil prices also imply competition for biofuel feedstocks and high correlation with some commodities.[14] However if oil prices are

[14]Studies establish co-integrating relationships between oil and biofuel feedstock prices with 'causality' from oil

low, so that fuel producers would prefer to substitute fossil fuels for biofuels, renewable fuel policy constraints may be binding, raising demand for, and returns to, biofuel futures despite depressed energy market conditions. These situations could change the correlation state. We look to see if correlations are sensitive to oil prices in general, where any thresholds might exist, and whether there is a difference in the way correlations respond to oil price movements for biofuel compared to other agricultural commodities.

Third, the food price index introduces market conditions for food in general. It allows us to account for the relative state of the energy and food markets. If more calories are consumed as fuel rather than food, and/or cultivated land is converted to produce biofuel crops, the resulting pressure may drive other food prices up. As a result, we would expect simultaneously higher food prices and energy prices, and consequently higher correlation between energy and food commodity futures returns. Our measure of food price is the FAO index, denoted FP_t. The FAO food price index is a monthly measure of the change in international prices of a basket of food commodities, calculated as a weighted average of price indices for cereals, oils and fats, dairy, meat and sugar. Weights are the average export shares of each of the groups for 2002–2004. We translate monthly deflated observations on the FAO index into weekly observations using a cubic spline so that we can use this variable in the DSTCC models.

Since this type of time series analysis is largely atheoretical, we are not really concerned about which is the best indicator, or which is the best model, but what insights we can gain from looking at a range of relevant indicators across heterogenous commodities. Our focus is on the timing of changes and the position of state-variable thresholds that show up switches in correlation states.

Figure 1 graphs state variables, oil and food prices over the past two decades. The World Bank Poverty Reduction and Equity Group (2011) estimated that a 10% increase in crude oil prices was associated with a 2.7% increase in food prices, via substitution towards biofuel production, higher input costs and higher transportation costs. In the last 5–10 years of this sample, co-movement is obvious, and is especially dramatic during the sharp boom and bust of 2008. Food prices rose quickly again in late 2010, eventually exceeding the 2008 peak. Unfavorable weather and strong demand from China contributed to the rise, along with increasing crude oil

to biofuels (surveyed in Serra and Zilberman, 2013).

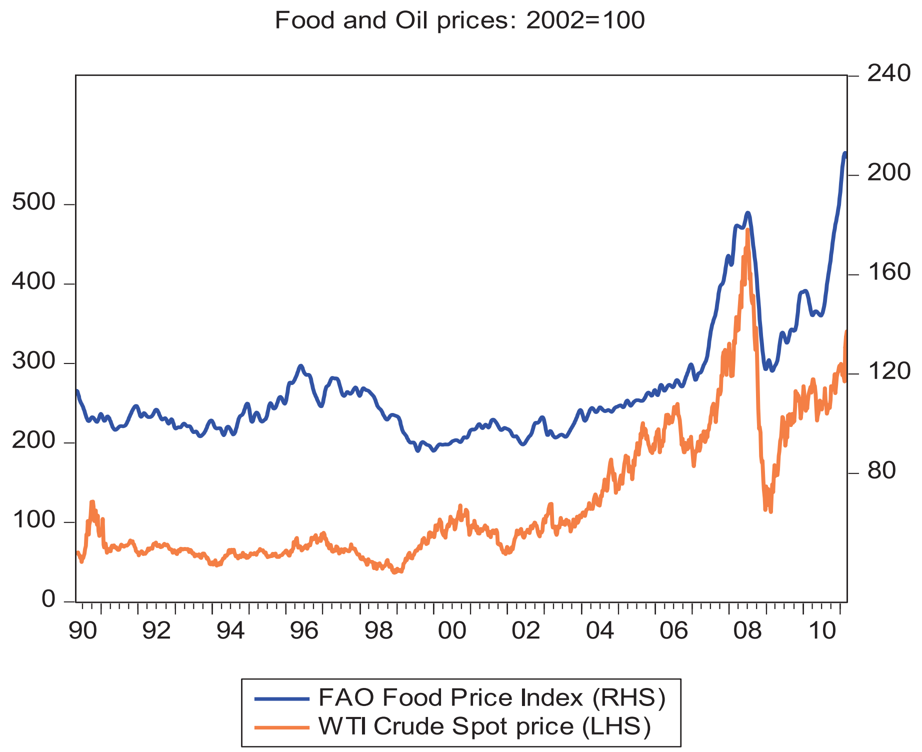

Figure 1: WTI crude oil spot price and FAO food price index, 1990-2011
Source: Food and Agricultural Organization of the United Nations; Bloomberg

prices.

4 RESULTS

4.1 Summary statistics and conditional means

Summary statistics for the annualized weekly returns to commodity futures and financial variables WTI crude spot prices, the FAO index, implied volatility of WTI crude futures, interest rates, exchange rates (DXY), equity market volatility (VIX) and means in non-commercial futures traders open interest over the sample are reported in Table 1. There is large variability in returns with sample standard deviations all exceeding 20% p.a. and many exceeding 30% p.a. The agricultural commodity futures returns generally show no or weak linear dependence with crude oil returns, as can be seen in the constant conditional correlation estimates. Most estimated correlations between crude oil and the meat and livestock futures, as well as cotton and orange juice, are not significantly different from zero. There is evidence of a weak positive correlation between crude oil and grains and oilseeds and sugar, as is largely consistent with integration between oil and biofuel feedstocks, but not with that integration expanding from oil into otherwise unrelated agricultural commodities.

For reasons of space we do not report estimated parameters for conditional mean equations, but we do note that, consistent with Hong and Yogo (2009), we find a significant relationship between commodity returns and financial asset pricing factors where lower interest rates and yield spreads predict higher futures returns.[15]

[15] The interest-adjusted basis is also significant in several cases although we do not always find the expected negative relationship between basis and futures returns (e.g., Hong and Yogo, 2009; Gorton et al., 2013). Results are available from the authors on request. We note (Hong and Yogo, 2009).

Table 1: Futures and financial asset returns series: Summary statistics, 2 May 1990 – 2 March 2011.

	mean	median	max	min	std.dev.	long OI	short OI	correl.
Food and Fibre								
Coffee	1.60	−2.23	2013.94	−1255.58	38.50	22.5	15.0	0.076
Cotton	2.20	3.67	834.61	−1263.05	28.54	19.1	19.3	0.058
Orange juice	−4.35	−2.00	1075.63	−863.02	31.09	28.1	17.0	0.037
Sugar	9.44	12.64	4754.19	−1727.57	39.29	19.5	10.1	0.107
Meat and Livestock								
Feeder cattle	7.12	8.30	358.85	−759.45	13.32	–	–	0.044
Live cattle	−0.54	54.77	597.88	−752.24	31.92	–	–	−0.033
Lean hogs	3.36	7.76	1051.70	−1012.25	33.73	–	–	0.048
Pork bellies	3.38	−5.87	1514.15	−1412.61	39.71	–	–	0.012
Grains and Oilseeds								
Corn	−3.00	−0.60	1202.80	−1250.10	27.52	19.2	10.9	0.121
Soybeans	19.76	56.08	213.50	−1036.81	21.60	21.0	11.6	−0.043
Soybean oil	3.65	6.21	744.94	−645.74	23.25	23.9	10.9	0.122
Wheat	−2.37	−4.49	1087.69	−959.47	29.45	16.5	32.4	0.074
Energy								
Crude oil	13.54	24.69	1227.95	−1913.21	35.36	10.8	9.0	–
Other financials								
Implied volatility	0.34	0.32	1.38	0.11	0.13	–	–	–
Oil prices	38.28	26.75	143.57	11.16	26.07	–	–	–
Food prices	113.12	105.31	209.10	89.00	22.82	–	–	–
Interest rate	3.51	3.92	7.85	0.00	0.27	–	–	–
USD	−0.92	−1.18	317.31	−416.24	8.55	–	–	–
Volatility	20.31	18.89	74.26	9.31	8.23	–	–	–

Table reports summary statistics for 1089 observations on weekly collateralized commodity futures returns, implied volatility (options on WTI futures), oil prices (WTI spot, level), food prices (FAO index, level), interest rates (USA 3-mth T bill), USD (DXY), and volatility (VIX, level). Long (short) OI are the mean percentage of open interest in commodity futures contracts held long or short by non-commercial traders. Correl. is the estimate correlation with return to WTI crude oil futures from CCC-GARCH model. Appendix lists all data sources and complete samples. Weekly returns are the log difference of Wednesday closing prices (or preceding Tuesday where Wednesday is missing) scaled by 100. Commodity futures returns are the average of weekly (rolling) returns on nearest to expiry and next nearest, collateralized by adding the 3-month Treasury Bill rate (adjusted to a weekly equivalent from annualized).

4.2 Estimation of conditional variances

If commodity markets are becoming more integrated with other financial markets and with each other, conditional variance equations should include a range of exogenous common and idiosyncratic factors and spillovers. Nonlinearities and asymmetries are also likely to be important. Omitting these can bias GARCH coefficient estimates and consequently bias conditional correlation estimation (Serra).

For this sample at least, direct volatility spillovers from crude oil derivatives markets are less important than other factors in explaining agricultural futures volatility. Table 2 shows that the implied volatility of oil futures prices (Impl vol) is significant only for coffee and live cattle volatility and with opposite signs. However financial factors matter, and the exclusion of these factors and other non-price related sources of volatility from previous studies might have caused biases.[16] For example, we fund that higher volatility in oil futures returns is predicted by the VIX, indicating equity and energy market integration (Barsky and Kilian, 2004). Also, increases in non-commercial futures traders' long open (OI) or long versus short interest (DOI) increase volatility of cotton, corn, wheat and live cattle returns, all components of the major investible commodities indices (Tang and Xiong, 2012). Depreciations in the USD cause increases in the DXY contract price, and these tend to dampen volatility significantly for orange juice, feeder cattle and soybeans. These results offer modest support for the importance of financial asset conditions and financial trader interest to commodity volatility.

As noted by Serra most studies of volatility transmissions between these markets do not allow for asymmetric responses, another possible source of bias. Asymmetric volatility responses to negative returns, as estimated by the GJR coefficient here, are also significant for half the commodities. The sign of the coefficient is positive for orange juice, hogs, pork bellies and soybeans, consistent with higher volatility in falling markets, and negative for coffee and wheat, consistent with stress in markets with very high prices (Deaton and Laroque, 1992; Fong and See, 2001; Carlson et al., 2007).

[16]See Serra, p.6.

Table 2: Estimated GARCH equations: Agricultural commodity and oil futures returns

	const	ADJB	BSPR	TBILL	DXY	VIX	OI	DOI	FAO Ind	Impl vol	ARCH	GJR	GARCH
Food and Fibre													
Coffee	15.888	−0.450						−6.489		−12.086	0.215	−0.232	0.560
Cotton	1.376						0.039				0.134		0.779
Orange juice	−0.123			0.025	−0.584						−0.021	0.037	1.004
Sugar	0.298										0.076		0.913
Meat and Livestock													
Feeder cattle	0.361			−0.033	−0.160						−0.001	0.116	0.873
Live cattle	1.413	−1.111				−0.046		0.974		3.715	−0.029		0.375
Lean hogs	1.135										0.010	0.090	0.884
Pork bellies	−2.918		0.927	0.732							0.071	0.130	0.781
Grains and Oilseeds													
Corn	0.816						0.034				0.082		.0859
Soybeans	0.016		0.008		−0.013						−0.065	0.558	0.778
Soybean oil	2.489			−0.202							0.105		0.719
Wheat	−6.136							2.947	0.112		0.154	−0.203	0.526
Energy													
Crude oil	−0.490					0.115					0.110		0.811

Table reports estimated coefficients of preferred conditional variance equations estimated using residuals from mean equations. GARCH models include a constant, ARCH, and GARCH terms, and where relevant at the 10% level or less, a GJR term, lagged interest-adjusted commodity basis (ADJB), the lagged yield spread (BSPR), the lagged 3-month Treasury Bill secondary market rate (TBILL), the lagged log change ($\times 100$) in the DXY US dollar future contract price (DXY), lagged levels of the VIX volatility index (VIX), lagged percentage of long open interest in the futures contract held by non-commercial traders (OI), and lagged proportional difference between net long and net short open interest held by non-commercial futures traders (DOI). All fitted values of the conditional variance are strictly positive.

4.3 Estimates of conditional correlation and correlation dynamics

We begin by testing whether the correlation dynamics are best modelled by a constant compared with either a single transition model allowing two extreme correlations, or a double transition model allowing four extreme states. Table 3 presents tests of constant conditional correlations against the single and double smooth transition alternatives. We reject the constant conditional correlation model for all commodities except orange juice and pork bellies, although meat and livestock futures are less responsive to the transition variables than grains and oilseeds and food and fibre. The dynamics of conditional correlation between oil and livestock are sensitive to time transitions rather than oil price levels or food price levels, possibly indicating latent macroeconomic factors at work, and/or the impact of fuel costs in production and transportation of livestock. On the other hand, correlations with oil futures returns are significant and more variable for most food and fibre commodities and grains and oilseeds.[17] In what follows, we will focus on one indicator at a time and take a closer look at the estimated models.

[17]Internationally, sugar, corn, soybean oil and wheat can all be directly used in the production of ethanol or biodiesel. However in the US, corn (ethanol) and soybean (biodiesel) and the primary feedstocks. Only by-products of cotton (seeds and cellulose) and coffee (husks) production can also be used in energy production.

Table 3: Tests of conditional correlation model structure

model tested against	STCC (t/T)	STCC (OP_{t-1})	STCC (FP_{t-1})	DSTCC (OP_{t-1},t/T)	DSTCC (FP_{t-1},t/T)	DSTCC (FP_{t-1},OP_{t-1})
Food and Fibre						
Coffee	0.0000	0.0000	0.0005	0.0000	0.0000	0.000
Cotton	0.0000	0.0003	0.0091	0.0008	0.0013	0.0022
Orange juice	0.8824	0.6908	0.2112	0.6151	0.4956	0.2755
Sugar	0.0003	0.0002	0.0001	0.0018	0.0001	0.0010
Meat and Livestock						
Feeder cattle	0.0297	0.2411	0.1709	0.0117	0.1243	0.5107
Live cattle	0.0273	0.0227	0.0357	0.1131	0.1196	0.1437
Lean hogs	0.0325	0.2457	0.1132	0.1362	0.0473	0.1030
Pork bellies	0.3916	0.5300	0.7406	0.7926	0.4124	0.3361
Grains and Oilseeds						
Corn	0.0533	0.0036	0.0010	0.0145	0.0090	0.0087
Soybeans	0.3617	0.7452	0.5136	0.6403	0.2283	0.0465
Soybean oil	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Wheat	0.0659	0.0863	0.0168	0.0497	0.0438	0.0486

The p-values of the tests of constant conditional correlations against smooth transition alternatives (top row). Transition variables used in the tests are time trend (t/T), lagged oil price (OP), and lagged food price (FP).

Before setting off to analyse the estimation results from the various conditional correlation models, a remark is in order. To keep the tables clear and readable, we have not reported the standard errors of the estimates of the parameters. However, all reported estimates of the extreme states of correlations are significantly different from each other. In models where the levels were not significantly different, restrictions of equal extremes were applied.[18]

4.4 Influence of time transitions on oil - agricultural correlations

If oil-agricultural futures return correlations respond to changes in biofuel policy, we expect to see gradual increases in correlations beginning in 2005-07 for corn and soy products, and possibly earlier for sugar. In fact, with the exception of orange juice and pork bellies, all commodities have an upward trend in their correlation with crude oil (Table 4). Most of the transitions are sudden indicating sharp breaks that are probably occurring around rapid changes in market conditions, including announcements of regulatory changes. The slower adjustment speed for soyoil (5.014) implies a transition to a higher correlation state later in the sample taking around 2.5 years (see Figure 2). Most of the the first steps up in correlation occur around the end of the 1990s when both energy and food prices began a long-term upward trend. However dramatic increases for soyoil, wheat, cotton and coffee occur around 2005–2007, and somewhat earlier for sugar. As noted in section 2, Brazil introduced mandatory ethanol use several decades before other major economies, and since ethanol in Brazil is mostly made from sugar, this may account in part for earlier changes in sugar-oil correlations.

Time-breaks in corn-oil correlation match up to US policy implementation: the RFS was first introduced in the US in 2005, with target ethanol percentages to be met in 2008. The latter upward shift in correlation regime (with a threshold in October 2007) is close to the structural break in corn-gasoline correlation identified by Du and McPhail (2012) in March 2008. Interestingly, corn de-couples from oil between 2005–2007 but then the correlation shifts up to a level of nearly 0.4 in late 2007–2008. Busse et al. (2012) find a similar period of instability in the European biodiesel market using a Markov-switching VECM.

This pattern is remarkably consistent with the regimes in corn markets described in Abbott (2014). Abbott describes the 2005–2007 period as the 'ethanol gold rush' when oil prices and

[18] See Silvennoinen and Teräsvirta (2009b) for the test of partial constancy.

Table 4: Estimated correlation dynamics with respect to linear time trends.

	$P_{(11)}$	$P_{(21)}$	$P_{(12)}$	$P_{(22)}$	c_1	c_2	γ_1	γ_2	s_{1t}	s_{2t}
Food and Fibre										
Coffee	−0.071	0.017	–	0.374	Oct 98	Feb 05	∞	∞	t/T	t/T
Cotton	−0.097	0.052	–	0.264	Mar 98	Dec 04	∞	∞	t/T	t/T
Orange juice	0.037	–	–	–	–	–	–	–	–	–
Sugar	−0.092	0.070	–	0.263	Oct 94	Jun 03	∞	∞	t/T	t/T
Meat and Livestock										
Feeder cattle	−0.020	0.140	–	–	Sep 03	–	∞	–	t/T	–
Live cattle	−0.162	−0.050	–	0.227	May 95	Nov 06	∞	∞	t/T	t/T
Lean hogs	−0.141	0.060	–	0.157	May 94	Jun 06	∞	∞	t/T	t/T
Pork bellies	0.012	–	–	–	–	–	–	–	–	–
Grains and Oilseeds										
Corn	0.090	−0.097	–	0.369	Nov 05	Oct 07	∞	∞	t/T	t/T
Soybeans	−0.177	−0.052	–	0.057	Jul 94	Feb 05	∞	∞	t/T	t/T
Soybean oil	0.011	−0.114	–	0.647	Sep 98	May 06	∞	5.014	t/T	t/T
Wheat	0.075	−0.019	–	0.397	May 99	May 08	∞	∞	t/T	t/T

Estimated correlations from an (D)STCC–GARCH model with time trend as a single or double transition variable. A CCC–GARCH model is maintained if the test of constant conditional correlations provide no evidence against the null. All level shifts in the estimated correlations are significant at 5% level. The symbol ∞ signifies an abrupt transition approximated by a step function.

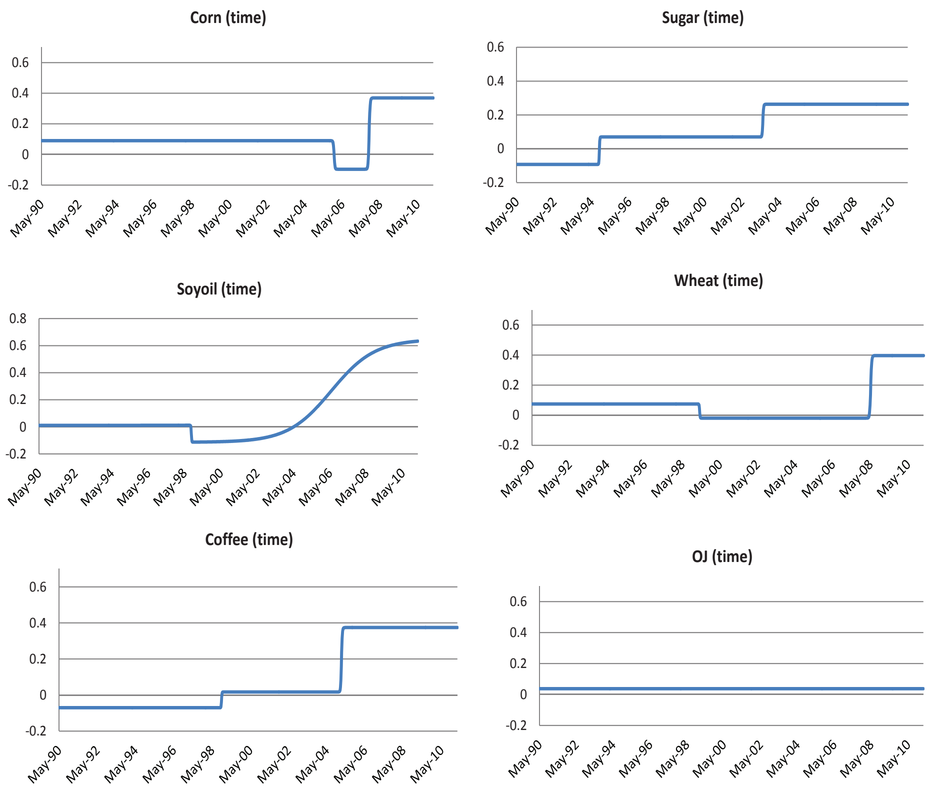

Figure 2: Time driven dynamics in oil and agricultural commodity correlations

corn prices were moving in opposite directions, but the incipient RFS created incentives to build ethanol production capacity. Food (and corn) and oil prices began to both rise in late 2007–2008, biofuel production took off, and then crashed with the financial crisis in late 2008. Recovery in 2009 ran into the constraint of the blend wall, that Abbott says was alleviated by producers selling ethanol into export markets. Panels in Figure 2 graph the correlation paths for six of the 12 commodities showing the timing of transitions to higher states for biofuel feedstocks and coffee. The time-transition models demonstrate increases in integration at the time that biofuel policy was being established, particularly between oil, grains, oilseeds and foods that could most easily be substituted for fossil fuel either as ethanol or biodiesel.

4.5 Influence of oil price level transitions on oil - agricultural correlations

Corn and sugar(outside the US) are important foodstocks and key biofuel feedstocks. Until late 2002, the oil price variation had no impact on the correlation between crude oil and sugar, whereas after that time an oil price higher than \$30 switches the correlation from zero to 0.26 (Table 5). Ethanol from sugar can often be produced at a lower cost than ethanol from corn, and the oil price inducing a high correlation threshold is also higher for corn. O'Connell (2007) estimate ethanol from sugar could be competitive at oil price ranges of \$40-\$80US p.b. around this time.

In fact the correlation dynamics between oil and corn are very different to any other commodity: early in the sample, an oil price over \$60 *reduces* the correlation from 0.1 to -0.1. But from late 2007, a high oil price indicates an *increase* in correlation from 0.1 to nearly 0.4. Our estimated threshold are similar to the estimate of \$75 by Natanelov et al. (2011).

These regime switches from the low to high correlation states in late October 2007 are also consistent with the regime timeline in Abbott (2014). Panels in Figure 3 graph the correlation paths for six of the 12 commodities show the timing of transitions to higher correlation states for biofuel feedstocks and coffee when the oil price was above the estimated threshold.

T

Even though energy is a major production cost in agriculture, we find that variations in the oil price level have no significant impact on the correlations between crude oil and orange juice, live hogs, pork bellies, and soybeans. For live cattle and wheat, an oil price level of around \$32 indicates an increase in correlation between the commodity and crude oil. For coffee and cotton the respective price level is about \$42, and for feeder cattle and soybean oil it is about \$64. For all these commodities, the higher levels of correlation induced by the oil price changes have not changed over time. This analysis shows first, that while correlations between many agricultural commodities and oil are either insensitive to the oil price level or relatively static, the two most important biofuel feedstock correlations have exhibited greater sensitivity to high oil prices since the introduction of renewable fuel policies.

Table 5: Estimated correlation dynamics with respect to lagged oil price index (OP) and a time trend.

	$P_{(11)}$	$P_{(21)}$	$P_{(12)}$	$P_{(22)}$	c_1	c_2	γ_1	γ_2	s_{1t}	s_{2t}
Food and Fibre										
Coffee	-0.025	0.333	–	–	41.735	–	∞	–	OP_{t-1}	–
Cotton	-0.017	0.250	–	–	43.857	–	∞	–	OP_{t-1}	–
Orange juice	0.037	–	–	–	–	–	–	–	–	–
Sugar	0.008	0.008	0.008	0.262	29.489	Nov 02	∞	∞	OP_{t-1}	t/T
Meat and Livestock										
Feeder cattle	0.016	0.179	–	–	63.623	–	∞	–	OP_{t-1}	–
Live cattle	-0.114	0.078	–	–	30.691	–	∞	–	OP_{t-1}	–
Lean hogs	0.048	–	–	–	–	–	–	–	–	–
Pork bellies	0.012	–	–	–	–	–	–	–	–	–
Grains and Oilseeds										
Corn	0.093	-0.092	0.093	0.388	59.884	Oct 07	∞	∞	OP_{t-1}	t/T
Soybeans	-0.043	–	–	–	–	–	–	–	–	–
Soybean oil	-0.030	0.680	–	–	65.588	–	2.279	–	OP_{t-1}	–
Wheat	0.012	0.151	–	–	33.041	–	∞	–	OP_{t-1}	–

Estimated correlations from an (D)STCC–GARCH model with lagged oil price index (OP) as one transition variable and, when appropriate, time as another. A CCC–GARCH model is maintained if the test of constant conditional correlations provide no evidence against the null. All level shifts in the estimated correlations are significant at 5% level. The symbol ∞ signifies an abrupt transition approximated by a step function.

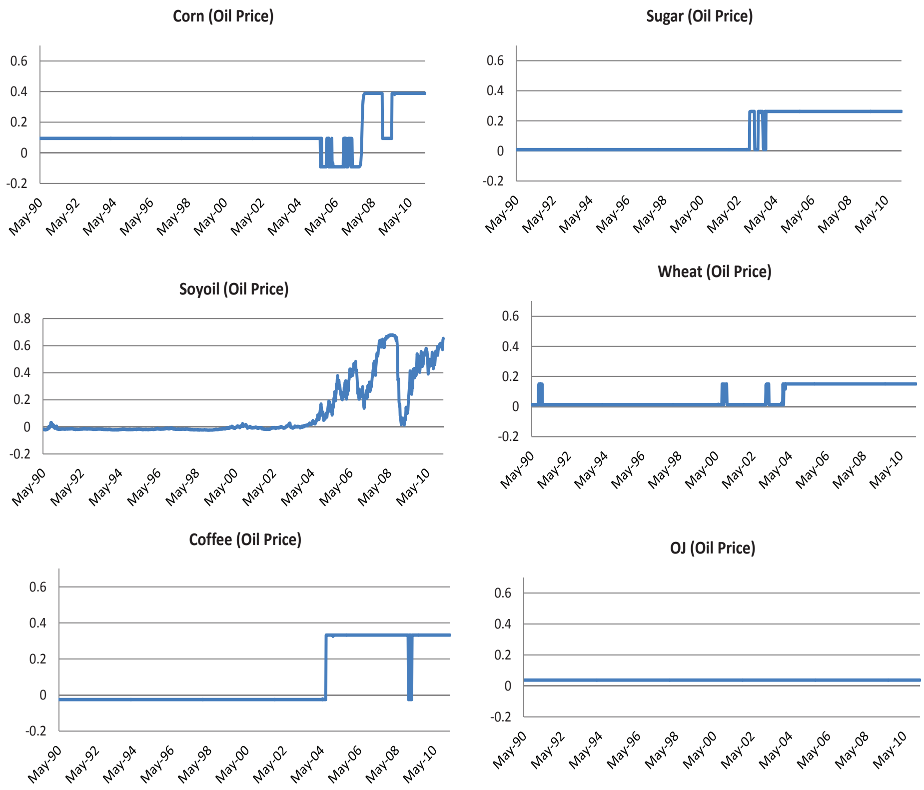

Figure 3: Oil price and time transitions in oil and agricultural commodity correlations

4.6 Influence of food price transitions on oil - agricultural correlations

Higher food prices may signal increased competition with energy markets for biofuel feedstocks, a situation that would coincide with higher energy costs generally. Further, increased demand for both food and oil is generated in periods of macroeconomic growth. The transition functions estimated here point to a role for food markets as well as energy markets in correlation dynamics. According to results in Table 6, a high food price index often signals increased correlation between crude oil and agricultural commodities .[19]

For live hogs this pattern began early in the sample before which the food price index in fact did not indicate any correlation variation. The situation is similar to cotton, for which the correlation pattern changed around the late 1990s. However for wheat, until the 1990s, the

[19]Many of the correlations show the impact of the food crisis that occurred around 1995 (see Figure 1).

correlation with oil was strongly affected by the food price level, varying from −0.15 with low food price index to 0.3 with a high food price index. The scale of those extremes has since diminished to zero and 0.1.

Table 6: Estimated correlation dynamics with respect to lagged food price index (FP) and a time trend.

	$P_{(11)}$	$P_{(21)}$	$P_{(12)}$	$P_{(22)}$	c_1	c_2	γ_1	γ_2	s_{1t}	s_{2t}
Food and Fibre										
Coffee	0.005	0.371	–	–	118.72	–	24.508	–	FP_{t-1}	–
Cotton	−0.097	−0.097	0.072	0.266	111.52	Mar 98	48.195	477.17	FP_{t-1}	t/T
Orange juice	0.037	–	–	–	–	–	–	–	–	–
Sugar	−0.068	0.286	–	–	107.37	–	3.650	–	FP_{t-1}	–
Meat and Livestock										
Feeder cattle	0.044	–	–	–	–	–	–	–	–	–
Live cattle	−0.087	0.139	–	–	114.95	–	138.26	–	FP_{t-1}	–
Lean hogs	−0.082	−0.082	−0.082	0.137	97.971	Jul 95	∞	∞	FP_{t-1}	t/T
Pork bellies	0.012	–	–	–	–	–	–	–	–	–
Grains and Oilseeds										
Corn	0.054	0.262	–	–	115.75	–	∞	–	FP_{t-1}	–
Soybeans	−0.043	–	–	–	–	–	–	–	–	–
Soybean oil	−0.127	0.619	–	–	117.73	–	2.731	–	FP_{t-1}	–
Wheat	−0.149	0.297	−0.035	0.124	102.57	Feb 97	218.25	∞	FP_{t-1}	t/T

Estimated correlations from an (D)STCC–GARCH model with lagged food price index (FP) as one transition variable and, when appropriate, time as another. A CCC–GARCH model is maintained if the test of constant conditional correlations provide no evidence against the null. All level shifts in the estimated correlations are significant at 5% level. The symbol ∞ signifies an abrupt transition approximated by a step function.

4.7 Influence of oil price and food price level transitions on oil - agricultural correlations

Results from Table 7 show that the food and fibre group, as well as grains and oilseeds, show evidence of dynamic correlations where the degree of co-movement depends on the state of *both* price indices.

Coffee, cotton and sugar need both high food prices and high oil prices to create a switch to high correlation (0.3 − 0.4) with oil. When the oil price level is low but food prices are high, coffee, sugar and cotton futures returns move to low or negative correlation with oil. High correlation with oil is really evident only when *both* food and energy markets are experiencing price pressure. These results show the importance of the interaction of both food and energy prices to the correlation dynamics.

Similarly, both high oil prices (above \$86) and high food prices (above the average for the sample) are needed to increase the correlation between corn and oil to 0.43; high oil prices alone are not sufficient. Above average food prices signal a switch to a high correlation state (0.52) for soyoil, but a crude price level above \$73 will raise the correlation further to 0.64 regardless of food price levels. Interestingly, if food prices are above average, the correlation between soybeans and crude oil as well as between wheat and crude oil weakens as oil price level increases. Panels

Table 7: Estimated correlation dynamics with respect to lagged food price index (FP) and lagged oil price index (OP).

	$P_{(11)}$	$P_{(21)}$	$P_{(12)}$	$P_{(22)}$	c_1	c_2	γ_1	γ_2	s_{1t}	s_{2t}
Food and Fibre										
Coffee	−0.008	−0.115	−0.008	0.377	107.22	34.57	∞	34.57	FP_{t-1}	OP_{t-1}
Cotton	0.023	−0.131	0.023	0.244	104.33	39.84	∞	12.49	FP_{t-1}	OP_{t-1}
Orange juice	0.037	–	–	–	–	–	–	–	–	–
Sugar	−0.141	0.074	−0.141	0.306	100.24	21.24	3.130	∞	FP_{t-1}	OP_{t-1}
Grains and Oilseeds										
Corn	0.007	0.191	0.007	0.432	108.59	85.71	2.604	∞	FP_{t-1}	OP_{t-1}
Soybeans	−0.101	0.140	−0.101	0.017	112.86	38.66	∞	170.76	FP_{t-1}	OP_{t-1}
Soybean oil	−0.127	0.515	0.637	0.637	115.87	73.15	2.836	∞	FP_{t-1}	OP_{t-1}
Wheat	−0.085	0.355	0.065	0.194	112.67	33.04	3.833	∞	FP_{t-1}	OP_{t-1}

Estimated correlations from an (D)STCC–GARCH model with lagged food price index (FP) as one transition variable and lagged oil price index (OP) as another. A CCC–GARCH model is maintained if the test of constant conditional correlations provide no evidence against the null. All level shifts in the estimated correlations are significant at 5% level. The symbol ∞ signifies an abrupt transition approximated by a step function.

in Figure 4 graph the correlation paths for six of the 12 commodities showing the timing of transitions to higher correlation states for biofuel feedstocks and coffee when the oil and food price levels passed the estimated thresholds.

4.8 Feedstock and Non-biofuel-feedstock commodities

A critical component of the biofuel debate is concerned with the crowding out food production in favor of transportation fuel. Correlation analysis allows us to make a comparison between correlation dynamics of feedstocks and other commodities. Information from the correlation

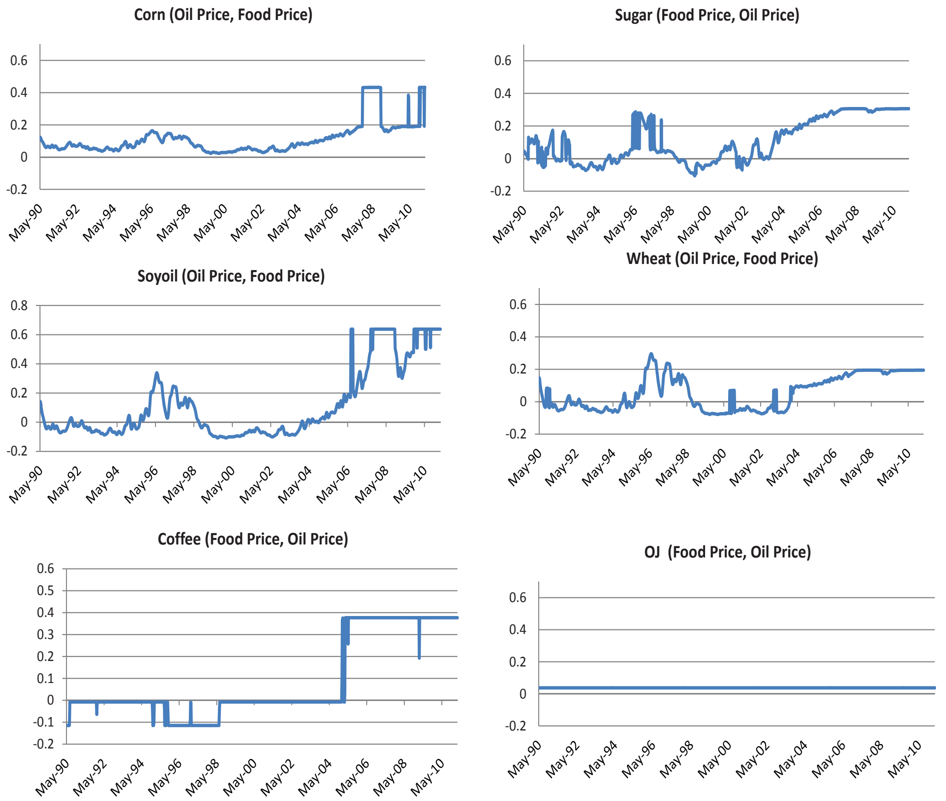

Figure 4: Oil price and and food price transitions in oil and agricultural commodity correlations

tables show that for all transition variables, conditional correlations for meat and livestock, orange juice and soybeans exhibit minimal dynamics. Commodities moderately linked to biofuel production, such as cotton, exhibit higher correlation with oil, and sensitivity to oil and food price regimes. Biofuel feedstocks, sugar, corn and soyoil have correlation regimes dynamically connected to renewable fuel policy changes and both oil and food price levels.

We reject a general finding that biofuel policy has so far created significant integration between *all* agricultural commodities and energy markets. Evidence of connection for feedstocks is clear, though extreme correlation regimes appear to depend on high prices in both food and energy markets. For many other commodities there is no evidence of increase integration, and others fall into the middle ground. Thus we concur with other studies rejecting excess co-movement such as Deb et al. (1996), Cashin et al. (1999) and Ai et al. (2006).

5 CONCLUSIONS

A large body of research has investigated whether the biofuel policies introduced because of environmental concerns of developed countries have had unintended consequences on world commodity. If agricultural commodity price dynamics are now driven by energy market shocks, developing countries may be exposed to new and large economic shocks and potential welfare losses. More generally, producers and commodity traders may find that conventional market fundamentals are less important than transmissions from energy markets. Here we assess energy and agricultural commodity market integration by mapping conditional correlation dynamics for WTI crude oil future returns and future returns for 12 agricultural commodities. While many researchers have studied cointegration relationships and volatility spillovers, to our knowledge, the contribution here is new.

We estimate DSTCC–GARCH models using weekly futures data over a sample from 1990 - 2011 that covers several food crises, biofuel policy changes, oil price cycles and the financial crisis. The models allow for both gradual and sudden switches between up to four separate correlation regimes. This technology is particularly suited to the correlation dynamics of commodity markets under policy variations and macroeconomic cycles.

First, we observe increases in correlations between most agricultural commodities and oil over the sample. For biofuel feedstocks, coffee and cotton, these correlation increases have been substantial. Second, these higher correlation regimes have generally begun in the 2005–2007 period when governments were stipulating renewable energy targets. Third, regimes in corn-oil correlations are connected both with the RFS and the ethanol production dynamics outlined in Abbott (2014) and Du and McPhail (2012). Estimated oil price thresholds (around \$40 and \$70) are consistent with estimates of prices at which biofuels can be competitive (O'Connell, 2007) and are consistent with threshold estimates from other studies (Natanelov et al., 2011). We add to the results of earlier studies, finding that for sugar, corn and soyoil both high oil and food prices are needed to create high correlation states, evidence for the importance of both food and energy markets to the level of integration between agriculture and energy, even for biofuel feedstocks. We observe that the degree of integration of an agricultural commodity with oil is very closely related to its degree of separation from the biofuel industry.

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Appendix

Bloomberg tickers and contract dates

Agriculture:

Corn: C1–C3 Comdty; Mar May Jul Dec; Soybeans: S1–S3 Comdty; Jan Mar May Jul Aug Nov; Soybean oil: BO1–BO3 Comdty; Jan Mar May Jul Aug Sep Oct Dec; Wheat: W1–W3 Comdty; Mar May Jul Sep Dec; Lean Hogs LH1–LH3 Comdty; Feb Apr May Jun Jul Aug Oct Dec; Feeder cattle: FC1–FC3 Comdty; Jan Mar Apr May Aug Sep Oct Nov; Live cattle: LC1–LC3 Comdty; Feb Apr Jun Aug Oct Dec; Pork bellies: PB1–PB3 Comdty; Feb Mar May Jul Aug; Coffee: KC1–KC3 Comdty; Mar May Jul Sep Dec; Cotton: CT1–CT3 Comdty; Mar May Jul Dec; Orange Juice: JO1–JO3 Comdty; Jan Mar May Jul Sep Nov; Sugar: SE1–SE3 Comdty; Mar May Jul Oct.

Energy:

Crude oil WTI: CL1–CL9 Comdty; 12 calendar months.

Financials:

Short rate: US Treasury Bill 3 month secondary market rate; Federal Reserve Board of Governors: H15/H15/RIFLGFCM03_N.B; Yield spread: Moody's AAA Corporate Bond yield less short rate; Bloomberg ticker MOODCAAA; Volatility: CBOE VIX volatility index; Bloomberg ticker VIX Comdty; USA exchange rate Index future DXY: US Dollar Index (average of US dollar exchange rate with six major currencies); Bloomberg ticker DXY Curncy; Implied volatility of options on crude oil futures from the authors on request.

Open interest

The CFTC reports weekly (Tuesdays) on the percentage of all open interest (number of specified futures contracts) held by commercial and non-commercial traders. Harmonizing the open interest series with other components of our weekly data requires managing gaps and breaks. First, we can match up the OI and Bloomberg futures for most of the commodities but in some cases the contracts underlying Bloomberg price data and the CFTC commodity codes underlying the OI data are not the same; in those cases we match by generic commodity name. Second, prior to October 1992, the open interest is reported mid-month and end-month, rather than weekly, so to enlarge our sample, albeit with limited information, we fill in the missing weeks by repeating the prior observation for the weeks of 2 May 1990 to 7 October 1992. Third, the specific CFTC commodity codes sometimes switch within sample, creating structural breaks. We model the breaks by regressing each long open interest series on a constant and as many indicator variables as needed to control for the switches. Each OI series thus enters the GARCH and transition equations as deviations from the mean. The DOI series is a proportion so we do not need to adjust it for structural breaks.

- Commodity Futures Exchange Commission, per cent of open interest non-commercial long, non-commercial short, and non-commercial spread, all, mid, and end month 15 May 1990 – 30 September 1992, then weekly 6 October 1992 – 1 March 2011; Contracts: *Coffee* – Coffee, Cocoa and Sugar Exchange; *Corn* – Chicago Board Of Trade; *Cotton No. 2* – New York Cotton Exchange; *Crude Oil, Light 'Sweet'* – New York Mercantile Exchange; *Frozen concentrated Orange Juice* – Citrus Association of NY Cotton Exchange; *Soybean Oil* – Chicago Board Of Trade; *Soybeans* – Chicago Board Of Trade; *Wheat* – Chicago Board Of Trade.