Biofuels or Financialization: Explaining the Increased Correlation between Grains and Crude Oil Prices

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Abstract

The correlation between grains and crude oil price returns has increased dramatically over the past decade. Alternative explanations are the use of food commodities as biofuels feedstocks, the financialization of agricultural futures markets and the claimed predominance of common demand over idiosyncratic supply side shocks in the post-Lehman period. We use a modified version of the standard Dynamic Conditional Correlation (DCC) multivariate GARCH model to examine these alternatives. This model proves superior to both the Constant Conditional Correlation (CCC) and the standard DCC models. We conclude that neither biofuels nor financialization can be the sole explanation of the observed increased correlations.

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1. Introduction

In 2008, the world experienced a dramatic surge in the prices of commodities. 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 (FAO 2010). 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 (Trostle et al., 2011). Sharp increases in agricultural prices are not uncommon, but it is rare for two price spikes to occur within 3 years as they normally occur with 6-8 year intervals. The short period between the recent two price surges has therefore drawn concerns and raised questions. What are the causes of the increase in world agricultural prices and what are the prospects for future price movements? Will the current period of high prices end with a sharp reversal as in previous price spikes, or have there been fundamental changes in global agricultural supply and demand relationships that may bring about a different outcome?

Several authors have discussed the factors lying behind the spikes though no agreement has been reached on the cause of these phenomena. The 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 speculative influences are some of the factors considered and cited as leading to high levels of commodity prices (Abbot et al, 2008, Gilbert, 2010; Wright, 2011). In addition to the above mentioned factors, the diversion of food crops as bio-fuels stands out as an important and new factor that many have seen as accountable for the food price spikes (Mitchell, 2008).

Price volatility in commodities has been considerable, making planning very difficult for all market participants. Sudden changes and long run trend movements in agricultural commodity prices present serious challenges to market participants and especially to commodity dependent and net food importing developing countries (FAO 2010). At the national level, food-importing countries face balance-of-payment pressure as the cost of food imports rise. When transmitted to domestic markets, high world prices erode the
purchasing power of urban households and other net food buyers. Poor urban households are particularly affected because they spend a large share of their income on food (Minot, 2009). This theme also has policy implications. Government and policy makers may decide to implement different policy measures given the problem at heart. Firstly, if the biofuels explanation is considered, policy makers would take action to limit food price increases of crops by focusing on the use of food crops for biofuel purposes by reducing biofuel mandates and/or increasing their flexibility. Secondly, if the financialization hypothesis holds then governments and policy makers efforts should aim at increasing futures markets regulations so as to curb index investment.

Our previous research has shown that in the recent decade there has been an increase in volatility grains, vegetable oils and meats (Gilbert and Morgan, 2010, 2011). These are commodities which are likely to be affected by the growth of biofuel production thus the heightened volatility for these commodities arises due to the importation of oil price volatility. On the contrary, crude oil price volatility has not been particularly high during the same period considered. This could imply that the nature of the relationship between crude oil on the one hand and grains on the other has changed in the recent decade. In particular, grains and crude oil returns have in the recent years been co-moving as shown by the increased conditional correlations between the two categories. The increased co-movement occurred when biofuel production increased and crude oil prices were high and this would be in line with the biofuels explanation.

The objective of this paper is to analyze the evolution of this relationship considering the role played by biofuels. We aim at verifying whether the increased grains-crude correlations has led to greater grains volatility as shocks from the crude oil markets are transmitted into the grains market. If this is the case, one would expect there to be a pass-through mechanism of crude oil shocks into the grains markets.

This paper extends the application of MGARCH models mainly used to analyze financial market data into commodity markets. We modify the Dynamic Conditional Correlations (DCC) Multivariate GARCH model (Bollerslev et al. 1988) to impose a causal structure in which crude oil price volatility is transmitted to food commodity prices. This modified DCC
(MDCC) model allows us to let the shock variable (innovations) from the crude oil markets in the grains volatility estimates.

Conditional correlations are calculated from MGARCH models estimated on daily data over the twelve year sample 2000-2011. A pass-through factor is estimated in order to measure the transmission of shocks across markets. Chicago Board of Trade (CBOT) daily grains prices for corn, wheat, soybeans, oats, and rice, are analyzed.

2. The co-movement of crude oil and food commodity prices

Global biofuels production has increased rapidly over the last 20 years. In the U.S. biofuels production began to rise rapidly in 2003 while in the E.U. it accelerated from 2005 (Trostle et al, 2011). 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 FAO went on to claim that increased biofuel production was a contributory factor in the 97 percent increase of the price of vegetable oils in the first three months of 2008 (FAO, 2008).

Crude oil prices can affect the prices of food commodities in two distinct ways. First, crude oil enters the aggregate production function of most primary commodities through the use of various energy-intensive inputs such as fertilizers, heating and pesticides and through transportation costs. However, agriculture is not highly energy-intensive so this impact is will not be large and there is no reason to suppose that it has increased markedly in recent years.

Secondly, some commodities can be used to produce substitutes for crude oil. This is true in particular of maize and sugarcane in ethanol production and oil seed rape and other vegetable oils for biodiesel production (Baffes, 2007). The attractiveness of production of ethanol and biodiesel, and of the investment in refining capacity to produce these products, depends directly on the price of crude oil. One should thus expect to find a relationship between food commodity prices and crude oil prices. Although the impact of higher crude prices on the demand and supply of grains and oilseeds takes time, efficient futures markets should anticipate these effects.
It is useful to distinguish the price level and price volatility effects of the expansion of biofuels production. The former arises through the diversion of supplies from food and feed consumption. This happens directly via competition between food and feed users and biofuel users for the same grain, but also indirectly, through the substitution of one grain, such as maize diverted to biofuel feedstock from use as food or feed rations, leading to substitution of a food grain, such as wheat, into animal feed. Soybeans are most directly affected by the demand for corn-based ethanol as corn and soybeans tend to compete for land area and can be used in rotation\(^1\).

The U.S. expanded maize area by 23 percent in 2007 in response to high maize prices and rapid demand growth for maize for ethanol production. This expansion resulted in a 16 percent decline in soybean area which reduced soybean production and contributed to a 75 percent rise in soybean prices between April 2007 and April 2008. The expansion of biodiesel production in the E.U. diverted land from wheat and negatively affected wheat production and stock levels. This was in response to the increased demand and rising prices for oilseeds, land cultivated for oilseeds - particularly rapeseed - increased. Oilseeds and wheat are grown under similar climatic conditions and in similar areas and most of the expansion of rapeseed and sunflower displaced wheat or was on land that could have been used for wheat cultivation (Mitchell, 2008). Grains prices also affect the price of meat and dairy products because grain is used as feed. Livestock feeding is the largest single use of corn and cattle, pigs and poultry all use corn feed.

The second effect of biofuels is it may increase the volatility of food prices. Gilbert and Morgan (2010, 2011) note that the volatility of any commodity price depends on the variances of shocks to production and consumption in conjunction with the elasticity of supply and demand. Within this framework, the biofuels link may be seen as introducing an additional source of demand variability – see Wright (2011) who emphasizes the transmission of energy market shocks into food commodity markets – and, if biofuel

\(^1\) The price of corn rose substantially in 2007-2008 reflecting the increase in demand, the cropping pattern changed, with more corn production relative to soybeans. This led to a decrease in overall soybean production and increased its price.
mandates are inflexible, through decreasing demand elasticities. The main focus of the current paper is on these volatility links.

The direct production function link from crude oil prices to energy prices is well-documented. Using different methodologies, Baffes (2007), Mitchell (2008) and Gilbert (2010) agree in seeing an energy price pass-through to grains prices of between 15 and 20 per cent. It is unlikely that this has changed over recent years. The indirect links, via the use of food commodities as biofuel feedstocks, are more difficult to quantify, in part because of the shortness of the relevant biofuels time series. Moreover, few of the formal models have been able to accurately capture the cross-commodity supply and demand linkages between corn – the primary grain used to make ethanol – and other commodities such as soybeans, wheat, and other feed grains. This motivates an examination of whether there has been a change or evolution of the relationship between food prices and the crude oil price over the period in which biofuels production has become important.

Gilbert (2010) used Granger-causality (GC) tests to examine the link between crude oil prices and both the IMF’s agricultural food price index and a grains sub-index. In both cases, his results showed a negative impact Granger-causal in the two decades up to 1989 and a positive Granger-causal impact in the two more recent decades. The pre-1989 results may reflect the fact that, over that period, the developed economies lacked a clear monetary anchor and hence a rise in oil prices would likely be met by a tough anti-inflationary monetary tightening. The production function pass-through-impact of higher oil prices only becomes apparent once the credibility of inflation targeting had been established.

Tyner (2010) confirms that since the ethanol boom took off in 2006, the correlation between energy and agricultural markets has been strong. 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. And when crude oil prices started to decline after the summer of 2008, so did the prices of most agricultural commodities. He highlights the blending wall as the determinant to this link. This factor is particularly influential in the case of high crude oil prices. Since ethanol production is limited by the blending wall, when crude oil prices are high, and the corn price increase is
dampened. Thus the crude-corn price link that has been established could be significantly weakened at high crude oil prices because of the blending wall limit (Tyner, 2010).

An opposing view is expressed by Tang and Xiong (2010) who emphasize financialization as the determinant of the increased comovement of crude oil and food prices. 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.

Both the biofuels and the financialization hypotheses entail increased comovement of crude oil prices and the prices of food commodities. However, the commodities affected by the comovement will be different. On the biofuels hypothesis, the effects will be confined to food commodities and will not extend to other agricultural commodities, such as coffee, cocoa and cotton, which are neither used as biofuels feedstocks nor directly substitute or are otherwise related to biofuels-related food commodities. Neither will the effects extend to metals. On the financialization hypothesis, metals and the non-biofuels group of agricultural commodities will share the common demand shock and hence will also exhibit greater comovement with crude oil prices. However, the impacts will not extend to food commodities, such as oats and rice, in which futures markets play a small or negligible role and which therefore do not directly experience the financialization demand shock.

A third alternative is that, in the post Lehman period, demand shocks have tended to predominate over supply shocks. Demand shocks tend to be common across commodities while supply shocks tend to be idiosyncratic and therefore commodity-specific. Gilbert (2010) argued that, for this reason, demand factors tend to dominate in explaining food price shocks. Figure 1 illustrates these alternatives.
Any hypothesis about comovement can be framed as a hypothesis about correlations. Increased commodity comovement implies a rise in inter-commodity correlations. We therefore pose these hypotheses within the DCC multivariate GARCH model (Engle, 2002).

3. The DCC framework

Bollerslev et al. (1988) provided a framework for multivariate GARCH (MGARCH) analysis. The general MGARCH (1,1) model for an $m$-dimensional vector $r$ of returns is

$$
    r_t \mid r_{t-1}, r_{t-2}, \ldots \sim N(\mu_t, H_t)
$$

$$
    h_{jt} = \omega_j + \sum_{k=1}^m \sum_{i=1}^k \alpha_{jk}(r_{x,t-1} - \mu_x)(r_{x,t-1} - \mu_x) + \sum_{k=1}^m \sum_{i=1}^k \beta_{jk} h_{k,t-1} \quad (j=1, \ldots, m; i=1, \ldots, j)
$$

$$
    h_{jt} = h_{jt} \quad (j=1, \ldots, m; i=1, \ldots, j-1) \quad (1)
$$

This representation is problematic if the dimensionality $m$ of the return vector exceeds two, firstly because the model becomes highly parameterized – the number of parameters is $2m + \frac{1}{2}m^2(m+1)^2$ – and secondly because it is difficult to impose positive definiteness of the conditional variance matrix $H_t$ at every date in the sample. For these reasons, the literature has tended to work with simplified versions of the general MGARCH model.
Two radically simplified versions of the MGARCH model are commonly used. The first is the constant conditional correlation MGARCH (CCC-MGARCH) model introduced by Bollerslev (1990). In the diagonal case, this has the structure

\[
r_{j,t} | r_{-1,t-1}, r_{-2,t-2}, \ldots \sim N(\mu, H_{j,t})
\]

\[
h_{jj,t} = c_{jj} + \alpha_{jj} \left( r_{j,t-1} - \mu_j \right)^2 + \beta_{jj} h_{jj,t-1} \quad (j = 1, \ldots, m)
\]

\[
h_{jj,t} = \rho_{jj} \sqrt{h_{jj,t} h_{jt}} \quad (j = 1, \ldots, m; i = 1, \ldots, j-1)
\]

\[
h_{jt} = h_{jt} \quad (j = 1, \ldots, m; i = 1, \ldots, j-1)
\]

with \( \alpha_{j} + \beta_{j} < 1 \) \((j = 1, \ldots, m)\). The scedastic equation in (2) may be written more compactly as

\[
H_{t} = D_{t} R_{t} D_{t} \quad \text{where} \quad D_{t} = \text{diag} \left( h_{11,t}^{\frac{1}{2}}, \ldots, h_{mm,t}^{\frac{1}{2}} \right)
\]

and \( R = \left( \rho_{jj} \right) \) is a constant positive definite correlation matrix. This reduces the parameterization to \( 4m + \frac{1}{2} m(m+1) \) (30 when \( m = 4 \)) but the imposition of positive definiteness remains difficult except in the equicorrelation case in which

\[
R = \begin{pmatrix}
1 & \rho & \cdots & \rho \\
\rho & 1 & \cdots & \rho \\
\vdots & \vdots & \ddots & \vdots \\
\rho & \rho & \cdots & 1
\end{pmatrix} = (1-\rho)I + \rho \ell \ell' \quad \text{where} \quad \ell \quad \text{is the vector of units.}
\]

The second widely used MGARCH model is dynamic conditional correlation (DCC) model of Engle (2002) defined by

\[
r_{j,t} | r_{-1,t-1}, r_{-2,t-2}, \ldots \sim N(\mu, H_{j,t})
\]

\[
H_{t} = (1-\alpha - \beta) \bar{H} + \alpha (r_{t-1} - \mu)(r_{t-1} - \mu)' + \beta H_{t-1}
\]

where \( \bar{H} \) is the unconditional variance-covariance matrix and \( \alpha \) and \( \beta \) satisfy \( \alpha, \beta > 0 \) and \( \alpha + \beta < 1 \). The conditional correlation matrix, which is now time-varying, is \( R_{t} = D_{t}^{-1} H_{t} D_{t}^{-1} \).

This is a highly parsimonious specification – given the unconditional matrix \( \bar{H} \), the model contains only 3 additional parameters. Positive definiteness is guaranteed by the inequality restriction on \( \alpha \) and \( \beta \).

It is apparent that the trade-off between the CCC and DCC MGARCH specifications is that CCC imposes a constant correlation structure but leaves the variance dynamics unrestricted.
across the difference returns while DCC allows a time-varying correlation structure but at
the expense of imposing homogeneity of the variance dynamics. Depending on the context,
one or other set of restrictions will be more appropriate. In our context, in which we are
interested in the increased comovement of various commodity futures prices, we are
obliged to choose the DCC route.

Consider a model for \( k > 1 \) commodity futures prices. Set crude oil as commodity 1 so that
the remaining commodities are 2, ..., \( k \). The standard DCC model treats the \( k \) prices
symmetrically so that equation (4) states

\[
\begin{align*}
    h_{ji,t} &= (1-\alpha-\beta)\overline{h}_{ji} + \beta h_{ji,t-1} + \alpha \left( r_{it} - \mu_{it} \right)^2 \\
    h_{ji,t} &= h_{ij,t} = (1-\alpha-\beta)\overline{h}_{ji} + \beta h_{ji,t-1} + \alpha \left( r_{it} - \mu_{it} \right) \left( r_{jt} - \mu_{jt} \right) \\
    (j &= 1, \ldots, k; i = 1, \ldots, j-1)
\end{align*}
\]

We consider a modified DCC (MDCC) model which allows shocks in the crude oil market to
be transmitted to the remaining \( k-1 \) markets. This model modifies equations (5) to

\[
\begin{align*}
    h_{1i,t} &= (1-\alpha-\beta)\overline{h}_{1i} + \beta h_{1i,t-1} + \alpha \left( r_{it} - \mu_{1t} \right)^2 \\
    h_{ji,t} &= h_{ij,t} = (1-\alpha-\beta)\overline{h}_{ji} + \beta h_{ji,t-1} + \alpha \left( r_{it} - \mu_{1t} \right) \left( r_{jt} - \mu_{jt} \right) \\
    h_{ji,t} &= (1-\alpha-\beta)\overline{h}_{ji} + \beta h_{ji,t-1} + \alpha \left[ \lambda_{jt} \left( r_{it} - \mu_{1t} \right)^2 + \left( r_{jt} - \mu_{jt} \right)^2 \right] \\
    (j &= 2, \ldots, k)
\end{align*}
\]

In this mild reformulation of the DCC model, shocks to the crude oil market are transmitted
to the volatilities of the remaining \( k-1 \) markets through the time varying regression
coefficients \( \lambda_{jt} \) relating the market in question to crude oil. The number of parameters
remains the same in the DCC and MDCC models.

4. Grains market volatilities

In this section we report results relating to the comovement of the WTI crude oil price and
the three principal grains and oilseeds traded on the Chicago futures market – corn, soft
wheat and soybeans. Although only corn is directly used as a biofuels feedstock but the
prices of the three grains move closely together as many north American farmers are easily
able to reallocate land from one crop to another (in particular from soybeans to either corn or wheat) at the time of planting.

We use daily data for the front contract on the NYMEX WTI market and the CBOT corn, wheat and soybeans markets from 5 January 2000 to 30 December 2011. Prices are excluded for a small number of days on which one market was closed while the other traded. Contracts are rolled on the first day of the expiration month and returns are contract-consistent.

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Univariate GARCH estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WTI</td>
</tr>
<tr>
<td>ARCH α</td>
<td>0.0552</td>
</tr>
<tr>
<td>GARCH β</td>
<td>(0.0286)</td>
</tr>
<tr>
<td></td>
<td>0.9245</td>
</tr>
<tr>
<td></td>
<td>(0.0382)</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>72398.71</td>
</tr>
<tr>
<td>Combined</td>
<td>31124.83</td>
</tr>
<tr>
<td>AIC</td>
<td>-62233.65</td>
</tr>
</tbody>
</table>

Sample: Daily, 5 January 2000 to 30 December 2011 (3001 observations)
Robust standard errors in parentheses.

Throughout we estimate GARCH(1,1) models in conjunction with mean processes without any dynamic structure. Tests indicate that these specifications are adequate. Table 1 reports the univariate GARCH estimates and Table 2 the CCC MGARCH estimates. A standard likelihood ratio test gives a clear rejection of the univariate models against the CCC alternative and this is confirmed by the lower Akaike Information Criterion (AIC) for the CCC model. Inspection of the estimated coefficients show reduced heterogeneity in the ARCH and GARCH parameters in the CCC model relative to the univariate models. The estimated correlations between the three grains and WTI have a similar order of magnitude in the range 0.18 to 0.23. The inter-grains correlations are higher, around 0.62 for the wheat and soybean correlations with corn but 0.48 for the wheat-soybeans correlation. This suggests that corn plays the central role in the grains complex.

2 The estimated μ and ω parameters are omitted from the tables.
Table 2
Multivariate CCC MGARCH estimates

<table>
<thead>
<tr>
<th></th>
<th>WTI</th>
<th>Corn</th>
<th>Wheat</th>
<th>Soybeans</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARCH α</td>
<td>0.0530 (0.0282)</td>
<td>0.0528 (0.0182)</td>
<td>0.0466 (0.0186)</td>
<td>0.0447 (0.0151)</td>
</tr>
<tr>
<td>GARCH β</td>
<td>0.9242 (0.0396)</td>
<td>0.9298 (0.0224)</td>
<td>0.9400 (0.0235)</td>
<td>0.9407 (0.0197)</td>
</tr>
<tr>
<td></td>
<td>0.2206 (0.0171)</td>
<td>0.1798 (0.0173)</td>
<td>0.6256 (0.0111)</td>
<td>0.2331 (0.0170)</td>
</tr>
<tr>
<td></td>
<td>0.6232 (0.0112)</td>
<td>0.4834 (0.0140)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Log-likelihood</td>
<td>32729.17</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>AIC</td>
<td>-65450.34</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Test of univariate null</td>
<td>$X^2(6) = 3208.68$</td>
<td>[&lt;0.0001]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Sample: Daily, 5 January 2000 to 30 December 2011 (3001 observations)
Standard errors in round parentheses (robust for coefficients); tail probabilities in square parentheses.

Table 3 reports the DCC and modified DCC estimates. The modified DCC model is associated with the higher likelihood and lower AIC and therefore appears to be preferred. The univariate and CCC models neither nest nor are nested within the DCC models so a formal test is not available. Nevertheless, the two DCC models are both associated with lower AICs than the CC and univariate models. We conclude that the modified DCC model is the preferred specification. We therefore henceforth focus on the modified DCC estimates.

Table 3
DCC and Modified DCC Multivariate GARCH estimates

<table>
<thead>
<tr>
<th></th>
<th>DCC</th>
<th>Modified DCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARCH α</td>
<td>0.0363 (0.0023)</td>
<td>0.0455 (0.0029)</td>
</tr>
<tr>
<td>GARCH β</td>
<td>0.9521 (0.0034)</td>
<td>0.9376 (0.0045)</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>32818.81</td>
<td>32801.00</td>
</tr>
<tr>
<td>AIC</td>
<td>-65625.62</td>
<td>-65590.00</td>
</tr>
</tbody>
</table>

Sample: Daily, 5 January 2000 to 30 December 2011 (3001 observations)
Robust standard errors in parentheses.
Figure 2 shows the estimated correlations between crude oil and the three grains from the MDCC model and Figure 3 does the same for the inter-grains correlations. The correlations of the three grain price returns with WTI returns (Figure 2) moves from the 0.1-0.2 range in the first half of the sample to the 0.4-0.5 range in 2008-09. These correlations have subsequently fallen back but remain around 0.3. By contrast, the inter-grains correlations are higher, in the 0.4-0.6 range, but appear broadly constant through the sample. These estimated correlations show considerable variability. The pattern is clearer if we look at annual averages, and also if we average across the grains. Figure 4 shows annual average of the three grain-WTI correlations both for the modified and standard DCC models. The correlations from the modified DCC model start a little lower than those from the standard model and end the sample a little higher. Figure 5 repeats this exercise for the three inter-grains correlations. There is little evident temporal pattern but the modified DCC correlations are again slightly lower than those from the standard model.

5. What causes comovement?

We now repeat the exercise replacing wheat and soybeans respectively by copper and rough rice. The copper price is the LME three months price which is widely taken as the market price is commercial transactions. The rough rice price is the CBOT front contract price. This is a thinly traded market which relates purely to U.S. domestic rice and is only weakly related to rice prices in international trade. CFTC Commitments of Traders data indicate that there is very little interest on the part of money managers and index-based investors in this contract.

The univariate GARCH estimates are reported in Table 4. Although the sample span (January 20900 to December 2011) is the same as that used for the estimates reported in Table 1, there are fewer observations since the sample now excludes U.K. as well as U.S. holidays. This has little effect on the corn estimates but increases the standard errors of the estimates for the WTI scedastic process. Also worth noting is the poor determination of the $\alpha$ and $\beta$ parameters for the rough rice scedastic process.

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3 The correlations from the standard DCC model are visually very similar.
### Table 4
Univariate GARCH estimates

<table>
<thead>
<tr>
<th></th>
<th>WTI</th>
<th>Corn</th>
<th>Copper</th>
<th>Rough rice</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARCH $\alpha$</td>
<td>0.0520</td>
<td>0.0577</td>
<td>0.0750</td>
<td>0.0520</td>
</tr>
<tr>
<td></td>
<td>(0.0959)</td>
<td>(0.0183)</td>
<td>(0.0240)</td>
<td>(1.1108)</td>
</tr>
<tr>
<td>GARCH $\beta$</td>
<td>0.9267</td>
<td>0.9331</td>
<td>0.9150</td>
<td>0.9270</td>
</tr>
<tr>
<td></td>
<td>(0.1331)</td>
<td>(0.0171)</td>
<td>(0.0221)</td>
<td>(0.0326)</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>6425.92</td>
<td>7824.71</td>
<td>8072.61</td>
<td>1625.90</td>
</tr>
<tr>
<td>Combined</td>
<td>23949.15</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>-47882.29</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Sample: Daily, 5 January 2000 to 30 December 2011 (2943 observations)

Robust standard errors in parentheses.

### Table 5
Multivariate CCC MGARCH estimates

<table>
<thead>
<tr>
<th></th>
<th>WTI</th>
<th>Corn</th>
<th>Copper</th>
<th>Rough rice</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARCH $\alpha$</td>
<td>0.0519</td>
<td>0.0577</td>
<td>0.0750</td>
<td>0.0520</td>
</tr>
<tr>
<td></td>
<td>(0.0959)</td>
<td>(0.0182)</td>
<td>(0.0240)</td>
<td>(1.1108)</td>
</tr>
<tr>
<td>GARCH $\beta$</td>
<td>0.9267</td>
<td>0.9331</td>
<td>0.9150</td>
<td>0.9270</td>
</tr>
<tr>
<td></td>
<td>(0.1331)</td>
<td>(0.0171)</td>
<td>(0.0221)</td>
<td>(0.0325)</td>
</tr>
<tr>
<td>Correlations</td>
<td>0.2648</td>
<td>0.2036</td>
<td>0.1261</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.1687</td>
<td>0.2380</td>
<td>0.1251</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>24080.33</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Test of univariate null</td>
<td>$X^2(6) = 262.36$</td>
<td>[&lt;0.0001]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>-48152.65</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Sample: Daily, 5 January 2000 to 30 December 2011 (2943 observations)

Robust standard errors in round parentheses; tail probabilities in square parentheses. The procedure failed to yield standard errors for the estimated correlations.

Table 5 reports the CCC MGARCH estimates. As previously, a standard likelihood ratio test gives a clear rejection of the univariate models against the CCC alternative and this is confirmed by the lower AIC for the CCC model. Inspection of the estimated coefficients show reduced heterogeneity in the ARCH and GARCH parameters in the CCC model relative to the univariate models. The estimated correlations all lie in the range 0.12 to 0.27. Table 6 reports the DCC and modified DCC estimates. As previously, the modified DCC model is

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4 The estimated $\mu$ and $\omega$ parameters are omitted from the tables.
associated with the higher likelihood and lower AIC and therefore appears to be preferred. The estimated scedastic coefficients differ little from those reported in Table 3.

<table>
<thead>
<tr>
<th>Table 6</th>
<th>DCC and Modified DCC Multivariate GARCH estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DCC</td>
</tr>
<tr>
<td>ARCH α</td>
<td>0.0304 (0.0020)</td>
</tr>
<tr>
<td>GARCH β</td>
<td>0.9611 (0.0029)</td>
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<td>Log-likelihood</td>
<td>31080.80</td>
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<tr>
<td>AIC</td>
<td>-62189.01</td>
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</table>

Sample: Daily, 5 January 2000 to 30 December 2011 (2943 observations)
Robust standard errors in parentheses.

Figures 5 and 6 show the estimated time-varying WTI correlations from the modified DCC model. The pattern is difficult to discern in Figure 5 but Figure 6 shows that there has been a general rise in return correlations starting from 2008 with the corn-WTI correlation leading the process from 2004. The fact that the WTI-rough rice correlation has risen, although not by as much as the WTI-corn correlation, implies that financialization cannot be the main, or at least the only, driver of increased comovement. The fact that the WTI-copper correlation has risen, although not by as much as the WTI-corn correlation, implies that biofuels cannot be the main, or at least the only, driver of increased comovement. A possible conclusion is that biofuels and financialization have both contributed to the rise in comovements. An alternative, but not necessarily exclusive, possibility is that increased comovement results from the prevalence of common demand over idiosyncratic supply shocks in the world commodity economy in the period from 2008. On the present evidence, we are unable to discriminate between these alternatives.

6. Conclusions
This paper has both methodological and substantive conclusions. From a methodological standpoint, we can confirm that the Dynamic Conditional Correlation model provides a simple and parsimonious “workhorse” model which accounts successfully for time-varying correlated scedastic processes. The model is restrictive in that it imposes homogeneity on
the variance dynamics across assets. In practice, at least I relation to commodity futures, these dynamics do not differ in dramatic ways across commodities so the restrictions are not very costly. The DCC model is therefore strongly preferred, on our data, to the Constant Conditional Correlation (CCC) alternative since correlations do appear to be highly variable over time.

The standard DCC model treats assets symmetrically such that each variance is updated in a diagonal manner solely in relation to shocks to its own price. We have suggested a modified DCC model in which one asset is given causal priority. In the commodities context, crude oil is the obvious choice for this asset. This formulation, which allows shocks to the crude oil price to directly impact the volatilities of the remaining futures prices, proves superior to the standard DCC model.

Substantively, we have shown that the rise in the comovement of grains prices with crude oil prices extends both to non-ferrous metals (copper) and to thinly traded commodities (we consider rough rice). The former finding is incompatible with biofuels demand being the sole driving force of increased comovement. The latter finding is incompatible with financialization being the sole driving factor. One possibility is that both forces are at play. A second is that the predominance of common demand side shocks over idiosyncratic supply side shocks is responsible for increased inter-commodity return correlations.
Figure 1: Estimated crude oil-grains correlations, modified DCC model

Figure 1: Estimated inter-grains correlations, modified DCC model
Figure 3: Average WTI-grains correlations, standard and modified DCC models

Figure 4: Average inter-grains correlations, standard and modified DCC models
Figure 5: WTI correlations, modified DCC model

Figure 6: Averaged WTI correlations, modified DCC model
References


