Paper Title	Can US Biofuels Policy Explain the Food Price Boom?

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Abstract

It is widely agreed that the expansion of US biofuels demand for corn was an important driver of high food prices from around 2005. There is less consensus on the scale of this effect. We use structural break methods to show that these impacts were important over the four years 2005-08 but not subsequently. Contrary to some assertions, competitive storage theory continues to explain much of the price movements over this period. The previously clear separation of commodities between food and energy groups has become less precise but corn never became a petro-commodity.

Keywords	Corn, biofuels, structural breaks
JEL Code	C51: Model Construction and Estimation Q11: Aggregate Supply and Demand Analysis; Prices Q42: Alternative Energy Sources

1. Introduction

The food price boom started in the second half of 2006 and lasted until 2014. At their peak, nominal corn prices exceeded December 2005 levels by 180%, wheat prices did so by 189% and soybean price by 156%. By December 2015, wheat prices were only 4% above their level ten years previously although corn and soybean prices remained 42% and 33% higher respectively.[1] A large literature has discussed the causes of these elevated prices and many have speculated that both the price rises, and the associated higher volatility, might be permanent.

We examine whether this growth in ethanol production, which largely used corn, a food commodity, as feedstock, but which was largely used in the manufacture of gasoline and diesel fuels, which are energy commodities, may have led to corn prices, and perhaps grains prices more generally, becoming more closely linked to energy prices. The impact of the use of corn (maize) as a biofuels feedstock has previously been discussed by Abbot et al. (2008, 2011), de Gorter and Just, (2009), Tyner (2008, 2010), Abbot (2014), Wright (2014) and de Gorter et al. (2015).

We now know that the post-2006 food price volatility increase was transient and that any permanent price level effects were much more modest than some expected – see OECD-FAO (2016, chapter 2). Policy interest has declined accordingly and the present authors therefore need to provide an apology for revisiting these events. Our excuse is provided by two recent accounts of food price movements over this period, both of which stress the importance of US biofuels policy as a cause of food price movements and both of which adopt a structural modeling methodology. Despite this, the studies reach radically different conclusions. Abbott (2014, page 128) concludes that around one half of the rise in corn prices over the period 2005-09 can be attributed to biofuels effects but that these impacts were dependent on food market factors which resulted in low stock levels.[2] Instead, de Gorter et al. (2015, page 65) argue that almost 80% of the increase in crop prices would have occurred, regardless of all other factors, due to biofuel policies alone". This is an enormous difference. The substantive issue here is whether we should analyze grains prices, at least over the high price period, using the standard techniques of supply and demand analysis in conjunction with the competitive storage model, or whether

[1] Source: IMF, *International Financial Statistics*. Deflation is by the UD Producer Price Index (all items).
[2] He indicates that biofuels policy may have induced a rise of 33% rise in corn prices over a period in which they rose overall by 65%.

instead we should see corn as a petro-commodity with the result that food prices become a tail wagged by the energy dog.

The structure of the paper is as follows. Section 2 provides a simplified account of US biofuels policy over the past fifteen years and in section 3 we set out a model which reflects the policy developments. Section 4 sets out our modeling methodology and section 5 applies structural break analysis to the corn-ethanol relationship. Section 6 asks whether food and energy from separate commodity groups and or asset classes distinguishing between sub-periods on the basis of biofuels policy. Section 7 concludes.

2. Biofuels

A successful explanation of the high food price episode must account for three features of this period:

a) the timing of the start and end of the high food price period;
b) the commonality of elevated prices across energy, metal and food commodities, but not soft tropical commodities;
c) the high correlations of price changes across food and energy commodities.

Competing early explanations of the high food price years include under-investment in agriculture (World Bank, 2007), supply shocks, in particular the Australian drought of 2006-07 discussed in Mitchell (2008) and Headley and Fan (2008), low inventory levels (Bobenrieth et al., 2013), speculative impacts and in particular commodity index investment, discussed in Cooke and Robles (2009) and Gilbert (2010) and the diversion of corn into US biofuels consumption (Mitchell, 2008). Throstle et al. (2011) is one of a number of studies which invokes a perfect storm in which a number of different factors combined to generate high food prices.

Biofuels in the sole explanation listed above that ticks all three boxes. Rapid growth in the Chinese and other emerging economies drove up crude oil and metals prices starting from 2004. Although there was no direct effect on corn or wheat prices, this demand growth extended to soybeans. Then, a 2006 EIA policy decision was instrumental in driving the demand for corn in the US as ethanol feedstock. This had the effect of linking corn prices to energy prices. The upward pressure on corn and soybeans prices extended to wheat through land substitution by farmers, particularly in the US Midwest. Although the rapid growth in US ethanol production tailed off after 2009, grains stocks were depleted and remained tight, a situation exacerbated by poor harvests in 2012 and 2013. The combination of higher grain stocks with the 2015 collapse of the crude oil price reduced both the incentive to use corn for ethanol production and the impact of both then level of ethanol production and that of crude oil prices on corn prices.

The United States began subsidizing biofuels in 1978 with the passage of the National Energy Policy Conservation Act of 1978 (Tyner, 2008; U.S. Congress, 1978). US ethanol production grew rapidly over the nine year period 2002-10 averaging over 25% per annum – see Figure 1 (dark line). Abbott (2014) summarizes the key policy measures that aimed at or resulted in increased production of biofuels. Key policy intervention dates are reported in the Table 1 which is similar to his Table 3.2. The crucial components of the policy are the RFS mandates, the MTBE ban and the blend wall.

The 2005 Renewable Fuels Standard (RFS) mandated minimum production levels for ethanol over future years (U.S. Congress, 2005). This legislation also included continued subsidization of ethanol production which initiated in 2004. Gasoline blenders were offered a tax credit of $0.51 per gallon referred to as the Volumetric Ethanol Exercise Tax Credit – (VEETC), and import tariffs were imposed to ensure foreign producers did not get the subsidy. The Energy Policy Act (EPA) of 2007 substantially increased RFS mandated minimum ethanol production levels for the future.

Table 1
US biofuels policy Interventions

May 2004	VEETC introduced for ethanol blending with gasoline
July 2005	Renewable Fuels Standard (RFS1) - Energy Act
June 2006	MTBE ban became effective - liability waivers not granted
December 2007	Renewable Fuels Standard (RFS2) - Energy Act
January 2009	VEETC credit tax reduced to $0.45 per gallon
December 2011	VEETC tax credit expired
January 2012	Import tariffs on ethanol for fuel cut

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

The combined effect of the RFS mandate and the subsequent MTBE ban was to create the incentives that induced the rapid growth in US ethanol production, illustrated in Figure 1. The growth started in 2002 and accelerated after the MTBE ban in 2006. .

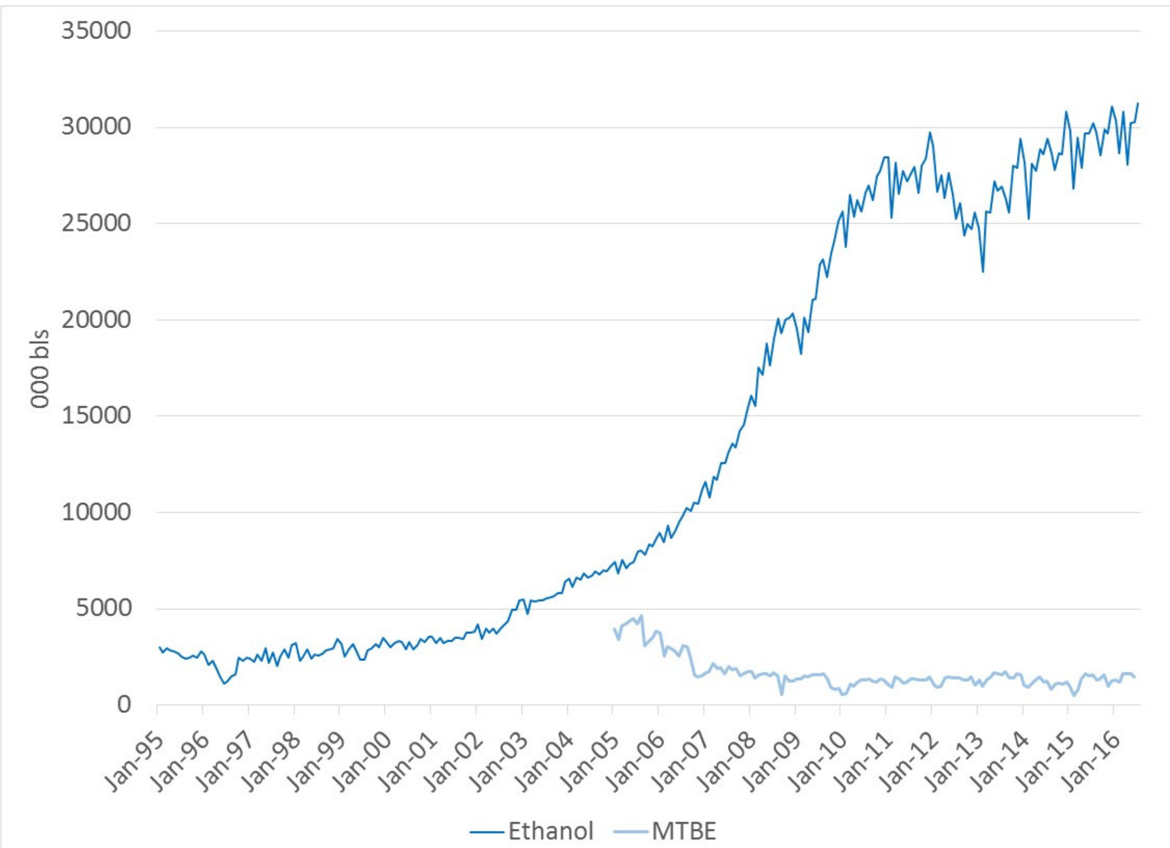

Figure 1: US monthly production of ethanol and MTBE, 1995-2016[3]

[3] EIA, http://www.eia.gov/dnav/pet/pet_pnp_oxy_dc_nus_mbbl_m.htm

While the RFS mandate and the MTBE ban incentivized ethanol production, a third factor had the opposite effect. Ethanol is corrosive and may damage older engines or engines that have not been designed to tolerate high concentrations. EPA regulations therefore imposed a limit on the amount of ethanol used in reformulated gasoline produced and sold by blenders. The EPA set a limit at 10% (E10) for gasoline not explicitly marketed as E85, and permitted up to 15% of ethanol (E15) to be blended for newer vehicles. Tyner and Viteri (2010) refer to this limit as the "blend wall". It results in a ceiling on ethanol demand for fuel use and is responsible for the levelling off of US ethanol production after 2009.

3. The impact of biofuels production on grains prices

Mitchell (2008) was the first economist to argue in print that US biofuels policy was the driver of high food prices and his contribution attracted considerable prominence both in policy circles and among the informed public. He argued that it was the steady growth of US biofuels production and the consequent diversion of corn away from food uses rather than any specific piece of legislation that was the price driver. Abbott et al. (2008) concurred but Gilbert (2010) remained unconvinced. A large subsequent literature attempted to trace the causal channels – see de Gorter at al. (2009). Abbott (2014) and de Gorter et al. (2015, page 20) placed particular emphasis on the 2006 MTBE ban. These structural models demonstrate that the interactions can be complicated and depend on whether refiners are constrained either by capacity limitations or by the blend wall since when constrained, refiners will have had little incentive to bid corn away from food uses.

The simple structure of the corn-energy interactions may be summarized in the following outline model which follows but simplifies the models set out in Abbott (2014) and de Gorter et al. (2015, chapter 2). Ethanol is the link between energy and food markets. We therefore follow de Gorter et al. in focusing on corn, ethanol and crude oil prices.

The competitive storage model implies that the corn price p will depend on availability a (equal to carryover from the previous crop year plus the current harvest) – see Williams and Wright (1991) and Deaton and Laroque (1992). This is captured by the nonlinear function $p(a)$ with $p'(a)<0$ and $p''(a)<0$. Now introduce biofuels demand and let the level of biofuels production be q. This reduces the availability of corn for food uses to a - αq where the coefficient $\alpha \approx 0.7$ takes into account recycling of corn as dried distillers' grains with solubles (DDGS) into animal feed. Ethanol production is constrained below by the mandated production level m and above by refining capacity k. (We assume that investment will ensure $k > m$). Profits in ethanol sales for gasoline production are $\pi = \pi\big(e, p(a - \alpha q)\big)$.

The blend wall constraint relates to the ethanol-gasoline price relationship. Write the associated level of consumption as b. We can safely assume $b > m$ but need to allow that b may either exceed or fall short of k. Write the marginal cost of ethanol production as c which we take to be independent of the level of production but which, given that it is produced either from a corn or a petroleum feedstock, which depends on the corn price as $c = c(p,g)$. These constraints gives rise to four possibilities

i) Ethanol production is unprofitable limiting it to the mandated quantity m. At the margin, ethanol is sold for non-fuel uses so that competition forces the price to marginal cost. This gives $p = p(a - \alpha m)$ and $e = c(p,g)$ with $\pi\big(c(p,g), p(a - \alpha m)\big) < 0$.

ii) Ethanol production is unconstrained by capacity or the mandate. In this instance, the ethanol price will be given by $e = e(g)$ such that consumers are indifferent on their blend choice at the margin. Given the ethanol price, the quantity q adjusts to until the corn price eliminates the profitability of ethanol production, i.e. $\pi\big(e(g), p(a - \alpha q)\big) = 0$ The resulting corn price is given by $p = P\big(e(g)\big)$.

iii) Ethanol production is constrained by the blend wall. With $k > b$, ethanol is sold for non-fuel uses at the margin and competition forces its price to marginal cost. This gives $p = p(a - \alpha b)$ and $e = c(p,g)$ with $\pi\big(c(p,g), p(a - \alpha b)\big) > 0$.

iv) Ethanol production is constrained by the capacity. With $k < b$, ethanol refiners are in a position to force up the ethanol price maximizing their rent at $e = e(g)$. This gives $p = p(a - \alpha k)$ and $e = e(g)$ with $\pi\big(e(g), p(a - \alpha k)\big) > 0$.

We acknowledge that this model is highly simplified. In practice constraints were typically fuzzy, not sharp and responses are not instantaneous. Nevertheless, we can use this structure to analyze price transmission between crude oil, ethanol and corn prices. In regime (i), where ethanol production is unprofitable, the only relationship is the pass-through from corn and gasoline to ethanol through the cost of ethanol production. Causation runs from corn and gasoline to ethanol. Regime (ii), where no constraints bind, sees a positive association between all three prices. In this instance, causation runs from gasoline to ethanol and thence to corn prices. Regime (iii), in which production is constrained by the blend wall, exhibits the same causal structure as regime (i). Finally, in regime (iv) in which refining capacity is the constraint, there is a causal relationship between gasoline and ethanol prices but corn prices are unaffected by either.

Table 2
Expected price relationships

	Ethanol regime	Corn and ethanol	Ethanol and gasoline	Corn and gasoline
(i)	Limited to mandate	Yes	Yes	No
(ii)	Unconstrained	Yes	Yes	Yes
(iii)	Constrained by blend wall	Yes	Yes	No
(iv)	Constrained by capacity	No	Yes	No

The table lists the expected price relationships in the four ethanol production regimes.

The lack of a relationship between the gasoline and the corn price in the two constrained cases (iii and iv) does not imply that corn prices are unaffected biofuels production since in both cases this reduces corn availability for food production. Simply that given these constraints, changes in the gasoline price do not change the level of diversion and hence do not affect the corn price. Mitchell's (2008) analysis of the impact of biofuels on grains prices was based on the quantity of US corn production diverted into biofuels production. de Gorter et al. (2015, page xxi) argue against the quantity-based approach and in favor of analysis based on price links. Our discussion, based on the de Gorter et al. model, suggests that quantity links may be more reliable than price links.

A further important conclusion from the model is that, irrespective of the ethanol production regime, grains market fundamentals continue to be important in determining grains prices. Any energy-based effect, however large, comes on top. This observation is in line with the conclusions of Abbott (2014) and the analysis in Wright (2014). It is at variance with the claim in de Gorter at al. (2014) that the 80% share of the rise in the corn price that they attribute to biofuels policies is independent “of all other factors”.

4. Modeling methodology

There is a widely held consensus that any grains market model which satisfactorily reflects the various constraints on biofuels production will necessarily be complicated. Even absent complications from biofuels, we should expect price responses to be nonlinear to reflect the level of stock overhang – recall $p''(a)<0$. In section 3, we identified four different production regimes depending which constraints are binding. Price behavior differs across regimes. Furthermore, it is possible that prices may move sharply as the market transits across regimes. This complexity is apparent in the models used in both Abbott (2014) and de Gorter at al. (2015).

A consequence of model complexity is that structural econometric estimation becomes very difficult. Abbott’s (2014) estimates are based on an Excel spreadsheet model calibrated on data for the 2005-06 crop year.[4] Calibration allows quantification of the implications of hypotheses but does not provide any test of these hypotheses. In what follows, we attempt to cut through this complexity by using a very simple two equation model linking corn and ethanol prices to each other, to the crude oil price and to market fundamentals but allowing for structural breaks in these relationships. The model is

$$\ln(Corn_t / PPI_t) = \alpha_0 + \alpha_1 \ln(WTI_t / PPI_t) + \alpha_2 \ln(Ethanol_t / PPI_t) + \alpha_3 Stocks_t + u_t \qquad (1)$$

$$\ln(Ethanol_t / PPI_t) = \beta_0 + \beta_1 \ln(Corn_t / PPI_t) + \beta_2 \ln(WTI_t / PPI_t) + v_t \qquad (2)$$

where *PPI* is the US producer price index which deflates prices to real terms and *u* and *v* are disturbances.

Competitive storage theory relates price to availability, equal to the carryover from the previous crop year plus the current harvest – see Williams and Wright (1991) and Deaton and Laroque (1992). This measure is only available on a crop year basis. We construct a stock estimate which is closely related to the availability concept. The USDA produces monthly estimates of

[4] de Gorter et al. (2014) do not explain how they obtained their equation estimates. This makes it difficult to evaluate their estimates.

closing stocks at the end of the northern hemisphere crop year – the WASDE estimates. To avoid seasonality issues, we construct a stock series by interpolating the WASDE estimate for forthcoming crop year with that for the current crop year, which the USDA updates as additional information becomes available.[5] The series measures world stocks excluding stocks held in mainland China.[6]

Within the model set out in equations (1) and (2), the demand for corn as a biofuel feedstock may affect the corn price indirectly, by lowering expected end crop year stocks, or directly, by shifting the stock demand function. In the latter case, the ethanol price may disrupt the structural stock-price relationship. At the same time, the use of corn as a biofuel feedstock may result in ethanol prices becoming dependent on corn prices.

This model is structural although it reflects some structural features of the markets. It does not permit direct evaluation of policy impacts and, in that sense, it cannot challenge the Abbott (2014) and de Gorter et al. (2015) models. Its virtue is that it does allow direct databased estimation of pass-through effects into corn prices. This is not true of calibrated models. In that sense it provides a check on the validity of the structural models and may help discriminate between them.

5. Structural break analysis

We proceed in two stages. We first look for structural breaks ignoring simultaneity and second take account of the simultaneity in estimation given estimated break points. The traditional econometric methodology for testing for structural breaks is to split the sample at the supposed break point and use a Chow (1960) test to ask whether the estimated coefficients are the same before and after the break point. Andrews (1993) generalized the Chow test to look for a break

[5] In North America, corn is harvested in October and November. The USDA issues its first estimate of closing stocks in the current crop year in May. Estimates in the spring and early summer are based solely on plantings and are not enormously accurate. The interpolated series gives a weight of 1/12 to the current crop year estimate in May and 11/12 to the updated estimate of the closing stock in the previous year. In June, we raise the current year weight to 1/6 and reduce that for the previous year to 5/6 etc.

[6] China does not report grain stocks and USDA estimates are based on very partial information. Major revisions have taken place in the WASDE China estimates which implies a lack of comparability in these figures over time. In any case, the extent to which stocks held in China would be available for the rest of the world is unclear – see Pfuderer (2015).

at an unknown date and Bai and Perron (1998) extended this procedure to multiple breaks. Then, at the second stage, we accept the breaks found at the first stage and re-estimate allowing for simultaneity.

The Andrews test works by computing the Wald version of the Chow test for each date in the sample. The highest value obtained for this process, measured by the sup *W* statistic, indicates a break date. This supremum is compared with critical values reported by Andrews (1993). An important qualification is that sup *W* procedure is only reliable away from the start and end of the sample. With a total of *T* observations, we confine the search for breaks to the range τT to $(1-\tau)T$. It is conventional to set $\tau = 0.15$. Using these data, we find a value $\tau = 0.2$ to be preferable in avoiding apparent breaks at the start of end of the test sample. Since we wish the estimated relationships to have a long run interpretation, we only test for breaks in sub-samples of at least 36 months.

We analyze monthly price data on eleven food and energy commodities – corn (maize), wheat and soybeans, where we look at both export and farmgate prices, and crude oil (WTI), wholesale gasoline, diesel and ethanol prices and the retail gasoline price. In this section we use the corn export price, WTI and the wholesale ethanol price data. We use the USDA WASDE end-year corn stock estimates as a corn market fundamental. The data sample extends for January 2000 to June 2016 (198 observations) to focus on the period over which biofuels demand was fast growing. Data definitions and sources are in an appendix.

In performing the structural breaks analysis, we test the α_1 and α_2 coefficients for constancy, but not the intercept. This allows for the possibility of omitted factors which may generate intercept shifts. Considering this entire 198 month period, the procedure locates a statistically significant break in December 2010. We therefore split the sample at that date and look for further possible breaks before and after this date. In the "before" sample, we find a second significant break in August 2006 while in the "after" sample there is a significant break in October 2014.

We also find three further structural breaks before and after these second breaks. Prodan (2008) has shown that the Bai and Perron (1998) procedure can be over-sized and generate too many breaks when none are present. We check on the number of breaks by minimization of the

AIC. On this basis, we prefer the model with two set of breaks (i.e. three breaks) to the model with three sets of breaks (potentially seven breaks, but we would find six since one of the potential sub-samples is too short to sustain a further break).

Table 3
Estimated coefficients by sub-period – corn regression

Dependent variable ln(Corn/PPI)	Intercept α_0	ln(WTI/PPI) α_1	ln(Ethanol/PPI) α_2	Stocks/100 α_3	R^2
January 2000 - January 2005	2.488 (6.08)	-0.189 (1.91)	0.038 (0.78)	-0.936 (8.17)	0.707
February 2005 - October 2008	-1.645 (3.35)	0.978 (9.35)	-0.107 (3.04)	-1.477 (11.92)	0.873
November 2008 - November 2014	3.282 (10.69)	-0.131 (1.76)	0.274 (3.29)	-1.504 (17.07)	0.862
December 2014 - June 2016	1.714 (8.25)	-0.062 (0.68)	0.088 (1.71)	-0.082 (0.35)	0.130

The table reports the OLS estimates of equation (1) over the four sub-periods identified by the Bai and Perron (1998) multiple break procedure. HACSE *t* statistics are given in parentheses.

The three break model implies four sub-periods. Table 3 reports the estimated β coefficients, together with HACSE *t* statistics, for each of the four sub-periods we have identified. The relationships are well defined except in the short final (2015-16) sub-period. The coefficient (α_3) of the stock fundamental is estimated as negative and statistically significant in all but the final sub-period. By contrast, we only find a statistically significant positive pass-through from the WTI price over the second (2005-08) sub-period and from the ethanol price in the third (2008-14) sub-period.

Table 4 reports estimates of equation (2) using the same division into sub-periods.[7] These estimates suggest that until 2005 ethanol prices were driven solely by crude oil prices but that subsequently they have also been affected by corn prices.

[7] Alternatively, we could apply the Bai and Perron (1998) procedure to equation (2). Structural breaks in one equation do not imply breaks in the other and any breaks may be at different dates. Nevertheless, the procedure does fins a break in equation (2) in February 2005.

Table 4 Estimated coefficients by sub-period – ethanol regression				
Dependent variable ln(Ethanol/PPI)	Intercept β_0	ln(Corn/PPI) β_1	ln(WTI/PPI) β_2	R^2
January 2000 - January 2005	-3.303 (2.80)	-0.275 (0.75)	1.006 (4.41)	0.371
February 2005 - October 2008	-1.693 (1.07)	-0.102 (0.31)	0.562 (1.37)	0.106
November 2008 - November 2014	-2.822 (6.00)	0.487 (3.20)	0.596 (4.69)	0.610
December 2014 - June 2016	-1.290 (1.76)	0.503 (1.53)	0.269 (1.96)	0.279
The table reports the OLS estimates of equation (2) over the four sub-periods identified in Table 3. HACSE *t* statistics are given in parentheses.				

There is an obvious concern that these estimates may be contaminated by simultaneity. Note however that any simultaneity bias in the estimated α_2 and β_1 coefficients should be expected to be positive. In that case, if either of these coefficients is found not to differ significantly from zero, we should feel confident about accepting that judgement. On that basis, simultaneity is only an issue from the end of 2008.

That judgement allows us to simplify the Table 2 estimates of the corn equation by eliminating variables with statistically insignificant or incorrect signs. The results are reported in Table 5. The first row of the table, which covers the period up to 2005, shows that corn price as driven solely be the stock fundamental. In the third row, which covers the post-Lehman period up to the end of 2014, shows both the fundamental and the ethanol prices as drivers of corn prices. (Recall there is no evidence of ethanol prices being affected by corn prices over this period). The evidence from the short (2015-16) period are too poorly determined to permit any clear conclusion to be drawn.

We have left until last discussion of the second, 2005-08, period which covers the food price boom. Here, the Table 3 estimates show both the ethanol and crude oil prices as affecting the corn price but those in Table 4 suggest a reverse relationship from the corn price to the ethanol price. Lacking a satisfactory instrument for the ethanol price,[8] we are unable to disentangle these two effects. Instead, in the second row of Table 5 we report estimates of a reduced form equation in which the ethanol price has been solved out of equation (1) using equation (2). The estimated WTI coefficient α_1 does not differ significantly from unity consistent with a penny-for-penny pass through of crude oil prices to the corn price over this period.

Table 5
Estimated coefficients by sub-period – restricted corn regressions

Dependent variable ln(Corn/PPI)	Intercept α_0	ln(WTI/PPI) α_1	ln(Ethanol/PPI) α_2	Stocks/100 α_3	R^2
January 2000 - January 2005	1.742 (22.01)	-	-	-0.860 (7.06)	0.652
February 2005 - October 2008	-1.515 (3.01)	0.929 (9.43)	-	-1.454 (7.42)	0.862
November 2008 - November 2014	2.694 (29.41)	-	0.229 (3.32)	-1.452 (16.80)	0.861
December 2014 - June 2016	1.622 (11.31)	-	0.102 (1.43)	-0.222 (1.59)	0.224

The table reports restricted OLS estimates of equation (1) over the four sub-periods identified in Table 3. The estimates in the first, third and fourth rows set statistically insignificant and incorrectly signed coefficients to zero. The estimates in the second row should be interpreted as those of a reduced form equation in which ln(Ethanol/PPI) has been solved out using equation (2). HACSE *t* statistics are given in parentheses.

Finally, we turn to the coefficient α_3 of the corn stock fundamental variable. This is well-determined in all the estimates except those for the short final period. The corn price is seen as more responsive to stocks after 2005 consistent with a nonlinear relationship in which price responds more when stocks are low. There is no evidence that the post-2004 sensitivity of corn prices to energy prices reduces the importance of corn market fundamentals – indeed, the two effects appear additive in line with the discussion in section 3. Indeed, both variables contribute

[8] Ethanol refining capacity is a possible variable although the EIA only produces annual figures. We experimented by interpolating onto a monthly basis. The resulting series differs little from a time trend and has no explanatory power for ethanol prices.

equally to movements in the corn price over this period – the stocks variable has a partial r^2 of 0.400 with the log corn price while the crude oil price has a partial r^2 of 0.486.

These results suggest that there was significant pass-through of both oil prices and the stock fundamental into corn prices over the four years 2005-09. We can sharpen this result by looking at the oil pass-through to the entire range of prices we have analyzed. We do this by estimating an ADL(p,p) model relating log changes in each price to log changes in WTI:

$$\Delta \ln price_t = \kappa + \sum_{r=1}^{p} \gamma_r \Delta \ln price_{t-r} + \sum_{r=0}^{p} \delta_r \Delta \ln WTI_{t-r} + \varepsilon_t \tag{3}$$

where ε is a disturbance.[9] The lag length p, set at 1 for the grains, 2 for retail energy prices and 3 for wholesale energy prices, was kept constant across different sub-samples. (We combine the short 2014-14 sub-sample with the 2008-14 sub-sample).

Long run responses are estimated as $\dfrac{\sum_{r=0}^{p} \delta_r}{1 - \sum_{r=1}^{p} \gamma_r}$. Results are reported in Table 9. The pas-through for the retail gasoline, is broadly constant over time and does not differ significantly from unity for wholesale gasoline. The two retail energy products exhibit a pass-through of around 0.7. There is a general tendency for the pass-through estimates to decline in the final period, possibly because WTI becomes a less clear measure of the international petroleum price. It is notable that the pass-through for ethanol declines most sharply from close to 0.9 to around 0.5.

[9] Inclusion of the zero lag is the WTI distribution supposes that the there is no contemporaneous influence of the prices under analysis on the WTI.

Table 6 **Estimated responses to a change in the crude oil price**					
		Jan 2001 - Jun 2006	Jan 2001 - Jan 2005	Feb 2005 - Oct 2008	Nov 2008 - Jun 2016
Wholesale energy ADL(2,2)	Gasoline	0.901 (0.069)	1.012 (0.177)	1.041 (0.225)	0.820 (0.087)
	Ethanol	0.603 (0.127)	0.886 (0.318)	0.404 (0.564)	0.522 (0.102)
Retail energy ADL(3,3)	Gasoline	0.679 (0.045)	0.734 (0.119)	0.731 (0.201)	0.649 (0.048)
	Diesel	0.619 (0.038)	0.702 (0.734)	0.649 (0.062)	0.548 (0.092)
Export grains ADL(1,1)	Corn	0.004 (0.091)	-0.191 (0174)	0.198 (0.178)	-0.019 (0.133)
	Wheat	0.151 (0.088)	0.071 (0.171)	0.420 (0.232)	0.081 (0.112)
	Soybeans	0.087 (0.090)	-0.393 (0.263)	0.344 (0.233)	0.135 (0.093)
	Pooled	0.093 (0.066)	-0.117 (0.122)	0.336 (0.164)	0.098 (0.079)
	Test $\chi^2(4)$	5.433 [0.246]	3.573 [0.467]	3.103 [0.541]	2.832 [0.586]
Farmgate grains ADL(1,1)	Corn	-0.005 (0.082)	-0.190 (0.212)	-0.034 (0.195)	0.035 (0.095)
	Wheat	0.051 (0.082)	0.129 (0.088)	-0.083 (0.269)	0.055 (0.088)
	Soybeans	0.054 (0.082)	-0.484 (0.301)	0.247 (0.156)	0.125 (0.080)
	Pooled	0.048 (0.058)	-0.089 (0.132)	0.016 (0.168)	0.090 (0.163)
	Test $\chi^2(4)$	1.099 [0.894]	3.603 [0.462]	6.774 [0.168]	2.389 [0.665]

The table reports the long run response to a unit shock in the log of the WTI price as implied by an ADL(p,p) estimated by OLS over the specified sample. Approximate standard errors are given in (.) parentheses. The pooled grains estimates restrict these long run responses to be equal over all three grains. Estimation is by FIML. The cross-equation restrictions are tested using a likelihood ratio test with tail probabilities reported in [.] parentheses.

The estimated pass-through for the grains is much less clearly defined, whether at the export of farmgate level. In order to get some traction on this response, we restrict is to be equal for the three grains.[10] The result is that only in the 2005-08 sub-sample can we reject the null hypothesis of zero pass-through and then only for export prices.[11] Both this evidence and the structural break analysis reported in Tables 3 and 5 indicate there was only a significant direct impact of energy prices on grains markets over the four years 2005-08. There is no evidence of any interaction in the years prior to 2005 while after 2008, there is some impact of ethanol prices on corn prices but the lower pass-through from the oil price to the ethanol price makes it difficult to see a clear impact of oil prices on grains prices.

We now relate our results back to the discussion in sections 2 and 3, and in particular to Tables 1 and 2. Over the initial five year 2000-04 the only clear price relationship is that from the oil price to the ethanol price. This was prior to the introduction of a biofuels mandate and no pass-through is apparent from either ethanol or oil prices to grains prices. Over the following four years, both these effects are apparent. This appears to correspond in a crude way to the unconstrained regime in the second row of Table 2, although this is not to imply that one or other constraint may not have been binding for particular periods of time within this period. The third (2009-14) period is more complicated with clear bidirectional relationships between ethanol and corn prices, a link between crude oil prices and ethanol prices but no apparent link between crude oil prices and corn prices.

A number of commentators have seen the June 2006 MTBE ban as being the crucial event that triggered the upward movement in food prices. Our results indicate a change in regime over a year previous to this and hence give more weight to the introduction of biofuel mandates. US biofuels production started to grow in excess of 15% per annum from 2002 – see Figure 1 but was particularly rapid over the three years 2006-08. This is the only period in which we find clear

[10] We do this by imposing two sets of restrictions. Within the ADL(1,1) we require the three δ coefficients to be equal (two restrictions) and the sum of the two γ coefficients to be equal for the three grains (a further two restrictions). In each case, a likelihood ratio test fails to reject these restrictions.

[11] Bivariate cointegration tests (not reported) show that export and farmgate prices are cointegrated for each of the grains and also for gasoline. The pass-through of oil prices into grains export prices must therefore eventually be reflected in farmgate prices. However, only a proportion of US grains sales are made on a spot basis so that it may take longer for the prices farmers received by farmers to reflect oil price changes than be captured in an ADL(1,1).

evidence of a petroleum-ethanol-corn price link. However, there are also competing explanations, such as index fund investment, which are powerful over precisely the same years.

6. The food and energy commodity classes

Wisner (2009) stated that "With rapid growth of the ethanol industry … corn has become very much an energy crop … . This transition has created a strong but still somewhat variable relationship between corn prices and those for crude oil, gasoline and ethanol". This statement was written at the close of the one period over which we have found some evidence of an impact of oil prices in grains prices. Discussing this period, Rausser and de Gorter (2012) state that corn and ethanol prices were tightly linked. This section asks whether the food and energy commodity groups can be regarded as well-defined.

Economists classify products into groups pragmatically on the basis of production and use. It is natural to suppose the eleven commodities we consider fall into two groups – food and energy commodities. Gas and diesel are produced from a mixture of crude oil and ethanol feedstocks. Changes in the crude oil price therefore feed into the prices of the derivatives while refiners are forced to adjust ethanol prices in line. In grains, the prices farmers receive vary directly with terminal market prices while the prices of the three major grains move together as the result both of common weather patterns across the grain-producing regions and the ability of a large proportion of farmers to switch crops in each planting season on the basis of likely harvest prices.

Financial economists discuss asset classes rather than commodity groups. Scherer and He (2008, p. 243) provide a useful characterization of as asset class as a "group of assets that investors regard as homogeneous enough (high internal correlation) as well as unique enough (low external correlation) to consider separate strategic allocations worthwhile". This is equivalent to stating that the class is associated with a risk premium that cannot be usefully explained by the risk premiums on other asset classes. Biegner and Ferlin (undated) have argued that food commodities should be considered as an asset class.

We adopt two related approaches in analyzing whether a group of commodities define a separate commodity sub-class. First, following Scherer and He (2008), quoted above, we compare the within class and without class correlations. Second, we use principal components analysis to identify the factors driving these returns.[12]

Table 7 **Average within and between correlations**		
	Energy	Foods
Energy	0.577	0.152
Foods	0.152	0.492
The table reports the average monthly correlation between the log changes in the nominal prices of each group of commodities. Sample: January 2000 – June 2016.		

Table 7 reports correlations in the log changes of nominal prices averaged cross the energy and food groups over the entire 2000-2016 sample. (The within averages exclude the unit correlations of each price with itself). Within group correlations are around one half while between correlations are equal to 0.15. These correlations indicate that energy and food are indeed distinct groups.

Tyner (2010) and Du et al. (2011) have both shown that food-energy correlations have varied over time in a manner consistent with the evolution of US biofuels policy. In Table 8, we report the same correlations over the sub-periods identified in section 3. (The short final sub-period from December 2014 to June 2016 is included with the third sub-period).

A number of interesting features emerge from this breakdown:

- The average correlation between the food and energy commodity returns second and third rows of the table) rose from a very low value of 0.05 prior to 2006 to 0.23 between the first and third sub-periods.
- Inter-energy correlations (top left) rose from close to 0.5 prior to 2005 to 0.6 at the end of the sample.
- Inter-food correlations were steady at around 0.5 throughout the entire period.

[12] A third alternative would be to use cointegration analysis. In the long run, given competitive markets, prices are determined by costs. While it is possible that the energy prices we analyze may be cointegrated since these products are all petroleum derivates, there is no reason to expect long run grains costs to move in line with each other. Cointegration is therefore an over strong requirement for defining an asset class.

Table 8 Average within and between correlations by sub-period			
	Jan 2000 Jan 2005	Feb 2005 Oct 2008	Nov 2008 Jun 2016
		Energy	
Energy	0.532	0.590	0.615
Foods	0.050	0.133	0.235
		Foods	
Energy	0.050	0.133	0.235
Foods	0.491	0.502	0.505

The two upper rows of the table report the average monthly correlation between the log changes in the nominal prices of the row commodities with the energy commodities over each sub-period. The two lower rows report average correlations with the food commodities.

The correlations for the food and energy groups over the initial pre-2005 subperiod correspond precisely to the Scherer and Ho (2008) characterization of an asset class as one with high inter-class and low extra-class correlations. However, the correlations between the two groups over the post-Lehman period are less clearly consistent with the existence of separate food and energy asset classes.

Table 9 Contribution of first two principal components to return variance				
	Jan 2000 Jun 2016	Jan 2000 Jan 2005	Feb 2005 Oct 2008	Nov 2008 Jun 2016
First	38.7%	38.1%	40.5%	43.9%
Second	23.8%	29.0%	25.2%	22.0%
Residual	37.5%	37.9%	34.3%	34.1%

The table reports the percentage of the overall return variance attributable to the first two principal components over the indicated sample.

We now apply principal component analysis using deflated returns in order to reduce the impact of any inflation component. Table 9 reports the proportion of the overall return variance explained by the leading two components both over the entire period and in the three sub-periods used in Table 7. The first component gives broadly equal weight to all eleven returns. This is uninteresting for the current analysis so we focus on the second component which is a contrast between the energy and food returns. This component contributes close to one quarter of the overall return variance throughout the more than two decades analyzed. Within the implied two factor model, around 35% of the return variance is seen as idiosyncratic.

Figure 2 charts the eigenvectors associated with the second component over the same periods. These are normalized to give a unit weight to WTI in each period. Taking the entire period (solid coloring), energy commodities have positive weights and food commodities negative weights in line with our earlier interpretation of this component as an energy-food contrast.

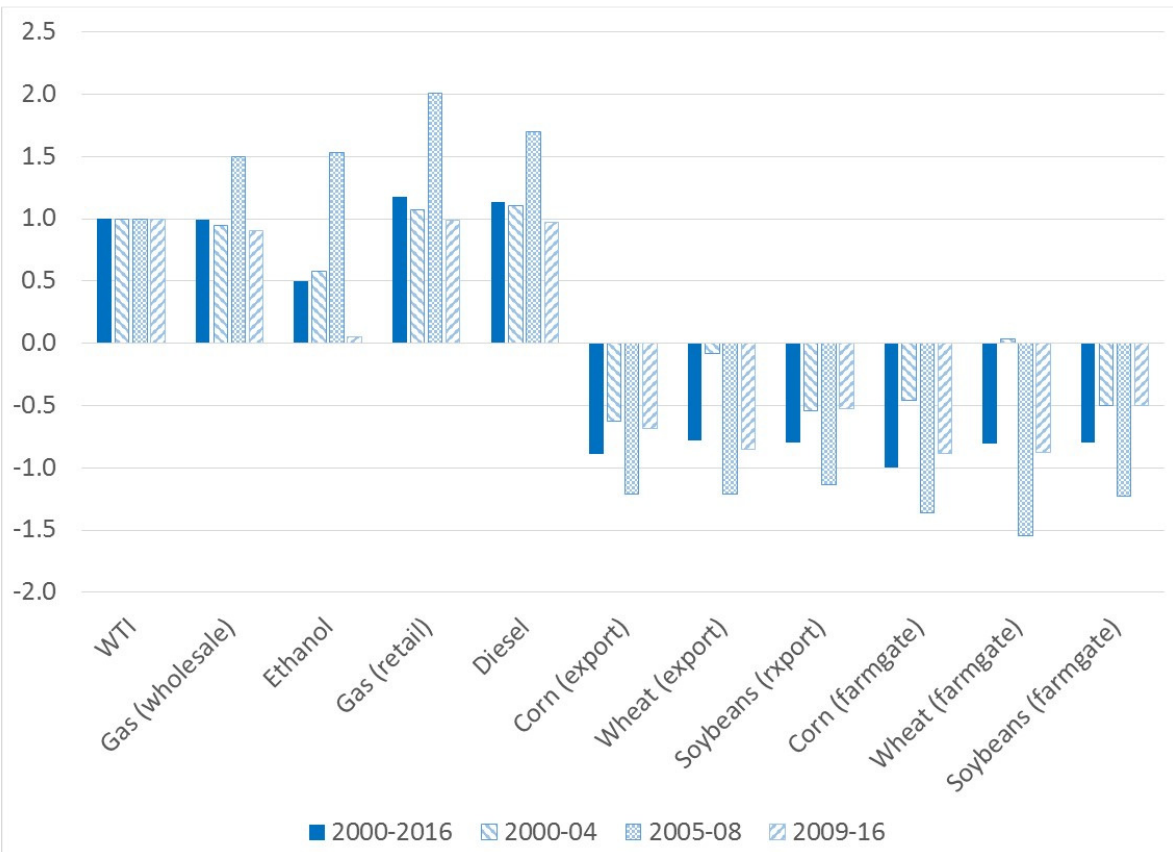

Figure 2: Normalized commodity weights

The pattern is broadly constant across all three sub-periods (shaded coloring). There are two exceptions:

- wheat returns fail to enter the second component over in the initial sub-period and instead dominate the third component;

- ethanol returns fail to enter the second component over in the final sub-period where they show little variability.

These results are generally consistent with a two factor (energy and food) model but suggest that wheat returns may be largely idiosyncratic at certain times and that ethanol may not fit neatly into the energy-food categorization.

The principal components analysis gives scant support for this claim either over the entire period or over relevant sub-periods. Despite this, the correlation analyses indicate that post-2006 price behavior has been more complicated than that in earlier years, exhibiting higher inter-group and lower intra-group correlation.

7. Conclusions

The food price boom, which started in 2006, has widely been regarded as an exceptional episode. In retrospect, there is little doubt that US biofuels policy played a role in generating high grains prices. A number of authors have made very strong claims suggesting that, by linking grains price to energy prices, these policies were responsible for most or all of these price movements. The analysis in this paper indicates that those claims are exaggerated. Our results are consistent with Abbott's (2014) estimate that biofuels may have been responsible for around half of the rise in corn prices over the 2005-09 period.

The ethanol-corn relationship provides the lynch-pin of this claim. However, that relationship is not straightforward and transmission of changes in oil prices to ethanol and of both to corn prices depends on the constraints affecting ethanol production. Different constraints bind at different times resulting in a variable relationship. The analysis in this paper shows that grains prices were unaffected by energy prices until 2005 despite the fact that US ethanol production started to grow fast from 2002. Over the pre-2005 period, food and energy prices formed distinct commodity groups and asset classes. However, the relationship became more complicated from 2005 and it is likely that developments in US biofuels policy were instrumental in these changes.

There is evidence of a structural break in the corn-ethanol price relationship at the start of 2005 and clear links between oil, ethanol and corn prices over the four years 2005-08. However, there is a second break at the end of 2008 and only weak evidence of oil prices feeding through into corn prices from 2009 onwards. It is still possible, post-2004, to regard foods and energy commodities as forming separate groups but the definition of the two groups becomes less sharp.

The most striking conclusion is that there is no evidence of any change in the relationship of the corn price to corn market fundamentals, as measured by expected end crop-year stocks, once we have controlled for changes in the relationship of the corn price to the oil and ethanol prices. Any energy market impacts were additional to those generated through the energy nexus. Indeed, the corn price became more sensitive to corn fundamentals over the high price period as stocks declined and the market tightened. Contrary to some claims, competitive theory of storage appears crucial to understanding the food price boom. The impact of biofuels policy on food prices can be best understood within that framework.

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Data appendix

We analyze monthly data covering the sample January 2000 to June 2016. (Data for 1999 enter in the construction of lagged variables where utilized). The dataset comprises the following variables:

World prices (all taken from IMF, *International Financial Statistics*, cd-rom)

WTI	Crude oil price, $/bl
Corn (maize)	Gulf ports, $/tonne converted to $/bu
Wheat	Kansas City, $/tonne converted to $/bu
Soybeans	Norther European ports, $/tonne converted to $/bu
US PPI	used as deflator, 2010=100

US farmgate agricultural prices (prices received by farmers)

Corn	*US Bioenergy Statistics*,[13] Table 14, $/bu
Wheat	University of Illinois, *Farmdoc*[14]
Soybeans	University of Illinois, *Farmdoc*, updated using data from USDA, National Agricultural Statistics Service[15]

US grain stocks, end crop year estimates (USDA, *World Agricultural Supply and Demand Estimates*, WASDE)[16]

Corn	World, excluding China (mn tonnes)

US bio-related energy prices (taken from *US Bioenergy Statistics*, Table 14)

Gasoline	Rack prices[17] fob Omaha, $/gl
Diesel	Average of daily prices, $/gl
Ethanol	Rack prices, inclusive of tax credit,[18] $/gl

US retail gas price (taken from US EIA)

Gasoline	Average of daily prices[19], $/gl

With the single exception of the corn stocks, variables are all transformed into logarithms.

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[13] http://www.ers.usda.gov/data-products/us-bioenergy-statistics.aspx

[14] http://www.farmdoc.illinois.edu/manage/uspricehistory/USPrice.asp

[15] https://www.nass.usda.gov/Charts_and_Maps/graphics/data/pricesb.txt

[16] http://www.usda.gov/oce/commodity/wasde/

[17] Wholesale truckload sales or smaller where title transfers at a terminal.

[18] Blenders tax credit: $0.60 per gallon through 1990, $0.51 through 2008, $0.45 from 2009 through December 31, 2011.

[19] https://www.eia.gov/opendata/qb.cfm?sdid=PET.EMM_EPM0_PTE_NUS_DPG.M , series ID: PET.EMM_EPM0_PTE_NUS_DPG.M