

The effects of US biofuels policy: A structural break analysis of the WTI pass-through to the corn price

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Abstract

There is evidence that the use of corn as a biofuels feedstock has increased the crude oil pass-through to the corn price. Changes in US biofuels policy can be seen as initially increasing and subsequently retarding the use of corn in ethanol production. Because the policy both mandates but also limits this use, different regimes can prevail depending on which constraints are binding. Structural break methods show that the pass-through was important over the four years 2003-07 but has subsequently been much more limited. Competitive storage theory continues to explain much of the price movement even over those four years.

Keywords: Structural breaks, corn, WTI, ethanol

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1. Introduction

At their June 2008 peak, nominal corn (maize) prices exceeded December 2005 levels by 180% and the WTI crude oil price was 125% higher over the same period. By December 2015, the corn price remained 42% higher and the WTI price 63% higher than their end 2005 levels.¹ The correlation between monthly averages of the two prices over the 10 years 2006-2015 was 0.633. The correlation over the previous ten year period (1996-2005) was -0.153. In this paper, we examine whether there were one or more structural breaks in the relationship between crude oil and corn prices and, if so, whether changes in US biofuels policy may have been responsible for these breaks. Specifically, 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 becoming more closely linked to energy prices.

The impact of the use of corn as a biofuels feedstock has been discussed by Abbot et al. (2008), de Gorter and Just, (2009), Tyner (2008, 2010), Abbot (2014), Wright (2014) and de Gorter et al. (2015). Different authors have reached 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 instead we should see corn as a petro-commodity with the result that food prices become a tail wagged by the energy dog.

An evaluation of the impact of biofuels policy on grains prices requires a model of the grains sector. We do not attempt that in the current paper. Instead we focus on the more limited issue of the pass-through from crude oil prices to corn prices. In section 2 of the paper, we argue that, contrary to widely held opinion, we should not expect to see any substantial

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 33% rise in corn prices over a period in which they rose overall by 65%.

pass-through from oil prices to deflated grains prices since the deflator is also affected by oil prices. It follows that if there is an impact of oil prices on corn prices, this must be demand and not cost-driven.

US biofuels policy may have generated this impact by linking demand for corn as an ethanol feedstock to the oil price. Section 3 provides a simplified account of US biofuels policy over the past fifteen years. We argue that, in the United States, ethanol production has been potentially constrained by at least three factors. In section 4 we set out a model of corn, ethanol and crude oil prices. The model implies that the impact, if any, of crude oil prices on corn prices depends on which of these constraints, if any, are binding. The model also implies that any such impacts are additional to the standard stock-based determinants of grains prices predicted by competitive storage theory.

In Section 5 we move to econometrics sets out our modeling methodology. The model set out in Section 4 implies that the existence and extent of any pass-through is likely to vary over time. For this reason, in Section 6, we apply structural break analysis to the corn-ethanol relationship. The results, reviewed in Section 7 which concludes, are broadly in line with the institutional and policy analysis in the first part of the paper.

2. The link between crude oil and grains prices

Energy prices may affect grains prices either by raising production and distribution costs, hence shifting the grains supply curve, or by augmenting or discouraging demand. Prior to the advent of biofuels, discussion focused almost entirely on the former effect. We argue that the latter, demand side effect, is much more important.

Energy is an input into the grains sector and on this basis, we should expect some transmission of crude oil prices into grains prices. The 2007 389 sector input-output tables for the US distinguish grain farming and petroleum refining as distinct sectors. They show a direct input share of petroleum refining into grains production of 9.8% (11.9% for all energy sectors). This share rises to 15.9% (22.9%) when indirect use is also included.³ Baffes (2007) estimated the pass-through of oil prices into agricultural commodity prices as 17%. Mitchell (2008) states that the combined effects of higher energy and transport costs were to raise

³ https://www.bea.gov/industry/io_annual.htm These calculations use files CxI_DR_2007_detail.xlsx, CxC_TR_2007_detail.xlsx and IOUse_Before_Redefinitions_PRO_2007_Detail.xlsx .

production costs in U.S. agriculture by 15%-20%. Both these estimates are in line with the requirements implied by the input-output data.

In the econometric modeling reported in section 5 of this paper, we analyze the pass through from the WTI price to the corn price where both prices are deflated by the US Producer Price Index (PPI). By deflating by the PPI, we are analyzing the pass-through between two relative prices. A change in crude oil prices, relative to the PPI basket, will affect both the numerator and the denominator of the corn price relative to the PPI basket. We should therefore only expect to see pass-through from deflated crude oil prices to deflated grains prices if the energy content of grains differs from the energy content of the PPI basket. In fact the differences are small, at least in the United States. Taking single digit NAICS 1-3 commodity products, which comprise 273 of the 389 sectors in the input output tables and include the primary and manufacturing industries, direct use of petroleum refining products amounts to 8.2% of output against 9.8% for grains. Adding in other energy inputs, we obtain a 13.7% energy content against 11.9% for grains. In summary, grains production differs little from the remainder of the US productive sector in terms of energy use.

The preceding argument shows that we should therefore not expect to see a cost-based pass-through from deflated crude oil prices to deflated grains prices. Any pass-through which is evident is therefore likely to have a demand side origin. This provides the background against which we examine the development of US biofuels policy.

3. 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.

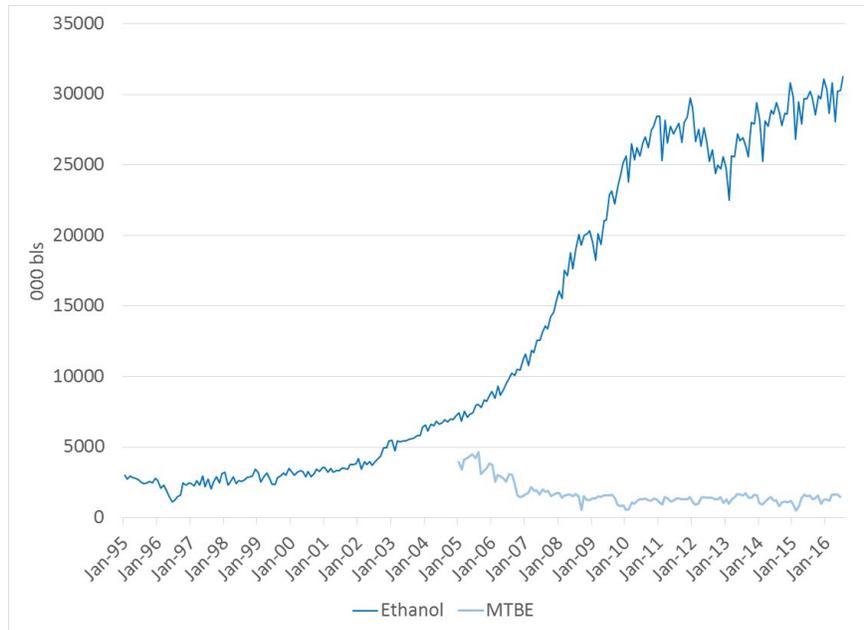


Figure 1: US monthly production of ethanol and MTBE, 1995-2016

Biofuels in the sole explanation listed above that ticks all three boxes. 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).⁴ 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 1.⁵ 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 (US 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 Excise Tax Credit – (VEETC), and import tariffs were imposed to ensure foreign producers did not get the subsidy.

⁴ EIA, http://www.eia.gov/dnav/pet/pet_pnp_oxy_dc_nus_mbb1_m.htm

⁵ Table 1 is similar to Table 3.2 in Abbott (2014).

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. The growth started in 2002 and accelerated after the MTBE ban in 2006.

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.

4. 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 et al. (2009). Abbott (2014) and de Gorter et al. (2015, page 20) placed particular emphasis on the 2006 MTBE ban.

The 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 model contains three prices – the corn price p , the ethanol price e and the gasoline price g . We simplify by supposing that the gasoline price is entirely determined by the crude oil price and use g to represent both the gasoline 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 $a - \alpha q$ 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 depend positively in the ethanol price and negatively on the corn price as $\pi = \pi(e, p(a - \alpha q))$.

The blend wall constraint relates to the ethanol-gasoline price relationship. Write the associated level of ethanol 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

$c = c(p, g)$. Abbott (2014) emphasized that different regimes will apply at different times. In our simple model, the mandate and capacity 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 its price to marginal cost. This gives $p = p(a - \alpha m)$ and $e = c(p, g)$ with $\pi(c(p, g), p(a - \alpha m)) < 0$.
- 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, biofuels production q adjusts to until the corn price eliminates the profitability of ethanol production, i.e. $\pi(e(g), p(a - \alpha q)) = 0$. The resulting corn price is given by $p = P(e(g))$.
- 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 $\pi(c(p, g), p(a - \alpha b)) > 0$.
- 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 $\pi(e(g), p(a - \alpha k)) > 0$.

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. The different regimes are summarized in Table 2.

Table 2			
Expected price relationships			
Ethanol regime	Corn and ethanol	Ethanol and petroleum	Corn and petroleum
(i) Constrained by 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 direct relationship between the petroleum and the corn prices in cases (i) and (iii) allows for the possibility of an indirect link via ethanol prices. In the case of refining constraint, there will be neither a direct nor an indirect link from petroleum prices to corn prices. This does not imply that corn prices are unaffected by biofuels production since in both cases this reduces corn availability for food production. However, given the refining capacity constraint, 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. That is to say, in regimes (i), (iii) and (iv) what matters is the quantity of corn used in as a biofuels feedstock and not the oil price.

Abbott (2014, page 93) argues that capacity constraints in ethanol refining were binding in 2005 and 2006 placing this period in category (iv) of Table 2. He goes on to argue that the blend wall may have limited ethanol production in 2011 and 2012 (category iii). Turning to the RFS mandate constraint, this is enforced through RINs (renewable identification numbers) which refiners are obliged to sell to the EPA. However, RINs can also be traded and a positive RIN price therefore indicates that the RFS mandate is binding. RIN prices were close to zero except from late 2008 and through 2009 and then jumped sharply at the end of 2012 to much higher levels than had previously been observed (Irwin and Good, 2013). These periods correspond to category (i) in Table 2.

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 et 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”.

5. 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 et 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. 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. The model is

$$\ln(\text{Corn}_t / \text{PPI}_t) = \alpha_0 + \alpha_1 \ln(\text{WTI}_t / \text{PPI}_t) + \alpha_2 \ln(\text{Ethanol}_t / \text{PPI}_t) + \alpha_3 \text{Stocks}_t + u_t \quad (1)$$

$$\ln(\text{Ethanol}_t / \text{PPI}_t) = \beta_0 + \beta_1 \ln(\text{Corn}_t / \text{PPI}_t) + \beta_2 \ln(\text{WTI}_t / \text{PPI}_t) + v_t \quad (2)$$

where *PPI* is the US producer price index which deflates prices to real terms and *u* and *v* are disturbances. Acknowledging the institutional discussion in section 4, we allow for structural breaks in these relationships. Within the model set out in equations (1) and (2), the demand for corn as a biofuel feedstock may affect the corn price by lowering expected end crop year stocks, or by changing the pass-through from the oil price to corn prices either directly or via the ethanol price.

This model cannot claim to be structural but it reflects some structural features of the markets. It does not permit direct evaluation of policy impacts. 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.

We proceed in two stages. For simplicity, 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 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 or sub-sample under analysis. 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.

There is a further problem. Agricultural data naturally falls into crop years with prices moving most acutely in the final months (July - September) of the northern hemisphere crop year. There is a danger that too short a sample will be heavily influenced by this seasonal pattern with the possible result of breaks being identified at the end of many or most crop years. To limit this possibility we require at least 30 observations in each sub-period. Setting the minimum test window to 12 months, we only consider breaks in samples of at least 72 months.

6. Structural break analysis

We analyze monthly export prices of corn (maize), the crude oil (WTI) price and the wholesale price of ethanol.⁶ Competitive storage theory relates price to availability, equal to the

⁶ Corn and WTI prices: *International Financial Statistics*, cd-rom. Ethanol prices: *US Bioenergy Statistics*, Table 14.

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 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.⁷ The series measures world stocks excluding stocks held in mainland China.⁸ The data sample extends for January 2000 to December 2016 (204 observations) to focus on the period over which biofuels demand was fast growing.

In performing the structural breaks analysis, we test the α_1 , α_2 , and α_3 slope coefficients for constancy, but not the intercept. This allows for the possibility of omitted factors which may generate intercept shifts. Considering this entire 204 month period, the procedure locates a statistically significant break in August 2007. 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 February 2003 while in the “after” sample there appears to be a significant break in January 2010. The BIC indicates that we should not look for further breaks.

Figure 2 graphs the sup W test statistics both for the first pass of the procedure which yields the August 2007 break (darker line) and for the second pass which yields the earlier and later breaks (lighter line). All three breaks are statistically significant at the 99% level using the Andrews (1993) critical values. Both the August 2007 and February 2003 sup W peaks are very sharp indicating clearly defined breaks. However, the January 2010 break occurs right at the start of the “after” test window. Moving the window back has the effect of moving the break back so that it remains at the start of the window. It is apparent that what we have

⁷ USDA, *World Agricultural Supply and Demand Estimates*. 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.

⁸ 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).

here is not so much a break as anomalous behavior associated with the 2008 financial crisis. On this basis, we accept two breaks – the first in February 2003 and the second in August 2007.

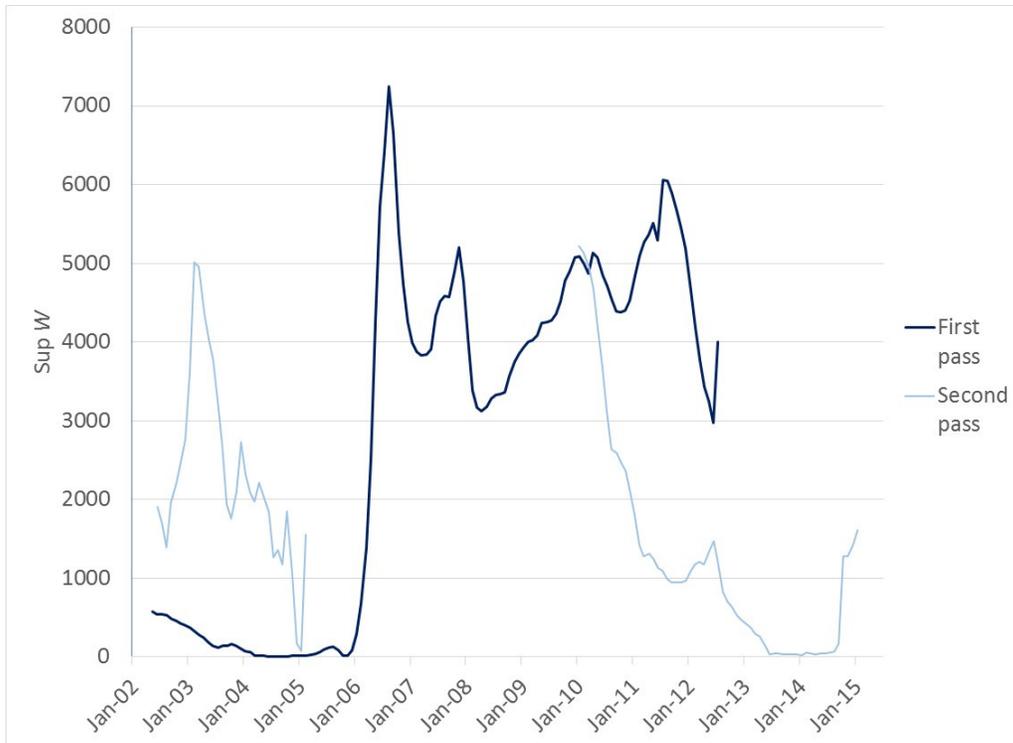


Figure 2: Sup W plots, corn regressions (including stocks)

The two break model implies three sub-periods. The first three rows of Table 3 report the estimated β coefficients, together with HACSE t statistics, for each of the three sub-periods we have identified. There is no evidence of any pass-through from either the crude oil or the ethanol price to the corn price in the initial (2000-02) sub-period. In the second (2003-07) sub-period, there is a well-defined pass-through from the WTI price to corn but none from the ethanol price. This situation is reversed in the final (2007-16) sub-period in which there is only pass-through from the ethanol price. The coefficient (α_3) of the stock fundamental is estimated as negative and statistically significant in all three sub-periods. The final row of the table reports the estimates from an equation estimated over the entire sample but including intercept shift dummies for the first two sub-periods. This shows impacts of the regressors averaged over the 17 year sample. An F test, reported in the notes to the table, rejects the homogeneity restrictions confirming that the responses were non-constant.

Table 3				
Estimated coefficients by sub-period – corn regression including stocks				
Dependent variable	ln(WTI/PPI)	ln(Ethanol/PPI)	Stocks/100	R ²
ln(Corn/PPI)	α_1	α_2	α_3	
January 2000 - January 2003	0.007 (0.06)	-0.033 (0.69)	-0.677*** (6.71)	0.710
February 2003 - July 2007	0.365** (2.38)	0.014 (0.21)	-0.984*** (5.57)	0.688
August 2007 - December 2016	-0.063 (1.26)	0.307*** (4.00)	-1.160*** (7.85)	0.819
January 2000 - December 2016	0.075* (1.75)	0.153*** (2.83)	-0.961*** (12.81)	0.732
<p>The first three rows of the table report the OLS estimates of equation (1) over the four sub-periods identified by the Bai and Perron (1998) multiple break procedure. The final row reports the estimate over the entire sample. The equations also include an intercept and, in the final equation, dummies for first and second sub-periods. HACSE <i>t</i> statistics are given in parentheses. An <i>F</i> test of the entire sample estimate (row 4) against the combined estimates by sub-periods (rows 1-3) gives a test statistic of $F_{6,192} = 11.09$ with tail probability less than 0.0001. The R² statistic reported in the fourth row is calculated relative to an equation which contain the two shift dummies.</p> <p>*, ** and *** indicate coefficients which differ significantly from zero at the 90%, 95% and 99% levels respectively.</p>				

The first three rows of Table 4 reports estimates of the ethanol equation (2) using the same division into sub-periods.⁹ The estimates for the short 2000-02 sub-period are problematic and may reflect short term trends.¹⁰ The estimates for the two later sub-periods suggest that ethanol prices were driven both by crude oil and corn prices. The final row of the table reports the “average” equation estimated over the entire 17 year sample. As was the case with the corn equation reported in Table 3, the homogeneity restrictions are rejected.

Simultaneity between the ethanol and corn prices may jeopardize the reliability of the estimates reported in Tables 3 and 4, particularly over the 2007-16 sub-period in which there is evidence that the causation between corn and ethanol prices is bidirectional.¹¹ In principle, we can use the corn stocks variable to instrument the corn price in the ethanol price equation

⁹ 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.

¹⁰ The correlation between the WTI and corn prices is very low over these three years so collinearity is not a problem.

¹¹ Any simultaneity bias in the estimated α_2 coefficients reported in Table 3 should be positive. In the first two sub-periods, the estimated ethanol price (α_2) coefficients are close to zero making it safe to accept the hypothesis that these coefficients were zero over this period. Simultaneity concerns are therefore confined to the final (2007-16) sub-sample.

but the structure defined by equations (1) and (2) does not offer an instrument for ethanol in the corn equation. However, by solving the ethanol price out of the corn price equation to obtain a reduced relationship involving just the WTI price and stock level, we can estimate the total (direct plus indirect) impact of crude oil prices on the corn price – see equation (3).

$$\ln(\text{Corn}_t / \text{PPI}_t) = \gamma_0 + \gamma_1 \ln(\text{WTI}_t / \text{PPI}_t) + \gamma_3 \text{Stocks}_t + w_t \quad (3)$$

Equation (3) allows us to infer the crude oil pass-through to corn but does not allow us to distinguish direct from indirect effects.

Table 4			
Estimated coefficients by sub-period – ethanol regression			
Dependent variable ln(Ethanol/PPI)	ln(Corn/PPI) β_1	ln(WTI/PPI) β_2	R ²
January 2000 - January 2003	-0.946* (1.97)	0.967** (2.61)	0.305
February 2003 - July 2007	0.468* (1.79)	1.160*** (7.31)	0.586
August 2007 - December 2016	0.494*** (3.43)	0.173* (1.83)	0.518
January 2000 - December 2016	0.171 (1.15)	0.503*** (4.17)	0.313
<p>The first three rows of the table report the OLS estimates of equation (2) over the four sub-periods identified by the Bai and Perron (1998) multiple break procedure. The final row reports the estimate over the entire sample. The equations also include an intercept and, in the final equation, dummies for first and second sub-periods. HACSE <i>t</i> statistics are given in parentheses. An <i>F</i> test of the entire sample estimate (row 4) against the combined estimates by sub-periods (rows 1-3) gives a test statistic of $F_{4,199} = 12.01$ with tail probability less than 0.0001. The R² statistic reported in the fourth row is calculated relative to an equation which contain the two shift dummies.</p> <p>*, ** and *** indicate coefficients which differ significantly from zero at the 90%, 95% and 99% levels respectively.</p>			

Estimation results for equation (3) are reported in Table 5. It is only in the 2003-07 sub-period that we find a pass-through from the crude oil price to the corn price that is either quantitatively or statistically significant. We now relate these results back to the discussion in sections 2 and 3, and in particular to Tables 1 and 2. Over the initial five year 2000-03 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, 2003-07, both these effects are

apparent. This corresponds to the unconstrained regime in the second row of Table 2. The third (2007-16) period is more complicated with clear bidirectional relationships between ethanol and corn prices, a link between crude oil prices and ethanol prices but only weak evidence of a link between crude oil prices and corn prices.

Dependent variable ln(Corn/PPI)	ln(WTI/PPI) γ_1	Stocks/100 γ_2	R^2
January 2000 - January 2003	-0.026 (0.33)	-0.701*** (9.00)	0.703
February 2003 - July 2007	0.385*** (3.32)	-0.993*** (6.25)	0.688
August 2007 - December 2016	0.001 (0.03)	-1.322* (9.43)	0.772
January 2000 - December 2016	0.161 (4.50)	-0.944*** (11.73)	0.699
<p>The first three rows of the table report the OLS estimates of equation (3) over the four sub-periods identified by the Bai and Perron (1998) multiple break procedure. The final row reports the estimate over the entire sample. The equations also include an intercept and, in the final equation, dummies for first and second sub-periods. HACSE t statistics are given in parentheses. An F test of the entire sample estimate (row 4) against the combined estimates by sub-periods (rows 1-3) gives a test statistic of $F_{4,199} = 6.91$ with tail probability less than 0.0001. The R^2 statistic reported in the fourth row is calculated relative to an equation which contain the two shift dummies.</p> <p>*, ** and *** indicate coefficients which differ significantly from zero at the 90%, 95% and 99% levels respectively.</p>			

Finally, we turn to the coefficient α_3 of the corn stock fundamental variable in the corn equation. This is well-determined in all three sub-periods. There is no evidence that the post-2003 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 to movements in the corn price over this period but stocks variable (partial r^2 0.636) does so more than the crude oil price (partial r^2 0.170).

7. Conclusions

We can relate the results found in Section 6 to the discussion in Section 4 and in particular to the classifications in Table 2. The initial 2000-03 sub-period is prior to the initial moves to

stimulate biofuels production. Over this period, we see neither a direct nor an indirect link from crude oil to corn prices. In line with the arguments in section 2, there is no pass-through from oil to corn prices. The second, 2003-07, sub-period sees both a direct link from crude oil prices to corn prices and an indirect link via ethanol prices. In terms of the model in section 4, this suggests that ethanol production was unconstrained, contrary to Abbott's (2014) argument that there was a lack of adequate refining capacity in 2004 and 2005. In the final 2007-14 sub-period we see no evidence of a direct link from crude oil to corn but some evidence of an indirect link via ethanol. This is compatible with either the blend wall or the RFS mandate constraints binding. Abbott (2014) argued that the blend wall was important in limiting ethanol production in 2011 and 2012 while positive RIN prices indicate that the mandate was binding in 2008-09 and again from the end of 2012. Overall, the results underline Abbott's (2014) conclusion that the price impact of US biofuel policy have been variable over time and have depended on which constraint, if any, was binding at each moment of time.

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. We have argued for three important but more limited propositions.

- We should not expect any cost-based pass-through from crude oil prices to deflated grains prices since the energy content of grains production is not very different from that of the productive economy more generally. Our results support this conclusion.
- Any demand-side pass through resulting from the use of corn as a biofuels feedstock will depend on the constraints affecting ethanol production. The pass-through will be variable over time. We find that the impact was strongest over the four years 2003-07, absent prior to 2003 and much weaker after 2007.
- Biofuel demand impacts on corn prices do not over-ride the standard harvest and stock-based impacts predicted by competitive storage theory. The latter remained the most powerful determinants of corn price movements even over the period of greatest oil price pass-through.

References

- Abbott P.C. (2014). Biofuels, binding constraints and agricultural commodity price volatility. In J.-P. Chavas, D. Hummels, and B.D. Wright (eds.), *The Economics of Food Price Volatility*, Chicago: University of Chicago Press.
- Abbott, P.C., C. Hurt and W.E. Tyner (2008). *What's Driving Food Prices?* Oak Brook (IL): Farm Foundation.
- Andrews, D.W.K. (1993). "Tests for parameter instability and structural change with unknown change point". *Econometrica*, 61, pp. 821-856.
- Baffes, J. (2007). "Oil spills on other commodities", Policy Research Working Paper #4333, Washington D.C., World Bank.
- Bai, J. and P. Perron (1998). "Estimating and testing linear models with multiple structural changes", *Econometrica*, 66, pp. 47-78.
- Bobenrieth, E., B.Wright and D. Zeng (2013). "Stocks-to-use ratios and prices as indicators of vulnerability to spikes in global cereals prices". *Agricultural Economics*, 44 (sup.), pp. 43-52.
- Chow, G.C. (1960). "Tests of equality between sets of coefficients in two linear regressions". *Econometrica*, 28, 591-605.
- Cooke, B., and M. Robles (2009). "Recent food price movements: A time series analysis", IFPRI Discussion Paper, 00942. Washington D.C.: IFPRI.
- de Gorter H., and D.R. Just (2009). "The economics of a blend mandate for biofuels". *American Journal of Agricultural Economics*, 91: pp. 738-750.
- de Gorter H., and D. Drabik and D.R. Just (2015). *The economics of biofuel policies*. New York: Palgrave Macmillan.
- Deaton, A.S., and G. Laroque (1992). "On the behaviour of commodity prices". *Review of Economic Studies*, 59, pp. 1-23.
- Energy Information Administration (EIA) (2000). *MTBE, Oxygenates and Motor Gasoline*. Washington DC: Department of Energy.
- Gilbert, C.L. (2010). "How to understand high food prices". *Journal of Agricultural Economics*, 61, pp. 398-425.
- Headley, D., and S. Fan (2008). "Anatomy of a crisis: The causes and consequences of surging food prices". *Agricultural Economics*, 39, pp. 375-391.
- Hertel T.W., and J. Beckman (2012): Commodity price volatility in the biofuel era: An examination of the linkage between energy and agricultural markets. In J.S. Graff Zivin and J.M. Perloff (eds.), *The Intended and Unintended Effects of U.S. Agricultural and Biotechnology Policies*, Chicago: University of Chicago Press.
- Irwin, S., and D. Good (2013). "Is Speculation Driving Up the Price of RINS?". *farmdocDAILY*, 24 April 2013. Urbana-Champaign: University of Illinois.
- Mitchell, D. (2008). "A note on rising food prices". *Policy Research Working Paper #4682*. Washington DC: World Bank, Development Prospects Group,
- Pfuderer, S. (2015). *Impacts of China on global wheat prices – Insights from the competitive storage model*. Paper presented at the 29th International Conference of Agricultural Economists, Milan, Italy, 8-14 August 2015.
- Prodan, R. (2008). "Potential pitfalls in determining multiple structural changes with an application to Purchasing Power Parity". *Journal of Business and Economic Statistics*, 26, pp. 50-65.
- Rausser, G.C., and G. de Gorter (2012). *US policy contributions to food grain commodity prices*. Paper presented at UNU-Wider Workshop on the Political Economy of Food Price Policy. Ithaca:

Cornell University. http://www.wider.unu.edu/publications/working-papers/2013/en_GB/wp2013-033/

- Throstle, R., D. Marti, S. Rosen and P. Westcott (2011). *Why have food commodity prices risen again?* WRS-1103. Washington DC: USDA, Economic Research Service.
- Tyner, W. (2008). "The US ethanol and biofuels boom: its origins, current status and future prospects". *BioScience*, 59, pp. 646-653.
- Tyner, W. (2010). "Integration of energy and agricultural markets". *Agricultural Economics*, 41: pp. 193-201.
- Tyner, W., and D. Viteri (2010). "Implications of blending limits on the US ethanol and biofuels markets". *Biofuels*, 1, pp. 251-253.
- U.S. Congress (2005). *Energy Policy Act of 2005*. Pub. L. no 109-158. Washington D.C.: U.S. Congress.
- Williams, J.C., and B.D. Wright (1991). *Storage and Commodity Markets*. Cambridge: Cambridge University Press.
- World Bank (2007). *World Development Report 2008: Agriculture for Development*. Washington DC: World Bank.
- Wright, B.D. (2014). "Global biofuels: key to the puzzle of grain market behaviour". *Journal of Economic Perspectives*, 28(1), pp. 73-97.