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Biofuels and Food Prices: Searching for the Causal Link

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Abstract. We analyze the relationship between the prices of ethanol, agricultural commodities and livestock in Nebraska, the U.S. second largest ethanol producer. The paper focuses on long-run relations and Granger causality linkages between ethanol and the other commodities. The analysis takes possible structural breaks into account and uses a set of techniques that allow to draw inferences about the existence of long-run relations and of short-run in-sample Granger causality and out-of-sample predictive ability. Even after taking breaks into account, evidence that the price of ethanol drives the price dynamics of the other commodities is extremely weak. It is concluded that, on the basis of a formal, comprehensive and rigorous causality analysis we do not find evidence in favour of the Food versus Fuel debate.

Keywords: Ethanol, Field Crops, Granger Causality, Forecasting, Structural Breaks

JEL Codes: C22, C53, Q13, Q42, Q47

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Biofuels and Food Prices: Searching for the Causal Link

1. Introduction

In recent years agricultural commodities have been a source of concern because of the tendency of prices to increase and become more volatile. The popular press and reports from international and non-government organizations have been voicing the responsibility of the significant expansion of biofuel production in causing increases of food prices, thus putting at serious risk the plight of millions of poor.[1] This has sparked the “Food versus Fuel” debate. According to the underlying view, the introduction of biofuels has strengthened the linkages between fuel and agricultural markets. In particular, because of the very rapid expansion of U.S.-produced ethanol whose main input is corn, the increased conversion of maize to ethanol reduced the supplies of food and increased food prices.

Over the last ten years the world biofuel production has increased dramatically.[2] Many developed countries are highly dependent on oil imported from politically sensitive regions. In addition, oil is today the most important energy source for transportation, a sector in continuous expansion throughout the world. Among the short-medium term strategies to reduce a country energy dependence from abroad are changes in the fuel mix of the road transport sector, mostly by increasing the use of biofuels. Indeed, between 2000 and 2010 ethanol output went up from 17 to 86 billion liters, while biodiesel grew from 0.8 to 19 billion liters. Today biofuels provide 2.7% of all global fuel for road transportation, up from 2% in 2009.

Since the aftermath of the first oil crisis in the early 1970s U.S. policy has aimed to establish and expand a domestic ethanol fuel industry. The United States and Brazil are the two largest producers of ethanol: in 2010, the United States generated 49 billion liters, or 57% of global output, and Brazil produced 28 billion liters, or 33% of the total. While sugarcane is the dominant source of ethanol in Brazil, corn is the primary feedstock for U.S. ethanol. Today’s ethanol production is made with about 40% of all America’s field corn, up from 12% in 2004-2005. The U.S. harvests around two fifths of world’s corn and accounts for 60% of the maize exported globally. Apart from providing feed for cattle, pigs and chickens, and having

[1] As an example, Fidel Castro claimed that George W. Bush's support for the use of food crops in fuel production would cause three billion deaths from hunger, according to a BBC report of March 29, 2007 (http://news.bbc.co.uk/2/hi/americas/6505881.stm). See also “As high as an elephant’s eye”, The Economist October 16th, 2010.

[2] Sorda et al. (2010) provide an overview of policies across the world. An account of the developments in the U.S. ethanol industry and of national policies is provided in Solomon at al. (2007) and Zhang at al. (2007).

dozens of industrial uses, flour from corn is a staple for millions of poor people.[3] Because in the U.S. most ethanol is made from corn, the observed growth in the production of such biofuel allegedly accounts for a large portion of the growth in the demand for corn. According to the latest report of the National Corn Growers Association (NCGA), more than 3400 million bushels of corn, equivalent to 27.3% of U.S. consumption, were used to produce ethanol in 2011; if compared to the figure for 1986, 290 million bushels, this implies an average annual growth rate over 3.6% (NCGA, 2012). Given that one bushel of corn allows to produce 2.8 gallons of ethanol, it follows that the U.S. ethanol production from corn has increased from 812 million gallons in 1986 to 9520 million gallons in 2011.

Ethanol was introduced in the early 80's as a transportation fuel to be blended with gasoline to increase its octane level. Later its role shifted to become an "oxygenate" to help gasoline to burn more efficiently. Lastly, ethanol was appreciated for its sustainability implications, been part of the renewable energy family and helping to reduce the energy dependence of a country. Blended into over 90% of motor gasoline, it is estimated that in 2011 U.S. ethanol will eliminate the need for over 212 million barrels of imported oil worth around 21 billion dollars.[4]

The great expansion of U.S. ethanol production has been largely policy-driven.[5] The U.S. ethanol industry has benefitted from preferential treatment from federal and state governments ever since the Energy Tax Act of 1978 which exempted 10% ethanol/gasoline blend (gasohol) from the federal excise tax. This decision was combined with a 54 cents/gallon ethanol import tariff introduced to provide incentives for the establishment and development of a U.S. biofuel industry. Various states, mainly the corn-producing Midwest, subsequently enacted additional ethanol fuel tax credits to further promote the industry. While tax credits and subsidies played only a modest role, the industry became a major

[3] It is estimated that out of the 45,000 products on sale in an American supermarket more than one fourth contains corn.

[4] "Global ethanol production to reach 23 billion gallons in 2011", retrieved from: http://ethanolproducer.com/articles/7482/global-ethanol-production-to-reach-23-billion-gallons-in-2011.

[5] Also in Europe biofuels development has been supported by legislation since the beginning of the century. The first European bill was the 2003 Biofuels Directive which, for the first time, established non-binding targets for renewable fuels in transport (2% by 2005 and 5.75% by 2010). In 2009 the Biofuels Directive was replaced by the Renewable Energies Directive (RED) which extended and increased, and also made mandatory, the proportion of renewable fuels on overall transport fuel to 10% by 2020. The European biodiesel market is much larger than the bioethanol one: in 2011, the former accounted for about 70% of the biofuels industry while the latter had only a 28% market share. The first reason behind these figures is that the European diesel consumption in the transport sector is considerably higher than gasoline. Secondly, the European local supply of feedstock for biodiesel such as rapeseed is larger than the one for bioethanol (grains and sugar beet), the opposite being true for the US.

supplier of fuel additives to the country especially following state bans on Methyl Tertiary Butyl Ether (MTBE) found to contaminate both ground and surface waters. This, in turn, involved a substantial improvement in the economic outlook for rural America.

The petrol in American cars nowadays contains up to 10% ethanol (E10), but in the Mid-West, where many of the bio-refineries are located, a blend containing 85% ethanol (E85) is also available for so-called "flex-fuel" vehicles. Lately, the Environmental Protection Agency (EPA) approved a blend with 15% ethanol (E15) for use in ordinary petrol-powered vehicles built from 2001 onwards. At the root of this is the Energy Policy Act of 2005 which established a mandate known as the Renewable Fuel Standard (RFS). Pushed by the farm lobby, the RFS program originally required that 28 billion liters of renewable fuel be blended annually into gasoline by 2012 to help reduce greenhouse-gas emissions and cut oil imports. In 2007 Congress passed the Energy Independence and Security Act scaling up the RFS mandate to 13.2 billion gallons of corn-based ethanol annually by 2012 and to an unprecedented 36 billion gallons by 2022.

In this paper we use modern statistical techniques to examine the causal nexus between ethanol, corn and other agricultural commodities, seeking support in favor or against the "Food versus Fuel" claim that food price inflation is primarily due to the ethanol production boom in the U.S. (see Figure 1). We study the relationship between the price of ethanol and the price of field crops and of cattle using data for Nebraska from January 1987 through March 2012. Although there are many ways of examining the interactions between time series of prices, our study is organized around two main blocks of results. First, we deal with long-run level relationships between ethanol and the other commodities by building on the bound testing approach of Pesaran, Smith, and Shin (2001). This approach allows the investigation when cointegration cannot be established because the series have different orders of integration. Next, we aim to determine whether ethanol has predictive power for the other series, or vice versa. We thus evaluate the short-run relationship between ethanol, field crops and cattle both in-sample, via Granger Causality testing, and out-of-sample, by analysing the predictive content of different models and comparing them against some benchmark specifications.

[Figure 1 about here]

The results of unit root tests indicate that field crops, cattle and price indices are integrated of order one. As to ethanol, its price can be best described as being stationary around a broken trend. The break date, June 2005, can be associated to major policy changes in the U.S. ethanol market since, as noted above, the EPA was first voted in April 2005 and finally signed into law in August of the same year. The analysis of long-run relations between series with different orders of integration reveals that there is some evidence of a level relationships running from the price of corn to the price ethanol, but not vice versa. This evidence is however limited to the post-break period. Turning the attention to the short-run, we find no evidence of Granger causality and predictability running from ethanol to the other commodities (there is weak evidence for soybeans) is found. On the contrary the ethanol price is predictable by using the price of field crops. No linkages with cattle. Ethanol price does not seem to be the long-run driving force for the price of field crops and cattle.

We conclude that, on the basis of a formal, comprehensive and rigorous causality analysis we do not find evidence in favour of the “Food versus Fuel” debate.

The remainder of the paper is organized as follows. Section 2 consider the causal nexus between ethanol and food prices and reviews the relevant literature and findings concerning the “Food versus Fuel” debate. Section 3 discusses the data and the recent trends in corn and ethanol prices. Section 4 presents the econometric methodology and the empirical results are shown for both the long-run and the short-run. Concluding remarks complete the paper.

2. Motivation and Related Literature

On a given portion of arable land farmers grow corn. Corn can be used to produce ethanol, in which case it is supplied to refineries and used as an input, or alternatively can be further processed to be converted into flour for food purposes, into other “food” uses such as feedstock for cattle – cows are mainly fed corn – and into various industrial uses (Anderson et., 2008). A large portion of growth in corn demand is associated with growth in ethanol production because most U.S. ethanol is made from corn. Policy-induced shifts in the demand for ethanol or higher gasoline prices foster ethanol production, increasing its supply. More ethanol plants and production translates into more demand for corn, which in turn increases corn prices, ceteris paribus. Higher corn prices make corn more profitable to grow, causing some farmers to shift from other crops to corn production. This will also push food, seed, and industrial users to shift from corn to other commodities, increasing their prices. This is the rationale for the “Food vs. Fuel” effect.

As noted in the Introduction, a few years back a major debate burst on the extent to which biofuels policies may contribute to high agricultural prices levels and volatility along the chain of effects just outlined. The debate, which is still ongoing, has moved from environmental and non-profit organizations to international institutions and eventually to the scientific community. A World Bank paper released in July 2008, for instance, concluded that: “The increase in internationally traded food prices from January 2002 to June 2008 was caused by a confluence of factors, but the most important was the large increase in biofuels production from grains and oilseeds in the U.S. and EU. (…) The large increases in biofuels production in the U.S. and EU were supported by subsidies, mandates, and tariffs on imports. Without these policies, biofuels production would have been lower and food commodity price increases would have been smaller" (Mitchell, 2008, p.17). In the same year, according to a report prepared by the United Nations Conference on Trade and Development “Biofuel demand has thus been a strong factor underpinning the upward shift in global agricultural commodity prices. However, the extent of this linkage is not yet fully clear and varies according to the biofuel crop in question, how much it is traded, possibilities for substitution and whether land utilized to produce biofuel feedstocks would otherwise have been used for growing food” (UNCTAD, 2008, p.8). While the FAO continued to warn against the food price effect of sustained biofuel production (OECD-FAO, 2009), an independent study by OECD became more cautious stating that "the impact of current biofuel policies on world crop prices, largely through increased demand for cereals and vegetable oils, is significant but should not be overestimated. Current biofuel support measures alone are estimated to increase average wheat prices by about 5%, maize by around 7% and vegetable oil by about 19% over the next 10 years" (OECD, 2008). And a new World Bank study concluded that its previous paper may have overestimated the contribution of biofuel production, as "the effect of biofuels on food prices has not been as large as originally thought” (Baffes and Haniotis, 2010).

The findings of the studies just reported have not generally been the result of rigorous statistical analysis. It has therefore been quite natural for the scientific community to get interested in the issue and analyze it with causality testing techniques. Under the “Food vs. Fuel” view causality would run from ethanol to corn prices and from corn price to the price of food and other corn-based products.[6] Could causality run in the opposite direction? In principle, yes. A food policy "away" from wheat, a supposedly close substitute of corn, could bring about a demand increase in the corn market and in turn an increase in its price (again assuming a fixed amount of arable land). As a consequence the price of a fundamental input to the refinery process would increase leading to higher ethanol prices.[7]

After the ethanol price boom a few studies appeared purporting to econometrically assess the relationships, if any, between fuel and agricultural prices. Zhang et al. (2009) estimate a vector error correction model (VECM) on U.S. weekly data for corn, oil, gasoline, ethanol, and soybean prices over the period March 1989 – December 2007. All series are found to have a unit root and for the pre-ethanol boom period 1989-99 the authors find that ethanol and corn prices cointegrate. In contrast, the results indicate no long-run relationship between the two variables in the ethanol boom period 2000-07. In contrast to popular belief, between 2000 and 2007 ethanol and corn do not appear to share any long-run price relationships. However, short-run relations may exist where ethanol prices do influence corn prices and vice versa. Interestingly, in the pre-boom period the price of corn is seen to Granger-cause the ethanol price, whereas a causality reversal occurs in the following period with fuel prices (ethanol, oil, and gasoline) now impacting corn prices.[8] Saghaian (2010) use monthly time series data on oil, ethanol, corn, soybean, and wheat prices collected from January 1996 – December 2008. ADF tests show that all variables are integrated of order one and Johansen's trace and maximum eigenvalue tests reveal the existence of a cointegrating vector among all price series. The author uses pairwise Granger-causality tests which indicate that there is a close bidirectional relationship between corn and ethanol prices. There are unidirectional relationships from soybeans and wheat price series to ethanol, and ethanol does not Granger cause soybeans or wheat price series. Ubilava and Holt (2010) study the relationship between energy and corn prices in the U.S.: using weekly averages of futures prices for the period October 2006 – June 2009 and a non-linear time series model for corn, the authors conclude that the inclusion of energy prices in the model does not yield better corn price forecasts. Using monthly data from 1990 to 2008 Serra et al. (2011) investigate whether ethanol, corn,

[6] Of course this assumed relationship rests upon a few implicit assumptions, such as the presumption that amount of arable land is fixed over the short-run (Abbott, 2012).
[7] Along these lines Zilberman et al. (2012) provide a conceptual justification of why causality may run from food to biofuel prices and vice versa within a partial equilibrium framework. Hertel and Beckman (2010) and Timilsina et al. (2012) are two studies which investigate the issue with the help of a computable general equilibrium model.
[8] For the sake of brevity we do not report the evidence regarding oil, gasoline, and soybean prices. Zhang et al. (2009) also investigate the volatility of prices by means of a MGARCH model.

oil, and gasoline prices in the U.S. are characterized by a long-run equilibrium relationship and whether the adjustment toward this equilibrium relationship is of a nonlinear nature. In particular, the authors fit an exponential smooth transition VECM to the data that allows for nonlinear adjustments toward long-run equilibrium.[9] An increase in energy prices is found to cause an increase in corn prices. This occurs mainly through the ethanol market and contributes to explaining the strong increases in corn prices during the ethanol boom in the second half of the 2000s. Corn price increases, however, also generate ethanol price increases, given the relevance of feedstock costs within the total costs of producing ethanol. Given the limitations to expanding corn production, at least in the short-run, an increase in the size of the ethanol market will cause corn price increases that in turn will yield higher ethanol prices.

Motivated by the strong co-movement and increasing volatility of energy and agricultural prices, Du and McPhail (2012) examine the behavior of ethanol, gasoline, and corn prices over the period of March 2005–March 2011. Studying pairwise dynamic correlations between the prices in a multivariate GARCH model the authors identify a structural change around March 2008. A structural VAR model is subsequently estimated on the subsamples before and after the change point. In the more recent period, ethanol, gasoline, and corn prices are found to be more closely linked with a strengthened corn-ethanol relation which can be largely explained by the new developments of the biofuel industry and related policy instruments.[10] Kristoufek, Janda, and Zilberman (2012a) analyze the relationships between the prices of biodiesel, ethanol and related fuels and agricultural commodities (corn, wheat, sugar cane, soybeans, sugar beets) using a minimal spanning trees and hierarchical trees approach. On the basis of monthly data it is found that the system splits into two well separated branches, a fuels part and a food part. Biodiesel tends to the fuels branch and ethanol to the food branch. When the periods before and after the food crisis of 2007-2008 are compared, the connections are much stronger for the post-crisis period. Kristoufek, Janda and Zilberman (2012b) use weekly price data for the period November 2003 – February 2011 to study price responsiveness and in-sample Granger Causality between biofuels (ethanol and

[9] Peri and Baldi (2010) apply a nonlinear threshold VECM to investigate the presence of asymmetric dynamic adjustment processes between the prices of rapeseed oil, sunflower oil, soybean oil, and the price of a mineral oil (diesel) in the EU for the period 2005–2007.

[10] A structural VAR model is also estimated by Zhang et al. (2007) and by McPhail (2011). There are a few studies in the literature concentrating on the relationship between fuel prices, including biofuels, but without reference to agricultural products. Similarly there are a few studies looking at the relationship between (sugar cane based) ethanol and sugar, among other fuels and products, but disregarding corn. We do not report them here.

biodiesel), their production factors (corn, wheat, soybeans and sugarcane) and fossil fuels (Brent crude oil, German diesel and U.S. gasoline). After controlling for seasonality and trends, they show that both ethanol and biodiesel prices do not contain a unit root. Their in-sample tests show that there is short-run Granger Causality running from corn to ethanol prices. Finally, Enders and Holt (2012) examine the underlying reasons for shifts in grain prices. An unrestricted VAR model is first used to analyze the relationship between grain prices and a number of macroeconomic variables including real exchange rates, interest rates, and energy prices. A VAR allowing for smoothly shifting means subsequently focuses on a larger set of agricultural commodities and variables more directly influencing commodity prices such as transport costs, climate conditions. It is shown that in addition to the general rise in real energy prices, the introduction of ethanol as an important fuel source has contributed to the run-up in grain prices.

3. Data

We use monthly time series of nominal spot prices for ethanol, corn, soybeans, wheat and cattle recorded in Nebraska from January 1987 through March 2012 (December 2010 for cattle). The price of ethanol is expressed in dollars per gallon, the prices of field crops (i.e. corn, soybeans and wheat) are in dollars per bushel, while the cattle price is expressed in dollars per hundredweight.[11] The ethanol price was extracted from the Nebraska Energy Office database, while prices of crops and cattle are available from the National Agricultural Statistics Service maintained by the U.S. Department of Agriculture. From this source we also took the dollar value of production of field crops and cattle that we used to construct the time-varying weights of two price indices: a “crops price index” (price index 1) that includes the three field crops and a “crops and cattle price index” (price index 2) which adds cattle to the crops.[12]

Our empirical analysis focuses on the state of Nebraska because of its importance in the U.S. ethanol industry and of the availability of a very long span of data. As shown in Figure 2, the nameplate capacity of Iowa, Nebraska and Illinois is equivalent to 26.10%, 12.97% and

[11] For wheat and soybeans one bushel is equivalent to 60 pounds or 27.22 kilograms; for corn one bushel corresponds to 56 pounds or 25.40 kilograms. A hundredweight is defined as 100 pounds, which is equivalent to 45.36 kilograms.

[12] More details about the data and the construction of the price indices are provided in an appendix available from the authors upon request.

9.02%, respectively of the nation's total (13596 million gallons per year).[13] Nebraska ethanol and corn prices data have been used by Elobeid and Tokgoz (2008), Serra et al. (2011), McPhail (2011), Blomendahl et al. (2011), and Enders and Holt (2012).[14]

[Figure 2 about here]

The dynamics of our price indices is shown in Figure 3. The price history of ethanol can be ideally divided in two periods. The first one runs from 1987 through the early 2000's and is characterized by relatively stable prices and low volatility; during the more volatile second period the dynamics of the Nebraska ethanol market can be described as succession of price ups and downs. As it can be seen from the upper panel of Table 1, over the period January 1987 – March 2012 the price of ethanol was on average 1.53 dollars per gallon and displayed a standard deviation equal to 0.53 and a coefficient of variation equal to 0.35. If we compute these statistics for the period running through December 2003, we get an average price of 1.23 dollars per gallon which is associated with a standard deviation and a coefficient of variation equal to 0.17 and 0.14, respectively. For the observations running from January 2005 through March 2012, the average, standard deviation and coefficient of variation increase to 2.15 dollars per gallon, 0.48 and 0.22, respectively.

[Figure 3 about here]

A joint inspection of Figure 3 and of Panel (a) and in Table 1 shows that the second period started with a price increase that culminated at a record high of 3.58 dollars per gallon in June 2006. The dynamics of the first price index, which includes only field crops, is very similar to

[13] According to the Nebraska Energy Office, as of February 2011 27 U.S. states had operating ethanol facilities and the state of Nebraska ranked second both in terms of nameplate capacity (1764 million gallons per year) and operating production (1739 million gallons per year). Moreover, according to Solomon et al. (2007) in 2006 four of the leading ethanol producing firms in the U.S. had distilleries in the state of Nebraska; among these Archer Daniels Midland accounted for 19% of total production.

[14] Although Iowa is the most important ethanol producer in the U.S., Nebraska data are preferable for the aim and the methods of our study. Iowa the time series start only in 2006 and contains less than 300 weekly observations. There are two problems with these data: first, we cannot appreciate the market developments prior to 2006 when the ethanol marked had already boomed; second, in order to have a reasonable number of observations for both estimation and forecast evaluation, out-of-sample tests should be carried out on samples starting after 2008, namely after the burst of the oil price bubble. Having such a volatile period in the evaluation sample makes the forecast evaluation more interesting and renders benchmark models more difficult to beat.

that of ethanol, while the pattern of price index 2 is heavily influenced by the presence of cattle price that, with a coefficient of variation 0.15, is the least volatile series. Price index 1 displays two main peaks, the most important one occurring in June 2011, two months before both corn and soybeans prices reached their maxima (6.93 and 13.30 dollars per bushel, respectively). The second peak was recorded in March 2008, three months before ethanol reached 2.9 dollars per gallon. This peak is the result of crop fields reaching very high or record price levels: corn reached 5.4 dollars per bushel in June 2008, while soybeans and wheat prices settled at their record levels (13.3 dollars per bushel in July 2008 and 9.84 dollars per bushel in March 2008, respectively).

[Table 1 about here]

Descriptive statistics for the percentage change of log-prices (i.e. returns) are shown in Panel (b) of Table 1. The unconditional distributions of all series is slightly asymmetric and displays different degrees of excess kurtosis. The last four rows of Panel (b) show correlation coefficients between returns on price indices, field crops, cattle and contemporaneous, lagged and leaded returns on ethanol, as well as the corresponding p-values indicating the probability of rejecting the null hypothesis of zero correlation. The contemporaneous correlation coefficients are all positive, but statistically nil at the 95% confidence level. Also the correlations between leads of ethanol and returns on price indices, field crops and cattle are all statistically not different from zero. On the contrary, the correlation coefficients between lagged ethanol returns, corn and soybeans are positive and statistically significant, suggesting that ethanol might prove useful in forecasting these series.

4. Methodology and Empirical Results

The empirical strategy we follow first aims at assessing whether or not a long-run cointegrating or, more generally, level relationship exists among the (log of the) price series of ethanol, aggregate price indices, field crops and cattle. We next turn to study short-run interactions and causality links based on (percentage) first differences of (log) prices.[15] In this process we pay special attention to structural breaks by using methods capable of taking them

[15] In the case of no cointegration Granger causality can be studied on the basis of first differences only, ignoring any linkages between price levels, that would otherwise have been captured with an error correction term.

into account. In terms of notation prices are represented by $P_{j,t}$ where $j = E$ (*ethanol*), *1* (*price index 1*), *2* (*price index 2*), *C* (*corn*), *S* (*soybeans*), *W* (*wheat*), *B* (*cattle*). Lower case letters denote the logarithm of prices (i.e. $p_{j,t} = \ln P_{j,t}$), while the percentage log-return on commodity j is $r_{j,t} = 100\times\Delta p_{j,t} = 100\times(p_{j,t} - p_{j,t-1})$. As a preliminary step we need to look at the stationarity properties of our price series.

4.1 Stationarity

To investigate the statistical properties of the log-price series we use the standard tests proposed by Dickey and Fuller (1979) in its augmented form (ADF), by Phillips and Perron (1988) (PP), and by Kwiatkowski, Phillips, Schmidt, and Shin (1992) (KPSS). It is just worth recalling that the null hypothesis of ADF and PP tests is that the series has a unit root, whereas the null hypothesis of the KPSS test is that the series is stationary around a deterministic trend. Therefore, in the case of ADF and PP failing to reject of the null provides evidence of unit root behaviour; on the contrary, the KPSS provides evidence of stationarity when the null is not rejected. The outcome of these tests for the log-price of ethanol, field crops, cattle and the two price indices is presented in Table 2.

[Table 2 about here]

All tests are carried out including either just a constant, or a constant and a trend in the test equation. For the majority of price series both the ADF and the PP test do not reject the null hypothesis of a unit root and the KPSS rejects the null hypothesis of trend stationarity. Interestingly, when the test equation includes a constant and a trend function, both ADF and PP reject the null hypothesis of a unit root in the log-price of ethanol.[16]

Because of the market and policy changes discussed in the Introduction, structural breaks cannot be ruled out for our series. In that event Perron (1989) has shown that standard procedures are biased towards non-rejection of the null. Therefore, he proposes a test of the null hypothesis that a series has a unit root with drift and that an exogenous structural break occurs at some known date, against the alternative that the series is stationary around a broken trend function, with an exogenous change at time T_b ($1 < T_b < T$). The main drawback of Perron's strategy is that the time of the break is assumed to be known. To circumvent this

[16] Results not shown here suggest that for the first difference of log-prices the null of a unit root can always be rejected.

problem Zivot and Andrews (1992) have developed a test statistic that allows to determine the break date within the testing procedure. The authors propose to use the ADF statistic to sequentially test Perron's null hypothesis by varying the break date that is then determined by the minimum of the ADF test over the sequence of tests. They provide critical values for their test and the null hypothesis is rejected when the minimum of the ADF test is lower that the critical value. The Zivot-Andrews test for a unit root against broken-trend stationarity is presented in Table 3.

[Table 3 about here]

Although for price indices, field crops and cattle the outcomes of the test are in agreement with those of the ADF and PP tests, the null hypothesis of a unit root in the price of ethanol is strongly rejected. Both model A (second column of the table), that includes a break in the constant, and model C (fourth column), that includes a break in the constant and in the slope of the trend function, select June 2005 as the break date.[17] Interestingly, as reported above, this date can be associated with major policy changes that have affected the U.S. ethanol market as noted above: indeed, the Energy Policy Act (EPA) was first voted by the U.S. House of Representatives on April 21, 2005 and then by the U.S. Senate in June 28, 2005; it was passed by the U.S. Congress on July 29 and finally signed into law by President George W. Bush on August 8 of the same year. The EPA has increased the amount of biofuel that must be mixed with gasoline sold in the United States. The EPA and the increasing restrictions on MTBE as a fuel oxygenate might be responsible for the rapid growth in U.S. ethanol production and use over the last decade (Solomon et al. 2007).

Given that the EPA might be the cause of the break in the ethanol price series in June 2005, in Table 4 we use such date to split the sample in a pre- and post-break period and present the ADF, PP and KPSS test.

[Table 4 about here]

[17] Model B in the table includes a break in the slope only.

The sample split highlights that ethanol can be considered as stationary before and after the break. The same can be said for price index 1 and the price of field crops before the break. For the post-break sample we can conclude that price indices and field crops have a unit root, while the results for cattle price are mixed. The main implication of these results is that ethanol price is stationary while most of the other price variables have a unit root: we cannot therefore apply cointegration techniques to study the relationship between these price levels.

4.2 Long-Run

Rejection of the null hypothesis of unit root has relevant implications. This implies that series can be analysed in their first differences, but that standard cointegration techniques cannot be applied. This however does not mean that we cannot study level relationships among our series. A methodology that allows to reduce pre-test biases is the “bound testing” approach proposed by Pesaran, Smith, and Shin (2001) (PSS): we can use it to check whether a relationship exists between the price of ethanol and other variables. The approach can be conveniently applied regardless of the order of integration and of cointegration of variables. In order to carry out the test we need to choose which variable is “long-run forcing”. For instance, the assumption that ethanol is long-run forcing for corn implies that the latter commodity has no long-run impact on the former. In this case a test of the null hypothesis of no long-run relationship running from ethanol to corn can be carried out after estimating the following model:

$$\Delta p_{C,t} = \lambda_0 + \lambda_1 t + \phi p_{C,t-1} + \delta p_{E,t-1} + \omega \Delta p_{E,t} + \Sigma_{j=1}^{p-1} \gamma_j \Delta p_{C,t-j} + \Sigma_{j=1}^{q-1} \eta_j \Delta p_{E,t-j} + \varepsilon_t \qquad (1)$$

The bound test is obtained by calculating the *F*-statistic for the joint significance of lagged prices, that is H_0: $\phi = 0$, $\delta = 0$. Pesaran, Smith and Shin (2001) provide two sets of critical values: a lower critical value bound, which assumes that all regressors are $I(0)$, and an upper critical value bound, for cases when all regressors are $I(1)$.[18] A value of the F-statistic below the lower bound implies that H_0 cannot be rejected and hence no long-run relationship exists; on the contrary, when the F-statistic exceeds the upper bound, H_0 is rejected and it is

[18] As a matter of fact, given that the distribution of the bound-F test depends on the exogenous variables included in the test equation, the authors provide more than two sets of critical values. For instance, in our empirical analysis we used a set of critical values that assume that both a trend and a constant are included in the model, and another set that is based on the assumption that only the constant enters the model.

concluded that there is a long-run relationship between prices. The test is inconclusive when the F-statistic falls within the lower and upper bound.

To implement the PSS test we estimate by OLS two sets of six bivariate models like (1), after having determined the number of lagged first differences of both the dependent and the independent variables with the Schwarz Information Criterion: in one case we assume that ethanol is long-run forcing for the other six series, in another case we assume that it has no long-run impact on the other variables (i.e. the series $j \neq E$ is long-run forcing for ethanol). The results are presented in Tables 5 and 6.

[Table 5 about here]

[Table 6 about here]

In Table 5 the ethanol price is assumed to be long-run forcing for the other variables. For each sample period – full, pre- and post-break – the bound test is carried out with and without the trend in the test equation. In most cases the F-test lies below the lower 5% critical value bound, thus rejecting the null hypothesis and suggesting that, when ethanol is assumed to drive the other variables in the long-run, no level relationship can be detected in any of the sample periods. In the remaining cases the value of the statistic lies between lower and upper bound ands the test is inconclusive.

Table 6 shows the results for the same tests when price indices, the price of field crops or cattle respectively are long-run forcing for ethanol. Some very interesting results emerge: (*i*) the sample split helps identifying a level relationship from corn to ethanol in the more recent post-break period, while no level relationship is detected over the full sample or before the break; (*ii*) a post-break level relationship with ethanol is identified also for wheat; (*iii*) ethanol and soybeans do not share any level relation; (*iv*) level relationships between ethanol and the two price indices are found in both sub-samples, but not in the full sample.

4.3 Short-Run

We now turn to study whether short-run movements of the ethanol price affect the price of field crops and cattle, or vice versa. We do so in a stepwise fashion, by first testing for Granger causality and then by analysing out-of-sample forecasting ability.

When testing the null of no Granger Causality (GC) running from ethanol to commodity *i* we estimate the following "two-by-two" models:

$$r_{i,t} = \alpha_i + \beta_E r_{E,t\text{-}1} + \gamma_i r_{i,t\text{-}1} + u_{i,t} \qquad i = 1, 2, C, S, W, B \tag{2}$$

Tests of the null hypothesis of no GC running from commodity *i* to ethanol are based on the estimation of the models:

$$r_{E,t} = \alpha + \beta_j r_{j,t\text{-}1} + \gamma_E r_{E,t\text{-}1} + u_{j,t} \qquad j = 1, 2, C, S, W, B \tag{3}$$

In this second case we also regress the ethanol price against the price of corn, soybeans and wheat together with (without) cattle:

$$r_{E,t} = \alpha + \beta_C r_{C,t\text{-}1} + \beta_S r_{S,t\text{-}1} + \beta_W r_{W,t\text{-}1} + \gamma r_{E,t\text{-}1} + u_t \tag{4}$$

$$r_{E,t} = \alpha + \beta_C r_{C,t\text{-}1} + \beta_S r_{S,t\text{-}1} + \beta_W r_{W,t\text{-}1} + \beta_B r_{B,t\text{-}1} + \gamma r_{E,t\text{-}1} + u_t \tag{5}$$

All parameters have been estimated with OLS using the entire sample of observations January 1987 – December 2010 when either cattle or price index 2 entered the specification, or January 1987 – December 2010 for all the other specifications. All standard errors are Heteroskedastic and Autocorrelation Consistent (HAC) following Newey and West (1987).[19] GC testing is carried out on the basis of F-tests of the null hypothesis that the estimates of the βs in a given model are jointly equal to zero.

One problem with this standard approach is due to the presence of structural breaks in some of the price series under scrutiny. This was found to be the case for ethanol. It is therefore likely that the relations (2)-(5) have changed. As shown by Rossi (2005), in the presence of instabilities traditional GC testing may have little or no power. To cope with this possibility

[19] HAC estimates of the covariance matrix have been calculated using a Bartlett kernel and setting the lag truncation equal to the nearest integer of $T^{(1/3)}$, where T is the number of available observations.

we preliminarily test for the null of parameter stability in equations (2)-(5) using the Quandt Likelihood Ratio (QLR) test developed by Andrews (1993).[20]

After ascertaining whether or not the estimated parameters are stable we carry out a test for the joint null hypothesis of stability and no GC proposed by Rossi (2005). Like the QLR test, Rossi's statistic is based on a sequence of tests of the joint null hypothesis of no break at date τ, where $[.15T] \leq \tau \leq [.85T]$, and of no GC: that is, are the αs and βs constant throughout the sample period and are the βs jointly statistically different from zero? The test, referred to as optimal Exponential Wald test, denoted as Exp-W*, has a non-standard distribution which has been tabulated by Rossi (2005). Rejection of the null hypothesis can occur either when parameters are not stable or when, even if they are constant, are different from zero. In both cases a rejection is evidence of GC.[21]

4.3.1 Does Ethanol Granger Cause Field Crops or Cattle?

Table 7 displays the (full sample) OLS parameter estimates for equation (2) and the outcome of the tests of the null hypothesis of no GC running from ethanol to returns on price indices, field crops and cattle.

[Table 7 about here]

We see that the AR(1) term is always statistically significant. Moreover, since these coefficients are positive and not very close to one, their average being .31, they suggest that returns on price indices, field crops and cattle have low degree of persistency. Only two parameters associated with lagged ethanol returns are statistically significant. They provide evidence of negative correlations between the lags of ethanol returns and returns on corn and soybeans. The remaining estimates are positive, but statistically insignificant.

The null of no GC is rejected for corn and soybeans. The strongest rejection is recorded for soybeans that displays a p-value lower than 1%, while the null that corn is not Granger-caused by ethanol is rejected only at 10% significance level.

[20] This test is the maximum of a series of Chow test statistics testing the hypothesis of no break at date τ, where τ is such that $[.15T] \leq \tau \leq [.85T]$, T is the number of observations and [.] denotes the integer part of a number. We use the QLR statistic to test the stability of the α and β parameters of our equations. The distribution of the test is non-standard and has been tabulated by Andrews (1993).

[21] If parameters are not constant over time it means that either before or after the break they are different from zero, and hence that GC is present at least in one of the two subsamples.

As noted above, if the parameters of the model underlying GC testing procedures are time-varying, traditional inferences have no power. The QLR test for the null hypothesis of stability of the constant and lagged ethanol returns reported in panel (a) of Table 8 does not provide evidence of parameter instability.

[Table 8 about here]

Rossi’s (2005) Exp-W* test is shown in panel (b) of the table. This test never rejects the joint null hypothesis of parameter stability and no GC running from ethanol to the other variables. Since the statistic is carried out on the constant and the parameter associated with the first lag of ethanol returns, a non-rejection of the null hypothesis means these parameters are stable and that a model including only the AR(1) term cannot be rejected.

On the basis of the above tests we can conclude that (*i*) parameters relating ethanol to price indices, field crops and cattle are stable and that (*ii*) there is weak evidence in favour of GC running from ethanol to corn and soybeans. We say “weak” for two reasons: first, the results of Rossi’s tests contradict those from traditional testing procedures; second, if one believed that these results are sufficient to state that there is evidence of GC running from ethanol to field crops, in fact the only conclusion that can be drawn is that those models could have a better performance in forecasting the returns of the other commodities if lagged returns on ethanol are used. We address below the issue of out-of-sample predictive ability of models with and without lagged ethanol returns, which helps understanding whether the previous weak evidence of GC actually translates into improved forecasts thanks to the information provided by ethanol.

4.3.2 Do Field Crops or Cattle Granger Cause Ethanol?

Turning now to ask whether field crops or cattle have in-sample predictive power for ethanol, the answer is provided in Table 9, with the issue of parameter stability and GC testing taken up in Table 10.

[Table 9 about here]

[Table 10 about here]

Table 9 shows OLS estimates and GC tests for the models in equations (3)-(5). The AR(1) coefficient is always statistically significant and in the range .24-.25, thus suggesting that also returns on ethanol do not show a high degree of persistence reverting quite quickly to their mean value. The correlation between ethanol returns and lagged returns on price indices is positive but statistically insignificant. Corn and soybeans also show a positive and significant correlation with ethanol in bivariate models, but are not statistical significant in the multivariate model (4). Lagged returns on cattle are positive and significant only in the multivariate model (5).

The GC test rejects the null hypothesis of no causality only for corn and soybeans. In general the p-values associated with these rejections are higher than those we obtained when looking at GC from ethanol to corn and soybeans. Coupled with the evidence in Table 8 these results point to the existence of a feedback relationship between ethanol, corn and soybeans. However, we concluded above that ethanol shows predictive ability only for soybeans.

The QLR test displayed in panel (a) of Table 10 provides very limited evidence of parameter instability; the Exp-W* test in panel (b) marginally rejects the null hypothesis of stability and no GC only for model (5) that includes lagged returns on field crops and cattle. This result implies that, if parameter instability is taken into account, there is some evidence of GC running from regressors in model (5) to ethanol, but this relationship might not be stable over time.

4.3.3 Ethanol and Field Crops: Granger Causality and Forecasting Ability

Only few studies, among those reviewed in Section 2, analyze the relationship between the prices of ethanol and corn, or more generally of biofuels and agricultural commodities, within a formal Granger-causality framework. When they do so, those papers in general entertained only in-sample testing procedures (see Saghaian, 2010; Zhang et al. 2007; Zhang et al., 2009). Nothing is said about the out-of-sample performance of the estimated models, although it can be argued that this perspective is more consistent with the definition of causality originally put forth by Granger (1969, 1980). In this subsection we aim to determine whether ethanol has predictive power for the other series, or vice versa. We do so by analyzing the predictive content of different models and comparing them against some benchmark specifications. This approach is in line with the one advocated by Ashley et al. (1980) who note that, since the definition of causality introduced by Granger (1969) is a statement about predictive ability, in-sample testing has to be considered merely as a first step, always to be complemented with an out-of-sample analysis.[22]

We compare the Mean Squared Forecast Error (MSFE) of forecasts from models (2)-(5) with three benchmarks: an first order autoregressive model, AR(1), and two random walk models, without and with drift, which we denote as RW and RWD respectively.[23] Forecasts are obtained using a rolling forecasting scheme: a window of $R = [.5T]$ observations is used to estimate models (2)-(5) and to generate one-month ahead forecasts. The iteration of this procedure, that moves the estimation window forward one month at a time, produces a set of forecast vectors, one for each model, of size T-R.[24] We finally evaluate the statistical significance of MSFE differentials (i.e. MSFE of each estimated model in (2)-(5) minus the MSFE of the benchmark b with b = AR(1), RW, RWD) with the Clark and McCracken (2001) encompassing test for nested models, denoted as ENC-NEW. The null hypothesis of the ENC-NEW test is that the additional information used by a model does not improve the forecasting performance of the benchmark model. A rejection of the null implies that the additional regressors that enter a model have out-of-sample forecasting power for the dependent variable. The distribution of the ENC-NEW test is non-standard and depends on the forecasting scheme, on the ratio between the size of the estimation sample and the size of evaluation sample, and on the number of restrictions that need to be imposed on the bigger model so as to obtain the benchmark.[25] Critical values for the ENC-NEW statistic are provided by Clark and McCracken (2000).

Results of the out-of-sample evaluation of the models in (2) against AR(1), RW, and RWD benchmarks are displayed in Table 11. We present two sets of results: the MSFE error differential and the p-values associated with the Clark and McCracken (2001) ENC-NEW.

[22] The point was also stressed by Granger (1980) who showed that in-sample tests of the null hypothesis of no-causality are essentially tests of goodness of fit which, in the case of a rejection of the null hypothesis, inform the analyst that one variable could help improving the forecasts for the other variable. The author noted that “this is quite different from actually producing improved forecasts” (Granger, 1980, p. 348): thus, tests comparing the predictive ability of different models (based on different information sets) out-of-sample are a necessary second step to be consistent with the original definition Granger causality.

[23] For equations (2) the benchmark AR(1) models can be written as $r_{i,t} = \alpha_i + \rho_i \, r_{i,t\text{-}1} + u_{i,t}$ where i = 1, 2, C, S, W, B. For equations (3)-(5) the benchmark AR(1) model is $r_{E,t} = \alpha_E + \rho_E \, r_{E,t\text{-}1} + u_{E,t}$. The RW forecast for t+1 is $r_{j,t}$ = 0, while the RWD model is $r_{j,t} = \alpha_j$ where $j = E$, 1, 2, C, S, W, B.

[24] For cattle and price index 2 the evaluation sample spans January 1999-December 2010 (144 observations), while for all the other forecasts it runs from September 1999 through March 2012 (151 observations).

[25] When evaluating the predictive performance of models against the RW and the RWD benchmarks, the autoregressive term is dropped from models in (2)-(5).

[Table 11 about here]

The MSFE differential is the MSFE of the model minus the MSFE of the benchmark: a negative (resp. positive) value suggests that the model including lagged ethanol returns is better (resp. worse) at forecasting the return of a given commodity than the benchmark. Since the table shows that majority of MSFE differentials are greater than zero, the benchmarks are rarely out-performed by models that make use ethanol to forecast price indices, field crops or cattle. A notable exception is soybeans, for which the model that includes ethanol leads to more accurate forecasts than the AR(1) and RWD benchmarks. However, ethanol does not improve the forecasting performance above that of the simple RW specification for soybeans.

The ENC-NEW test rejects the null hypothesis when forecasts based on ethanol for price index 2 and soybeans are evaluated against the AR(1) model as well as the RWD benchmark. Therefore, for both price index 2 and soybeans there is evidence that ethanol improves the out-of-sample predictive ability of some of the benchmarks.

On the basis of the results in this and the previous sub-sections we can conclude that there is only very limited evidence of Granger causality and out-of-sample predictability running from ethanol to field crops. The most robust result is for soybeans, for which ethanol seems to have predictive power both in-sample and out-of-sample. In addition, we can conclude that ethanol has no predictive power, neither in-sample, nor out of sample for wheat, cattle and price index 1.

Ethanol forecasts have been obtained in the same way as the forecast of field crops, cattle and price indices just presented; MSFE differentials and the ENC-NEW tests are shown in Table 12.

[Table 12 about here]

When forecasting ethanol, models that use corn or soybeans lead to lower losses than any of the benchmarks: MSFE differentials are negative and the ENC-NEW test always rejects the null hypothesis. Therefore those models out-perform the benchmarks. In some cases we can marginally reject the null hypothesis of the ENC-NEW test also for multivariate models (4)-(5): these models outperform both AR(1) and RWD benchmark forecasts.

To conclude, we are now able to draw more robust conclusions on GC between the prices of ethanol, field crops and cattle. First, the overall predictive in-sample and out-of-sample ability of ethanol for the other variables is very low. Second, corn and soybeans have both in-sample and out-of-sample predictive power for ethanol. Therefore, we can argue that ethanol is Granger caused by corn and that there is a feedback relation between ethanol and soybeans. Third, no causality is found between ethanol, wheat, cattle and price indices. Lastly, we can state that these relations are quite stable over time.[26]

5. Conclusions

In this paper we have examined the causal nexus between ethanol and corn and other agricultural commodities, seeking support in favor or against the "Food versus Fuel" claim that food price inflation is primarily due to the ethanol production boom in the U.S. Our analysis studied the relationship between the price of ethanol and the price of field crops and of cattle in Nebraska from January 1987 through March 2012. Although there are many ways of examining the interactions between time series of prices, our study was organized around two main blocks of results. First, we dealt with long-run level relationships between ethanol and the other commodities by building on the bound testing approach of Pesaran, Smith, and Shin (2001). This approach allows the investigation when cointegration cannot be established because the series have different orders of integration. Next, we aimed to determine whether ethanol has predictive power for the other series, or vice versa. We evaluate short-run the relationship between ethanol, field crops and cattle both in-sample, via Granger Causality testing, and out-of-sample, by analysing the predictive content of different models and comparing them against some benchmark specifications.

Among other results we found no evidence of Granger causality and predictability running from ethanol to the other commodities (weak evidence was found for soybeans). On the contrary the ethanol price is predictable by using the price of field crops. No linkages with cattle. Ethanol price does not seem to be the long-run driving force for the price of field crops and cattle.

We conclude that, on the basis of a formal, comprehensive and rigorous causality analysis we did not find evidence in favour of the "Food versus Fuel" debate.

[26] An appendix available from the authors provides additional results based on the Toda and Yamamoto (1995) procedure to test the null hypothesis of no GC within a Vector Autoregression for log-prices. The procedure can be applied to series, whether integrated or cointegrated. The results confirm the findings presented here.

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Figure 1: Ethanol and Corn Prices and Percentage of Corn Used for Feedgrain, Fuel Ethanol, and Exports (1980-2011)

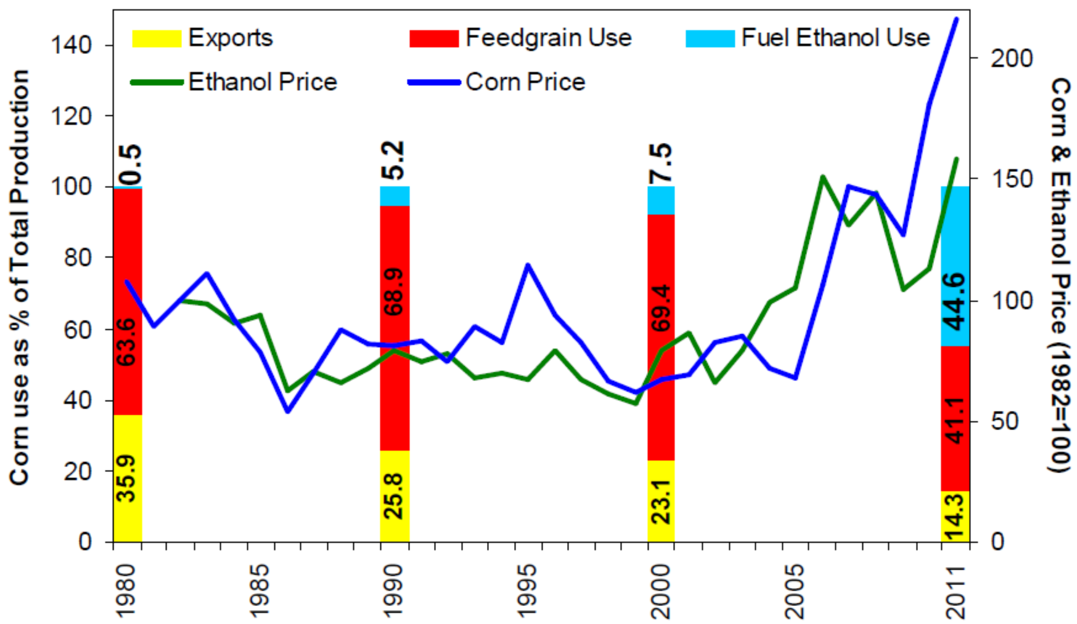
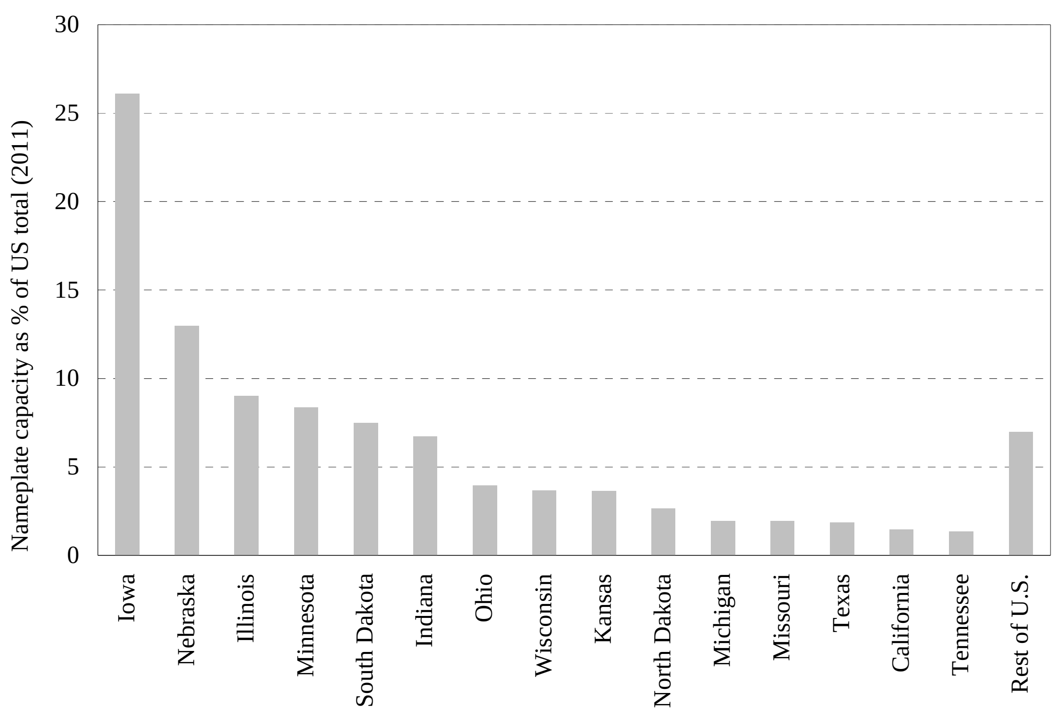
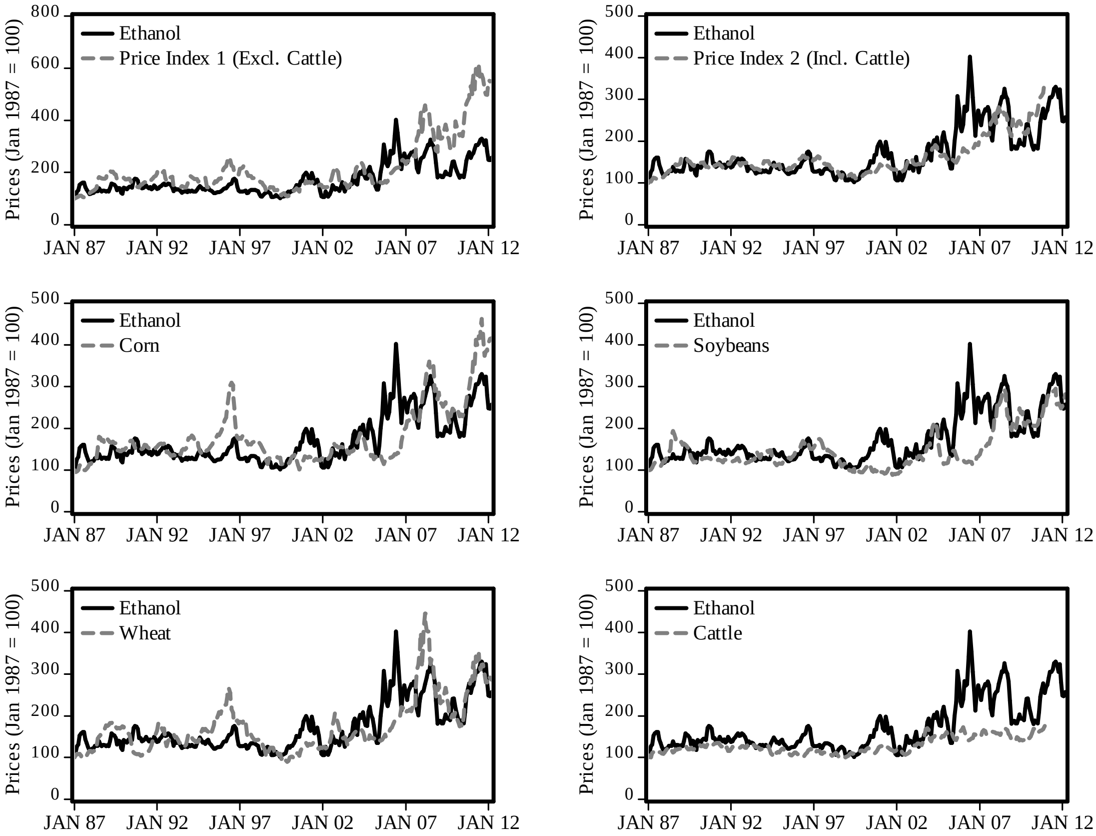


Figure 2: Ethanol Nameplate State Capacity as Percentage of Total U.S. in 2011



Note: data from the Nebraska Energy Office (as of February 2011). The nameplate capacity is the full–load continuous rating of a generator, prime mover (i.e. the engine, turbine, water wheel, or similar machine that drives an electric generator), or other electric equipment under specified conditions as designated by the manufacturer. It is usually indicated on a nameplate attached to the equipment.

Figure 3: Ethanol Price, Price Indices, Field Crops and Cattle Prices



Note: all prices are in current dollars and have been multiplied by 100 and divided by their value in January 1987 to put them on a common scale.

Table 1: Descriptive Statistics

Panel (a): Prices

	Ethanol	Price Index (Excl. cattle)	Price Index (Incl. Cattle)	Corn	Soybeans	Wheat	Cattle
Average	1.53	102.63	347.25	2.70	6.71	3.84	76.52
Coef. Var.	0.35	0.51	0.28	0.40	0.33	0.38	0.15
Min	0.89	47.46	215.08	1.43	4.00	1.99	58.60
Date Min	01/1987	01/1987	01/1987	02/1987	10/2001	11/1999	09/1998
Max	3.58	287.70	723.11	6.93	13.30	9.84	104.00
Date Max	06/2006	06/2011	12/2010	08/2011	08/2008	03/2008	12/2010
T	303	303	288	303	303	303	288

Panel (b): First Difference of Log-Prices

	Ethanol	Price Index (Excl. Cattle)	Price Index (Incl. Cattle)	Corn	Soybeans	Wheat	Cattle
Average	0.09	0.15	0.06	0.09	0.05	0.08	0.19
Coef. Var.	82.05	38.80	55.55	60.25	93.56	66.21	17.67
Skewness	0.40	0.53	0.37	-0.62	-0.23	-0.54	0.02
Kurtosis	4.26	10.76	5.79	6.60	4.81	6.57	4.51
Corr (E_t,X_t)	-	0.06	0.10	0.05	0.06	0.05	0.07
(p-value)	-	(0.2799)	(0.0781)	(0.4122)	(0.2738)	(0.3982)	(0.2586)
Corr (E_t,X_{t+1})	-	0.07	0.04	0.16	0.15	0.03	0.05
(p-value)	-	(0.2198)	(0.4949)	(0.0060)	(0.0085)	(0.5533)	(0.4122)
Corr (E_{t+1},X_t)	-	0.03	0.08	-0.06	-0.09	0.06	0.05
(p-value)	-	(0.6378)	(0.1679)	(0.3118)	(0.1247)	(0.3126)	(0.4280)

Notes: In Panel (b) "Corr (E,X)" denotes the correlation coefficient between ethanol and the series on columns (2)-(7).

Table 2: ADF, PP and KPSS Unit Root Tests

Test:	ADF		Phillips-Perron		KPSS	
	C	C & T	C	C & T	C	C & T
Ethanol	0.2012	0.0473**	0.1696	0.0539*	NS	NS
Price Index 1 (Excl. Cattle)	0.8145	0.7809	0.7453	0.6441	NS	NS
Price Index 2 (Incl. Cattle)	0.9536	0.9508	0.9280	0.9085	NS	NS
Corn	0.5011	0.5270	0.7000	0.7327	NS	NS
Soybeans	0.4432	0.4570	0.5094	0.5425	NS	NS
Wheat	0.4503	0.5380	0.2591	0.2760	NS	NS
Cattle	0.7296	0.0821*	0.5386	0.3742	NS	NS

Notes: All prices in logs. The values in the table are p-values of the null hypothesis that a series has a unit root. In the case of the KPSS test “NS” denotes rejection of the null hypothesis of trend stationarity at 95% confidence level. “C” and “ C&T” indicate whether a constant and a constant and a trend have been respectively included in the test equation.

Table 3: Zivot-Andrews Unit Root Test

	Model A		Model B		Model C	
Series	t-stat	Date	t-stat	Date	t-stat	Date
Ethanol	-5.41***	6/2005	-4.64**	12/1998	-5.39**	6/2005
Price Index 1 (Excl. Cattle)	-3.85	-	-4.29*	5/2003	-4.55	-
Price Index 2 (Incl. Cattle)	-3.04	-	-3.85	-	-4.27	-
Corn	-4.26	-	-4.25*	1/2005	-4.52	-
Soybeans	-4.17	-	-4.10	-	-4.62	-
Wheat	-4.15	-	-3.49	-	-4.33	-
Cattle	-4.45	-	-3.78	-	-4.61	-

Notes: Prices in logarithms. The test evaluates the null hypothesis of unit root against the alternative of broken-trend stationarity. The symbols (*), (**), and (***) denote rejection of the null hypothesis at the 10%, 5%, and 1% confidence levels respectively. Critical values for models A, B, and C are from tables 2-4 of Zivot and Andrews (1992).

Table 4: Unit Root and Stationarity Tests Before and After the Break: Log-Prices

Panel (a): First Sample, January 1987 - June 2005						
Test:	ADF		Phillips-Perron		KPSS	
Exogenous:	C	C & T	C	C & T	C	C & T
Ethanol	0.0126**	0.0439**	0.0015***	0.0078***	S	NS
Price Index 1 (Excl. Cattle)	0.0097***	0.0551*	0.0135**	0.0751*	S	S
Price Index 2 (Incl. Cattle)	0.0262**	0.1178	0.0349**	0.1661	S	S
Corn	0.0029***	0.0152**	0.0404**	0.1454	S	NS
Soybeans	0.0177**	0.0684*	0.0593*	0.1829	S	S
Wheat	0.0542*	0.1896	0.0636*	0.2174	S	S
Cattle	0.0612*	0.1461	0.2049	0.4115	S	NS
Panel (b): Second sample, July 2005 - March 2012 (December 2010)						
Test:	ADF		Phillips-Perron		KPSS	
Exogenous:	C	C & T	C	C & T	C	C & T
Ethanol	0.0027***	0.0151**	0.0371**	0.1302	S	S
Price Index 1 (Excl. Cattle)	0.5480	0.3096	0.5735	0.3391	NS	S
Price Index 2 (Incl. Cattle)	0.7709	0.5706	0.8039	0.5698	NS	NS
Corn	0.7783	0.8445	0.7421	0.7446	NS	NS
Soybeans	0.8430	0.7630	0.7608	0.5254	NS	NS
Wheat	0.2837	0.6738	0.2630	0.6249	S	NS
Cattle	0.0475**	0.1682	0.2378	0.5230	S	S

Notes: values in the table are p-values of the null hypothesis that a series has a unit root. For the KPSS test "S"denotes that the null hypothesis of trend stationarity cannot be rejected at 95% confidence level. "C" and "T" indicates whether a constant and/or a trend have been included in the test equation.

Table 5: F-statistics for Testing the Existence of a Level Relationship (Ethanol Long-run Forcing)

Panel (a): Constant						
	Jan.1987-Mar.2012		Jan.1987-Jun.2005		Jul.2005-Mar.2012	
	p,q	F-test	p,q	F-test	p,q	F-test
Price Index 1 (Excl. Cattle)	1, 1	2.88(a)	1, 1	6.09(c)	1, 1	2.45(a)
Price Index 2 (Incl. Cattle)	1, 1	2.11(a)	1, 1	5.96(c)	1, 1	0.57(a)
Corn	1, 1	2.22(a)	1, 1	3.16(a)	2, 1	0.77(a)
Soybeans	1, 1	2.40(a)	1, 1	3.96(a)	1, 1	0.40(a)
Wheat	1, 1	4.41(a)	1, 1	3.66(a)	1, 1	2.51(a)
Cattle	3, 1	5.19(b)	3, 1	3.27(a)	1, 1	4.85(a)
Panel (a): Constant and Trend						
	Jan.1987-Mar.2012		Jan.1987-Jun.2005		Jul.2005-Mar.2012	
	p,q	F-test	p,q	F-test	p,q	F-test
Price Index 1 (Excl. Cattle)	1, 1	3.35(a)	1, 1	6.08(a)	1, 1	1.93(a)
Price Index 2 (Incl. Cattle)	1, 1	1.97(a)	1, 1	6.15(a)	1, 1	1.48(a)
Corn	1, 1	2.18(a)	1, 1	3.04(a)	2, 1	2.39(a)
Soybeans	1, 1	2.81(a)	1, 1	3.63(a)	1, 1	1.01(a)
Wheat	1, 1	4.26(a)	1, 1	3.64(a)	1, 1	1.00(a)
Cattle	3, 1	6.62(b)	3, 1	3.65(a)	1, 1	6.26(a)

Notes: the null hypothesis of the bound F-test is of no level relationship. (a) indicates that the statistics lies below the 0.05 lower bound (i.e. the null is not rejected), (b) that it falls within the 0.05 bounds (i.e. the test is inconclusive), and (c) that it lies above the 0.05 upper bound (i.e. the null is rejected). The asymptotic critical value bound for the F-statistic is [4.94, 5.73] for the case with constant and [6.56, 7.30] for the case with constant and trend; see Pesaran and Shin (2001), Table CI(iii) and CI(v).

Table 6: F-statistics for Testing the Existence of a Level Relationship (Commodity *i* Long-run Forcing)

Panel (a): Constant						
	Jan.1987-Mar.2012		Jan.1987-Jun.2005		Jul.2005-Mar.2012	
	p,q	F-test	p,q	F-test	p,q	F-test
Price Index 1 (Excl. Cattle)	2, 1	4.17(a)	2, 1	6.25(c)	1, 1	5.71(b)
Price Index 2 (Incl. Cattle)	2, 1	4.85(a)	2, 1	6.68(c)	1, 1	7.70(c)
Corn	2, 1	3.11(a)	2, 1	4.75(a)	1, 2	9.30(c)
Soybeans	2, 1	3.22(a)	2, 1	4.66(a)	1, 1	5.58(b)
Wheat	2, 1	4.30(a)	2, 1	5.25(b)	1, 1	7.17(c)
Cattle	2, 1	6.44(c)	1, 1	11.70(c)	1, 1	7.92(c)
Panel (a): Constant and trend						
	Jan.1987-Mar.2012		Jan.1987-Jun.2005		Jul.2005-Mar.2012	
	p,q	F-test	p,q	F-test	p,q	F-test
Price Index 1 (Excl. Cattle)	2, 1	6.88(b)	2, 1	7.57(c)	1, 1	8.84(c)
Price Index 2 (Incl. Cattle)	2, 1	6.45(a)	2, 1	7.85(c)	1, 1	19.53(c)
Corn	2, 1	6.52(a)	2, 1	6.34(a)	1, 2	9.53(c)
Soybeans	2, 1	6.09(a)	2, 1	6.22(a)	1, 1	5.81(a)
Wheat	2, 1	7.31(c)	2, 1	6.75(b)	1, 1	7.44(c)
Cattle	2, 1	7.90(c)	1, 1	12.59(c)	1, 1	13.32(c)

Table 7: OLS Estimates and Granger Causality Test Models (Ethanol Price Models)

	Const	Ethanol	AR(1)	GC
Price Index (Excl. Cattle)	0.13	0.01	0.18 **	0.12
Price Index (Incl. Cattle)	0.04	0.03	0.20 ***	1.64
Corn	0.06	-0.06 *	0.47 ***	3.23
Soybeans	0.04	-0.07 ***	0.44 ***	7.23
Wheat	0.06	0.03	0.29 ***	1.04
Cattle	0.12	0.01	0.30 ***	0.25

Notes: Equations (2) in the paper. The dependent variables are listed in column (1). OLS estimates are show in columns (2)-(4). "Ethanol" is the lagged value of the first log difference of the ethanol price, "AR(.)" denotes the first lag of the dependent variable and "GC" is the Granger Causality test. (*), (**), (***) denote rejection of the null hypothesis at the 10%, 5% and 1%, respectively.

Table 8: Parameter Instability and Granger Causality Test (Ethanol Price Models)

Panel (a): Andrew's QLR Test for Instabilities

	Price Index (Excl. Cattle)	Price Index (Incl. Cattle)	Corn	Soybeans	Wheat	Cattle
QLR Test	9.65	9.76	6.59	2.78	7.33	3.57
Break Date						

Panel (b): Rossi's Granger Causality (Exp-W*) Test Robust to Instabilities

	Price Index (Excl. Cattle)	Price Index (Incl. Cattle)	Corn	Soybeans	Wheat	Cattle
Exp-W* Test	2.36	4.45	2.68	4.17	1.52	0.72

Notes: (*), (**), (***) denote rejection of the null hypothesis at the 10%, 5% and 1% levels, respectively. For the QLR test the null hypothesis is that parameters are stable; the Exp-W* test is a joint test of stability and no Granger Causality. These tests involves both constant and the lagged first difference of (log) ethanol price. The dependent variables are reported as column headers. They refer to equations (2) in the paper. When the QLR test rejects the null hypothesis we report the time of the break (i.e. mm/yyyy) below the value of the statistic. Rejection of the Exp-W* null hypothesis indicates evidence in favour of Granger Causality.

Table 9: OLS Estimates and Granger Causality (GC) Test Models (Commodities Price Models)

Model	Const	AR(1)	Price Index (Excl. Cattle)	Price Index (Incl. Cattle)	Corn	Soybeans	Wheat	Cattle	GC
Price Index (Excl. Cattle)	0.08	0.24***	0.07						1.35
Price Index (Incl. Cattle)	0.04	0.25***		0.07					0.05
Corn	0.07	0.24***			0.21***				7.62***
Soybeans	0.08	0.24***				0.21**			6.49**
Wheat	0.08	0.25***					0.03		0.20
Cattle	0.03	0.25***						0.07	0.16
Multivariate	0.05	0.24***			0.11	-0.08	0.24***		1.96
Multivariate (incl. cattle)	0.04	0.24***			0.12	-0.09	0.07	0.24***	1.48

Notes: Equations (3)-(5) in the paper. The dependent variable is "Ethanol", while explanatory variables are shown as column headers. OLS estimates are show in columns 2-8. "Ethanol" is the first log difference of ethanol price, "AR(.)" denotes the first lag of "Ethanol" and "GC" is the Granger Causality test. The remaining explanatory variables the lagged value of the first difference of the log price of the variables in column headers. (*), (**), (***) denotes rejection of the null hypothesis at the 10%, 5% and 1%, respectively.

Table 10: Parameter Instability and Granger Causality test (Commodities Price Models)

Panel (a): Andrew's QLR Test for Instabilities

Model	Price Index (Excl. Cattle)	Price Index (Incl. Cattle)	Corn	Soybeans	Wheat	Cattle	Multivariate	Multivariate (including Cattle)
QLR Test	9.15	4.26	12.45*	10.84	5.55	6.17	11.98	15.54
Break Date			06/1991					

Panel (b): Rossi's Granger Causality (Exp-W*) Test Robust to Instabilities

Model:	Price Index (Excl. Cattle)	Price Index (Incl. Cattle)	Corn	Soybeans	Wheat	Cattle	Multivariate	Multivariate (including Cattle)
Exp-W* Test	1.91	1.00	5.48	4.87	1.41	3.96	6.08	10.49*

Notes: (*), (**), (***) denote rejection of the null hypothesis at the 10%, 5% and 1%, respectively. For the QLR test the null hypothesis is that parameters are stable; the Exp-W* test is a joint test of stability and no Granger Causality. These tests involves both the constant and the lagged first difference of all explanatory variables excluding the lagged value of "Ethanol". The dependent variable "Ethanol" is the first difference of the log price of ethanol. The columns corresponds to equations (3)-(5) in the paper. When the QLR test rejects the null hypothesis we report the time of the break (i.e. mm/yyyy) below the value of the statistic. Rejection of the Exp-W* null hypothesis indicates evidence in favour of Granger Causality.

Table 11: Mean Squared Forecast Error and Encompassing Test (Ethanol Price Models)

Benchmark	Price Index (Excl. Cattle)	Price Index (Incl. Cattle)	Corn	Soybeans	Wheat	Cattle
AR(1)	1.01	0.32*	0.66	-0.43**	0.66	1.22
Random Walk (RW)	0.89	0.40	1.92	0.20	1.17	0.85
RW with Drift	0.83	-0.09**	1.23	-0.24*	0.74	0.69

Notes: Figures in the table are the Mean Squared Forecast Error differential (rescaled by their sample standard deviation). A positive number indicates that the benchmark is on average more accurate than the forecast of the model including "Ethanol". The models refer to equation (2) in the paper. When the benchmark is either the RW or the RWD, the models do not include the lagged value of the dependent variables. Asterisks (*), (**), (***) denote rejection of the null hypothesis of the Enc-New encompassing test at the 10%, 5% and 1% significance level, respectively. Critical value of the test are from Clark and McCracken (2000). A rejection indicates that the model is better than the benchmark.

Table 12: Mean Squared Forecast Error and Encompassing Test (Commodities Price Models)

Benchmark	Price Index (Excl. Cattle)	Price Index (Incl. Cattle)	Corn	Soybeans	Wheat	Cattle	Multivariate	Multivariate (incl. cattle)
AR(1)	0.17	2.22	-0.87**	-0.78**	1.39	1.36	-0.02*	0.30*
Random Walk (RW)	0.44	2.76	-0.78**	-0.63**	1.33	1.89	0.17	0.51
RW with Drift	0.09	2.06	-0.96**	-0.75**	1.22	1.42	0.02*	0.36*

Notes: Figures in the table are the Mean Squared Forecast Error differential (rescaled by their sample standard deviation). A positive number indicates that the benchmark is on average more accurate thatn the forecast of the model. The models refer to equations (3)-(5) in the paper. When the benchmark is either the RW or the Random Walk with drift, Models 7-14 do not include the lagged value of the first difference of the log price of ethanol. Asterisks (*), (**), (***) denote rejection of the null hypothesis of the Enc-New encompassing test at the 10%, 5% and 1% significance level, respectively. Critical value of the test are from Clark and McCracken (2000). A rejection indicates that the model is better than the benchmark.