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On the drivers of commodity co-movement: Evidence from biofuels*

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Abstract

We use the recent introduction of biofuels to study the effect of industry factors on the relationships between wholesale commodity prices. Correlations between agricultural products and oil are strongest in the 2005-09 period, coinciding with the boom of biofuels, and remain substantial until 2011. We disentangle three possible drivers for the linkage: substitution, energy costs, and financialization. The timing and magnitude of the biofuels-to-oil relationships are different to those of other commodities, and far higher than can be justified by costs and financialization. Substitution and costs drive the monthly correlations of long-term futures, and each of the three contribute equally to the daily co-movement of the short-term ones. The findings survive many robustness checks and appear in the stock market.

JEL codes: G15, Q18, O13

Keywords: biofuels, commodities, co-movement, ethanol, oil, structural breaks.

I Introduction

In this paper, we contribute to the study of how microeconomic fundamentals mediate in the linkage between futures markets. We focus on the recent boom-and-bust of the biofuels industry, and its

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influence on the co-movement between oil and agricultural future prices. Biofuels – mainly made from corn, sugar, and soybean – offer a number of advantages to studying the connection between futures markets and industry-level microeconomic factors. First, there are several possible connection channels between them, including inter-fuel substitution, fuel costs, and commodity "financialization". Second, their timing provides the basis for a difference-in-differences approach. Third, various commodity groupings yield benchmarks that help us analyze the true contribution of each channel. Finally, correlations between energy and food products are interesting in their own right, as they are fundamental for human life.

Between 2006 and 2008, the corn prices which increased by 60 percent and soybeans by 76 percent, were then reduced by equally drastic amounts and have started a new increase in recent years. In the meantime, the West Texas Intermediate oil benchmark increased from about \$70 to \$140 per barrel (Runge and Senauer, 2008), and then decreased to approximately \$40, in what some have called a speculative bubble (e.g., Eckaus, 2008), only to regain the \$100 mark in 2010.

Many observers (e.g., Banse et al. 2008; IHT, 2008; Rajagopal et al., 2007; Ren21, 2007) have pointed out the role of the biofuels industry in the new linkage. Ethanol was favored by high oil prices (e.g., FAO, 2006) and by new regulation promoting its expansion, mainly the US Energy Policy Act (United States Congress, 2005). Its expansion also coincided with the widespread adoption of the new biofuels in the transportation sector, as well as the introduction of a futures contract in the Chicago Board of Trade.

A substitution linkage is economically plausible. Higher oil prices increase the demand for ethanol and hence its equilibrium quantity. This increases the demand for the input commodities and leads to higher prices. Ceteris paribus, oil and biofuel commodity prices could co-move.[1] However, other elements suggest that the biofuels link could be weak. Commodities like copper, live cattle or oats also have higher oil correlations, which could indicate a wider linkage. For example, the increasing commercialization of commodity index funds could have contributed to the co-movement. Furthermore, energy prices are an important agricultural cost component and, as such, it seems plausible that they should influence output prices. Other possible explanations include demand increases in emerging markets and oil stocks.

In addition, the biofuels boom may have been short-lived. Factors that have affected the industry include the 2008 oil price reductions, the surge in ethanol supply, the unreliability of federal tax credits and subsidies in the US, and growing environmental criticisms. This has caused the bankruptcy of

[1] Completely replacing gasoline with biofuels is unlikely, but even small substitutions could have large effects on agricultural markets. For example, 14.3% of the 2005 US corn harvest was processed to produce the energetic equivalent of only 1.72% of US gasoline usage (Hill et al., 2006).

many companies. Their coup de grâce seems to have arrived in late 2009, when the US Congress removed a tax credit given to ethanol producers, as many companies could not be profitable without it.

We measure the contribution of the interfuel substitution, energy costs and financialization channels to the new co-movement. We obtain daily futures prices for the main non-energy commodities traded in the US and proceed in three steps: First, we use the Bai and Perron (1998, 2003) method to estimate the timing of structural breaks in their co-movement with oil. Second, we use difference-in-differences (DiD) to study the discrepancies between biofuel feedstocks and other commodities, and thus disentangle the substitution, cost and financialization channels. Third, we seek further evidence in the stock market.

The main results are as follows. Most oil correlations increase in 2005 and decrease in 2008, but remain strong, particularly for biofuel feedstocks, at least until mid-2011. The biofuel co-movements present a single structural break in the first half of 2005, close to the introduction of a recent US Energy Policy Act. Breaks for non-biofuels are scattered in the 2006-08 period.[2] The oil-to-biofuels link remains strong up to 2011. The correlation increases are significantly higher for biofuels than for other commodities. The daily biofuel correlation increases of short-term futures are due to the costs, financialization, and substitution channels of about the same proportion. Substitution and costs drive the monthly correlations of long-term futures. Finally, correlations also increase between oil and the stock returns for the world's most influential ethanol producer, the Archer Daniels Midland Corporation, and between those of corn and an oil equity index. The linkages remain strong through mid-2011.

Despite its practical importance, systematic evidence on the existence and the effects of cross-commodity correlations is sparse. Exceptions are due to, e.g., Salvo and Huse (2011), who study the substitution of gasoline and ethanol in Brazil, and Tang and Xiong (2010), who associate the 2005-2008 co-movement of oil and non-energy commodities with indexation. We follow the co-movement literature (e.g., Pindyck and Rotemberg, 1990; Fleming et al., 2006) with the measurement of the timing and magnitude of daily correlations. In that context, our contribution is to formally estimate co-movement breaks, to disentangle the interfuel substitution, cost, and indexation channels, and to analyze the post-2008 de-coupling.

More generally, we contribute to the body of knowledge analyzing the foundations of futures prices. This has important ramifications in several contexts, such as the international integration of liquefied

[2] For comparison, we also apply this methodology to natural gas. We estimate two breaks instead, one at the beginning of the 2000s and another at the end. The intermediate period displays the highest correlation with oil.

natural gas, the emergence of Asia in commodity markets and the varying role that gold holds as a refuge value in times of crisis. The importance of the inter-relationships of commodity futures will likely grow in the future, as economic liberalization, technological advancements, global competition, and environmental concerns induce firms to search for greener, lower cost production methods which often cross conventional technological and national boundaries.

The paper proceeds as follows. Section II provides an overview of biofuels, introduces the data, and reports descriptive correlations that highlight our main results. Section III includes formal structural break methods and Section IV empirically disentangles the substitution, financialization and cost channels. Section V is devoted to equity markets. We conclude with some remarks. The Appendices include a stylized model of the biofuel channel and an oil threshold regression analysis.

II The empirical setting

A Biofuels

The OECD (2006) defines biofuels as "transportation fuels derived from biological (e.g. agricultural) sources". Their main production inputs are Brazilian sugarcane ethanol, US corn ethanol and soybean oil biodiesel (OECD, 2006). Less important feedstocks include rape seed and sunflower seed, palm and jatropha oil, as well as yellow grease (i.e., recycled cooking oil from restaurants). Wheat (France, Germany) and rape seed (mostly in Germany) are used in small amounts. In 2006, global ethanol production was 9.66 billion gallons, of which Brazil produced 45.2 percent from sugar and the US 44.5 percent from corn (Runge and Senauer, 2007; Ren21, 2007).

The US ethanol production increased from less than two billion gallons in 2000 to more than eight by 2008. In 2010, US grew 38% of the world's soybean production. Its fields yield 2,585 million bushels every year. Brazil and Argentina follow closely with 27 and 15% market share (World Soybean Statistics at http://www.soystats.com/2010). Futures markets trade two soybean products: soybean meal is generally an animal feedstock and soybean oil is used for biodiesel production, and also to produce human food products like margarine.

The biofuel production technologies are fairly standard, so their main profitability drivers are the feedstock costs, the price of energy inputs, the output prices and the possibility to sell by-products. There are three possible ways in which oil can influence biofuel prices: as a competing fuel, as a global pre-eminent commodity and as a production input.

First, oil and biofuels compete in retail markets and are often considered substitutes. That is the case in the 2005 US Energy Policy Act, passed on July 29, and signed into law by President George

W. Bush on August 8, 2005 (United States Congress, 2005).[3] It consists of a $14 billion national energy plan including provisions that promote energy efficiency and conservation, modernize the domestic energy infrastructure, and provide incentives for both traditional energy sources and renewable alternatives.[4] Importantly, Section 942 authorized the use of incentives to ensure a substantial biofuel production increase by 2015. It included a tax credit for blenders of one cent per gallon of agro-biodiesel blend, up to $1.00 for 100% biodiesel blend and another for small agro-biodiesel producers of 10 cents per gallon off the biodiesel produced (these are important in our empirical strategy as they were later removed). In addition, Section 1501 establishes a Renewable Fuels Standard requiring refiners to double the volume of biofuel added to the US fuel supply to 7.5 billion gallons by 2012 (United States Congress, 2005).

Biofuels have important advantages with respect to conventional fuels. They can be blended with them and hence require only minor adjustments to existing engine technology and fueling infrastructure.[5] In addition, most countries can produce them domestically, reducing demand for oil imports and increasing national energy independence. Moreover, they can be environmentally friendly. Finally, they can be an income source for local rural communities in the consuming countries.

If interfuel substitution were important, the "netback" value of ethanol would change with oil prices, and that would change the price of commodities used in its production. For example, Salvo and Huse (2010) provide a stylized model of the sugar/ethanol industry which incorporates substitution with gasoline at the pump, and producers' substitution with sugar across regional and export markets. They show that the model stands up well to the retail price co-movement in a panel of Brazilian states. In this paper, we look into whether substitution also has an influence on wholesale markets. Appendix I includes a simple model of the substitution mechanism.

Second, oil is the world's most important commodity. As such, it is the reference in futures markets and accounts for over half of the weight in most commodity indexes. Investment institutions increasingly sell commodity funds to their clients as a way to diversify the risk in equity and bond

[3] Some other elements suggest that 2005 is an important year for biofuel commodities. The Congressional Budget Office (CBO) estimates that the break-even point for corn ethanol (without any subsidies) is when gasoline costs 90% of what a bushel of corn costs or 70% with subsidies. This has happenned only once in recent decades, in 2005 (CBO, 2009). The introduction of a Chicago Board of Trade futures ethanol contract may also have contributed to a biofuels' link after March 2005.

[4] Other laws that have helped in the development of the US ethanol industry include the Biomass R&D Act of 2000 and parts of the 2002 Farm Bill.

[5] Low-level blends of biofuels can be used in most cars produced today, and the use of higher-level blends, or even of pure biofuels, often requires only relatively small modifications to engines. In addition, ethanol can also be used together with isobutene, an oil coproduct, to produce a gasoline additive (OECD, 2006).

portfolios (Bessembinder, 1992; de Roon et al., 2000). Thus, billions of dollars have gradually flown into commodity markets in recent times. This could have created a new investment style (Barberis and Shleifer, 2003; Barberis et al., 2005). The subsequent co-movement would influence all index components, regardless of whether they are related or not to the production of biofuels. The increase in biofuel commodity prices might then just be the result of an investment boom affecting many commodities (Tang and Xiong, 2010). Their oil linkage would be one of its manifestations. However, there are also authors such as Irwin et al. (2009) that cast some doubts on the influence of index funds in commodity prices.

Third, the use of fertilizers, transportation and field machinery are all energy intensive activities that together account for between 50-80% of the non-feedstock biofuel manufacturing cost (NASS, 2011).[6] Higher energy prices can therefore lead to higher agricultural prices. However, note the following. One, most, if not all, agricultural commodities require the use of fertilizers, machinery, and transportation, so the cost channel should also affect them. Two, soybeans production is particularly energy intensive (NASS, 2011), and this could account for a clearer oil linkage. Three, the soybeans cost effect should appear for both soybean meal and soybean oil. Changes in their *relative* price dynamics are not attributable to fuel cost changes.

Ultimately though, market observers seem to agree that the 2009 reduction in oil prices, the supply growth, the lack of US public support, and growing environmental pressure had a damaging effect on the ethanol industry (e.g., FT, 2008; JP Morgan, 2009). These forces put pressure on its commercial margins which, combined with the substantial amount of debt held by some companies, led many of them into bankruptcy. Examples include big players, e.g., VeraSun and Pacific Ethanol, and smaller companies. A particularly important factor is the US Congress non-renewal of the Energy Policy Act $1/gallon tax credit in late 2009. This could have led to a fast de-coupling of the wholesale oil and biofuel markets on that year.

To summarize, the introduction of biofuels is a good setting to study the connection between microeconomic fundamentals and inter-relationships in futures prices. There are three possible sources of correlation between oil and the biofuel inputs: costs, financialization, and inter-fuel substitution. The timing of legislation suggests two main candidate dates for the presence of substitution structural breaks. One is around the introduction of the Energy Policy Act in 2005. The other coincides with the January 1, 2009, removal of the US tax credits. The Appendix includes a simple model of the biofuels channel.

[6] Feedstocks account for more than half of total production costs.

B The data

Our data set includes daily futures prices from January 1990 to June 2011 of the main US commodities, taken from Datastream. We focus on the Datastream "Type 0" roll method because it produces the longest series,[7] and leave alternative rolling methods for the robustness section. Table 1 includes the series mnemonics, earliest collection dates, available contracts, and trading venues. Note that the rice data is from 2000 only. There are four non-energy categories: grains, softs, livestock, and metals. We consider five agricultural commodities related to biofuels production: corn, sugar, soybean and its two end-products, soybean meal and soybean oil. At times, we consider sub-groups without soybean meal and soybean oil. Apart from sugar, which belongs to the softs group, the biofuel commodities are all grains.

We control for several factors that are also available on a daily frequency: the Standard & Poor's 500 index, the JP Morgan United States Government Bond price index, the Datastream's US$ major currency exchange index and the Morgan Stanley emerging market equity index. These controls capture the link of commodity markets with equity markets, interest rates and the dollar exchange rate. Regarding equity markets, we include both the US and emerging markets, with the latter also capturing growth in emerging economies. As our main interest is in co-movement and its changes, most of the paper will rely on daily data. However, we also use weekly and monthly frequencies in later sections. Nevertheless, we also study weekly and monthly frequencies in later sections as a robustness exercise. Monthly data have the shortcoming of substantially reducing the number of observations, but facilitate the introduction of some relevant controls that are available on a monthly frequency only: inflation, oil stocks, and Kilian's (2009) index of global real economic activity.

`<<Table 1: Data description>>`

Figure 1 displays the price time series of West Texas Intermediate (WTI) crude oil and the biofuel-related commodities. Units are the standard for each commodity and follow Datastream. There is a visual co-movement among them: prices are relatively stable until 2004, when they substantially increase. They reach a peak around 2008, followed by a drop (e.g., corn from about 750 to 350), a short stability period, and new increases until the end of the sample period. A different issue is whether there are any econometrically robust patterns.

Thus, we use daily percent log-price changes (Figure 2). As a first overview, Figure 3 shows the daily returns' correlation between biofuel feedstocks and oil. We compute them on a one-year rolling

[7] Type 0 series switch to the next futures contract when the current one reaches its expiry date or on the first business day of the notional contract month, whichever is sooner. See Datastream (2010) for details.

window, and calculate 95% confidence intervals by mapping the estimates in a generalized method of moments set-up (Hansen, 1982), with robust standard errors as in Newey and West (1987). The Figure includes total correlations, that is, without controls. Residual correlations after subtracting the four daily controls feature the same qualitative characteristics, albeit less markedly.

`<<Figure 1: Daily prices for oil and biofuel feedstocks>>`

`<<Figure 2: Daily log-price changes for oil and biofuel feedstocks>>`

`<<Figure 3: One-year rolling window correlations between log-price changes of oil and biofuel feedstocks>>`

The correlations have historically been statistically insignificant. They start increasing in 2004 and become statistically positive for corn, soybeans, and soybean oil in 2005. This coincides with the approval of the Energy Policy Act, the introduction of the new ethanol futures contract and the oil price increases. Correlations remain around .40 between 2008 and 2010 and then decrease to about half that value, except for soybean oil. They remain statistically significative up to 2011, although at a smaller level. The correlation intensity may be related to oil price levels (e.g., Congressional Budget Office, 2009; International Energy Agency, 2007). From 2005, oil prices increase to $145.66/barrel (July 2008) drop to a minimum of $40.02 (December 2008), and regain the $100 mark in 2010.[8]

Correlations are stronger for corn, soybeans (.45-.50) and, especially, soybean oil (.55-.60), and weaker for sugar and soybean meal (only significant after 2008). This is consistent with the substitution channel. Soybean oil is a gasoline substitute, while soybean meal has no energy value. The soybean meal estimates also provide some support for the cost channel. Moreover, sugar is a biofuel mainly in Brazil, outside the jurisdiction of the Energy Policy Act, and is subject to entry barriers in the US (Elobeid and Tokgoz, 2006).

`<<Figure 4: Non-biofuel daily prices>>`

`<<Figure 5: One-year rolling window correlations between log-price changes of oil and non-biofuel commodities>>`

Figure 4 reports the non-biofuel prices. In several cases, large increases in 2008 are followed by reductions in late 2009 and early 2010. Yet, their patterns are less stable. For example, platinum and palladium increase in 2010. Gold increases steadily from 2000. Lean hogs, live cattle, lumber, and

[8] For comparison, the correlations between crude oil and natural gas are significant since 1998. They are about .30 in 2004 and reach a maximum close to .60 in the end of 2005. After that, they drop and then increase again to about .55 in late 2008.

silver oscillate in 2010. Agricultural products (wheat, oaks and rice) are the most similar to biofuels. Figure 5 includes the rolling window correlations between the non-biofuel commodities and oil. They are either non-significant (e.g., lean hogs, lumber, orange juice) or become statistically significant only in 2008 (e.g., wheat, cocoa, coffee, rice). Metals are the exception, but are significant only after 2006 in some cases.

We obtain similar evidence with Engle's Dynamic Conditional Correlation (2002).[9] The figures are available upon request to the authors. As in Figures 3 and 5, we find highly persistent correlations, which may be due to breaks in their steady states. We study the existence of co-movement breaks in the next section.

III Structural breaks

In this section we start our formal analysis. In particular, we estimate the dates of any structural breaks in the co-movement with oil.

A Methodology

We use the Bai and Perron (1998, 2003) method (B-P, hereafter) to identify structural breaks in the co-movement of each commodity with oil and estimate their timing.[10] B-P considers an unknown number of OLS break points under fairly weak conditions. Their set-up allows correlation and heteroskedasticity in the residuals, and also different distributions in the errors and the regressors after each break (e.g., the residual variance may change). Unit roots are not allowed, but we apply the methodology to return data, which are not too persistent.

They express a linear model with m breaks (or $m+1$ regimes) as

$$y_t = \mathbf{x}_t'\boldsymbol{\beta} + \mathbf{z}_t'\boldsymbol{\delta}_j + u_t, \qquad t = T_{j-1}+1, ..., T_j$$

for $j = 1, ..., m+1$. $\mathbf{x}_t$ denotes the covariates whose coefficients $\boldsymbol{\beta}$ are not subject to breaks, and $\mathbf{z}_t$ are the covariates whose coefficients $\boldsymbol{\delta}_j$ may change. Given a sample of T observations of $(y_t, \mathbf{x}_t, \mathbf{z}_t)$ and a particular m, the goal is to determine the estimates $(\boldsymbol{\beta}, \boldsymbol{\delta}_1, .., \boldsymbol{\delta}_{m+1})$ and break points $(T_1, .., T_m)$ that minimize the squared residuals' sum across coefficients and break points.

B-P compute robust standard errors and confidence intervals, and develop several tests. In particular, B-P construct tests of ℓ versus $\ell+1$ breaks, which are based on the sums of squared residuals

[9] Büyüksahinn, Haigh and Robe (2010), and Chong and Miffre (2010) use DCCs to study the linkage between commodities and traditional asset classes, i.e., equity and fixed income. They do not find a correlation increase in spite of the recent increase in commodity investment.

[10] We rely on their code, available at http://people.bu.edu/perron/code/multivariate-breaks.rar.

for an additional break at each interval of the $(T_1, .., T_\ell)$ estimates. These tests are used to construct a sequential procedure to determine m. In our implementation, the confidence level is 5%, there can be up to five breaks, and the "trimming" parameter (minimum size of a segment with respect to T) is 15%. We allow for heterogeneity and autocorrelation in the residuals, and also regressor heterogeneity across segments.

B Empirical results

Table 2 displays the application of the B-P method to the relationship between oil and commodity returns. There is clear evidence against the existence of constant relationships. Most series display a single break. Exceptions are lean hogs and pork bellies with none, and Chicago wheat, and gold with two. The main biofuel series exhibit breaks in a three-week interval in early 2005: corn February 17; soybean oil January 25; soybeans January 21. Their confidence intervals overlap substantially. Non-biofuel breaks, if existing, seem to have different timing, as no other breaks fall in this narrow time span. Also notice that the variation is larger even within the same commodity (wheat) at different locations: Chicago Dec 3/04 and Feb 28/08; Kansas City Apr 25/06 and Minnesota Mar 6/08.

The table also documents the pre- and post-break slope coefficients. The series feature small pre-break (mostly non-significant) and higher post-break slopes (all $p < .01$). This applies to both biofuels and non-biofuels. For example, corn changes from .0191 to .2817, and Minnesota and Kansas wheat vary from less than .02 to slightly more than .25. The widespread high post-break values are consistent with the presence of common factors influencing many commodities. For comparison, natural gas features two breaks, with coefficients .1908 pre-2001, .6138 in 2001-2008 and .2097 post-2008. Notice that the second post-break slope is decreasing.[11]

`<<Table 2: Structural break regressions of non-energy commodities, and natural gas, on crude oil>>`

Table 3 shows that the estimates are robust to standardizing the series with their corresponding GARCH(1, 1) volatilities. The biofuel break locations remain unchanged except for soybean meal. Slopes are still very small pre- and quite large post-break. For example, corn slopes change from .0187 to .3281. This is similar to other agricultural estimates (e.g., wheat changes from .03 to .33).

`<<Table 3: Structural break regressions of non-energy commodities, and natural gas, on crude oil after controlling for GARCH effects>>`

[11] We also applied this method to ethanol futures data, which are only available from 2006. There are two breaks, in June 2007 and December 2008. The slope first increases from 0.2022 to 0.4765, and then decreases to 0.1704.

Table 4 summarizes the B-P values with the four daily controls.[12] The corn, soybean, soybean meal and soybean oil estimates lay in an even narrower interval than before (January 21 to February 8, 2005, $p < .01$). No other commodity displays 2005 breaks, and only a handful have them either in 2004 (e.g., wheat, copper) or 2006 (cocoa and oats). Several series exhibit more than one break and/or their estimates change considerably: there are two copper, wheat, and palladium breaks; three for silver and up to four in gold. The post-break biofuel slopes are somewhat higher, but not much. They are .20 for corn and, on average, about .16–.17 for wheat.

`<<Table 4: Structural break regressions of non-energy commodities, and natural gas, on crude oil and controls>>`

The B-P tables share some stylized facts: The biofuel feedstocks display a single structural break in the second half of the 2000s that lays close to the introduction of the Energy Policy Act. Other commodities display mostly posterior breaks and/or several of them. Pre-break slopes are small, while the post-break slopes are strongly significative. These facts provide some, albeit weak, evidence in support of specific biofuel dynamics. Moreover, we do not find evidence of a recent disappearance of the oil-to-biofuels link, neither of significant changes due to the boom and bust oil of 2008 nor the financial crisis starting with the fall of Lehman that same year, as this would manifest itself in a batch of 2008/09 structural breaks. The evidence for non-biofuels is mixed.

Interestingly, the patterns are similar when we condition the breaks on oil price levels rather than time. Threshold regressions suggest that oil prices might had triggered the biofuel correlations as they exceeded $40/barrel in 2005. This is consistent with both the International Energy Agency and Congressional Budget Office calculations. See Appendix II for these estimations.

IV Interfuel substitution, energy costs and financialization

In this section, we disentangle the influence of the inter-fuel substitution, cost and financialization channels.[13] We are interested in the average variation differences between groups from one period to another, with biofuels as the treatment group and varying subsets of the remaining commodities as control groups. We consider two structural breaks and hence three periods, pre-2005, 2005-2009 and post-2009. We follow the BP results and the apparent consensus amongst practitioners. The B-P

[12] Breaks are not necessarily linked to oil in this case, as the control slopes may also change.

[13] An additional channel outside the scope of this paper is within the energy category. For example, the correlation between oil and natural gas has increased as the market experienced liberalization. This is an important issue deserving attention in future research.

analysis suggests a single biofuel break in 2005, but we also want to explore possible differences after 2009, as this year coincides with the removal of the ethanol subsidy in the US and results in decreases of the rolling correlations of Figure 3. The main results are largely invariant with other break dates like 2004 to capture a potential financialization break as in Tang and Xiong (2010), or 2008 to account for the financial crisis and the oil price reductions.

The analysis relies on the following facts. One, energy intensity is similar across agricultural commodities, regardless of whether they are used for biofuels production or not. Two, there is no a priori reason to suppose that financialization influences corn, soybeans, and sugar any more than other indexed commodities. Thus, non-biofuel agricultural correlations may account for the energy cost channel, and indexed (non-biofuel) commodities reflect financialization. We interpret the differences between biofuels and these categories to arise from inter-fuel substitution.

We will work with the following groups of commodities. Eleven non-biofuels are part of the SP-GSCI and/or the DJ-UBS indices, and we label them as "indexed". We refer to the other seven commodities as "off-index".[14] Soybean meal is the only biofuel-related commodity that is "off-index", moreover it cannot be used for biofuel production. Biofuel-related commodities belong to the grains and softs categories, see Table 1. Hence we construct another subset of commodities with the nine non-biofuel grains and softs, which we refer to as "agricultural". Most of them are human foodstuffs, but not all (e.g., cotton). We also decompose agricultural commodities into indexed and off-index.[15] We exclude the rice series from the analysis of this section because it starts in 2000, much later than the others.

A Correlations with oil

We work both with the total correlations, and also residual correlations after removing the influence of the four daily controls. In this section we favor correlations over simple OLS slopes to compare estimates across commodities. On the other hand, correlations can also be estimated as OLS slopes when computed with standardized variables. Hence, first we standardize the variables with the corresponding means (which include the controls for residual correlations) and variances in each of the three sample periods. Then we estimate the three correlations as OLS slopes of standardized non-energy commodities onto standardized oil. We can express the joint estimation of these correlations as a

[14] This classification is similar to Tang and Xiang (2010). Indexed non-biofuels: Chicago wheat, cocoa, coffee, copper, cotton, feeder cattle, gold, Kansas wheat, lean hogs, live cattle, and silver. Off-index non-biofuels: Lumber, Minnesota wheat, oats, orange juice, palladium, platinum, and pork bellies.

[15] Indexed agricultural: Chicago wheat, cocoa, coffee, cotton, and Kansas wheat. Off-index agricultural: Lumber, Minnesota wheat, oats, and orange juice.

system of moments by means of dummy variables associated to the sample periods, and apply the generalized method of moments to compute robust standard errors.

Table 5 reports total and residual correlations between oil and each non-energy commodity returns, and we add natural gas for comparison. The pre-2005 estimates are mostly non-significative. The pre-2005 biofuel values are low and similar to those of non-indexed series. Soybean oil, which should be the most clearly influenced by the biofuels' channel, presents a total correlation of only 0.01, at the level of live cattle and orange juice. Not surprisingly, natural gas displays the highest correlation with oil.

By group, indexed commodities have the highest average correlations (0.0406), followed by biofuels and non-indexed commodities (0.0188). Three precious metals display high values: gold (0.1765), silver (.1271) and platinum (.0718, all $p < .01$). Note that the results are extremely similar to the ones with controls.

`<<Table 5: Oil correlations for non-energy commodities and natural gas>>`

The 2005-09 and post-2009 values are statistically significant and economically meaningful in most cases. Exceptions are three livestock products, feeder cattle, lean hogs, and pork bellies. The small feeder cattle and lean hogs values would seem to suggest that the indexation effect is not as general as one would expect. The implications for the cost channel are not strong though, as none of them is strictly agricultural. In 2005-09, all biofuels have large, statistically significant ($p < .01$) correlations. The soybean oil estimate is 27% above the highest non-biofuel (copper 0.4001, vs. 0.5075) and 37% higher than the second one, silver (0.3713). It is also over 40 times its own pre-2005 correlation. The metals estimates are high, but their percent increase is modest due to their high pre-2005 values. Natural gas does not display the highest correlation with oil after 2005. Total correlations are higher for several commodities during 2005-2009, but once we take controls into account only soybean oil displays a higher correlation. In fact, there is a big post-2009 drop in the correlation between natural gas and oil, and hence many non-energy commodities have a higher correlation in the last years of our sample.

Note that the soybean oil correlation increase after 2005 is around twice the soybean meal increase, both in total and residual terms. This can be interpreted as a first approximation to the additional correlation that the interfuel substitution and the financialization channels contribute on top of the energy cost channel. Supporting this, the corn and soybean increases lay inbetween, while the wheat increase is similar to the soybean meal increase for the three wheat commodities.[16] In all these

[16] In the United States, wheat is not grown in the same fields as soybean and corn.

agricultural commodities though, changes in 2009 are relatively minor compared to 2005.

By groups, biofuels display both the largest increase and post-2005 figures. Their post-2005 averages are 0.3521 and .3404, while the non-biofuel averages are 0.2153, and .2664. The indexed post-2005 averages are .2362 and .2950, and the agricultural averages are .2010 and .2609. The biofuels correlations are 69% and 78% higher than the indexed and agricultural benchmarks, and 41% higher than their combination. The residual biofuel correlations are proportionally more important, e.g., the biofuels variation is 119% higher than that of the indexed group. Metals increase more than agriculturals. In addition, indexed commodities increase more than non-indexed ones, which provides some support for the financialization channel.

After 2005, the biofuel magnitudes increase slightly without soybean meal (.3753 and .3651), and are substantially smaller when one excludes soybean oil (.3312 and .3194). This is not surprising given our previous comparison of both commodities, and fits nicely with the substitution story, as soybean meal is unrelated to biofuel production, and soybean oil is a direct gasoline substitute. The 2009 biofuels break is hardly noticeable in all cases.

B Difference-in-differences analysis

To test for the presence of a biofuel channel, we follow the spirit of the difference-in-differences (DiD) tradition in the program evaluation literature. We think of biofuels as the treatment group and varying subsets of the remaining non-energy commodities as control groups. The DiD approach takes into consideration both group- and time-specific effects. The average biofuel correlation changes do not help us disentangle inter-fuel substitution from alternative channels. Similarly, post-break cross-sectional variation may reflect systematic differences between groups.

`<< Table 6: Difference-in-differences analysis of daily oil correlations>>`

In Table 6, the 2005 DiDs between biofuels and the other classes range from .11 to .23 (all $p < .01$). This indicates that biofuels increase their oil correlation significantly more than the other groups. The values are higher when one excludes soybean meal and lower without soybean oil. Note also that the 2005 DiD with respect to off-index agricultural commodities is more than double the one with respect to indexed agricultural commodities. The 2009 DiD values are between -.08 and -.06 though (also significant), because biofuels slightly decrease their oil correlation while the other groups slightly increase that correlation in the last years of our sample.

The introduction of daily controls does not have a noticeable 2005 effect. The biofuel values are clearly above the index and agricultural groups, 13.41 and 13.56 percent points respectively for all

biofuels. On the other hand, the 2005 DiD with respect to off-index agricultural commodities is not that far from the indexed agricultural commodities. In 2009, the DiD coefficients slightly decrease in absolute value, most of them becoming non-significant.

As the post-2009 behavior does not seem all that different, we approximate the relevance of the substitution, financialization, and cost channels in the post-2005 break. We can see in Table 5 that the post-2005 total oil correlation increases were 0.13 for off-index agricultural commodities, 0.23 for indexed agricultural commodities, and 0.33 for biofuels. Hence we can decompose the 0.33 increase of biofuels in three components: 0.13 from the cost channel, 0.10 from the financialization channel, and 0.10 from the biofuel channel. Each channel seems to contribute around one-third for the total biofuels increase. With residual correlations, the increments are 0.07, 0.14, and 0.25 for the previous groups. With this numbers, we can decompose the 0.25 increase of biofuels in three components: 0.07 from the cost channel, 0.07 from the financialization channel, and 0.11 from the biofuel channel. Again it seems that each channel contributed around one-third for the total increase in biofuels, with a slightly higher relevance of the biofuel channel after taking into account the controls.

<< `Table 7: Difference-in-differences analysis of daily Goldman Sachs Commodity Indexes correlations`>>

We complement the previous analysis of oil correlations with a DiD analysis of correlations with two commodity indices in Table 7. The Goldman Sachs Commodity Index (GSCI) is such that energy is the most important category, 78.65% of the total, of which crude oil and Brent add up to more than half. Its non-energy subindex excludes crude oil, Brent, unleaded gasoline, heating oil, gas oil, and natural gas. Thus, it is not surprising that the correlation patterns on the left-hand side panel, i.e., with the total GSCI, are similar to those in Table 6. However, the right-hand side panel shows that the 2005 DiD estimates with the non-energy GSCI sub-index are much lower, and even non-significant in many cases. Biofuels behave like other commodities with respect to the non-energy index but not with respect to the general one. The main significance is the 2005 DiD against the off-index agricultural commodities.

Tables 5-7 form a solid body of evidence in support of different biofuel behavior, which seems consistent with the existence of an enduring inter-fuel substitution channel. The rest of this section is devoted to a robustness analysis.

C Lower frequencies and alternative futures series

First, we revisit the DiD analysis with lower frequency data. Table 8 reports DiDs for weekly and monthly frequencies. The left-hand side panel shows the results with weekly data. Importantly, the magnitudes and significance are similar to those with daily observations. The 2005 DiDs are noticeable, and also stronger than those for 2009.

The shortcoming of using monthly data is that there is a big drop in the number of observations. This drastically reduces the accuracy of the co-movement estimates, and the power of the statistical tests. Still, we use it for two reasons. One, it may provide a cleaner assessment of the long-term correlations between wholesale food and energy markets. This is particularly relevant for developing countries that import both types of products. Second, potentially useful control variables like global real economic activity, inflation, and oil reserves are only available on a monthly frequency. Now we can include Kilian's index of global real economic activity in industrial commodity markets (see Kilian, 2009), US core inflation (excluding food and energy) from Federal Reserve price indexes and Energy Information Administration (EIA) US oil reserves (excluding the strategic reserves).[17] The results are very similar when one uses total inflation and reserves.

`<<Table 8: Difference-in-differences analysis of weekly and monthly oil correlations>>`

The right-hand side panels in Table 8 report the monthly DiDs. Their sign and ordering are supportive of the patterns at higher frequencies. This applies to the total correlations, as well as those with the daily and monthly controls. The total 2005 values are clearly positive, but not the ones in 2009. With this type of series, which tracks short-term futures prices, the results are not statistically significant at the monthly frequency, except some results that include soybean oil.

Second, we consider alternative futures series. A constant issue with futures is how to construct the relevant time series. Until now, we have based our analysis on the "Type 0" Datastream series, as it is the longest, dating back to 1990 for many commodities. This series switches to the next futures contract when the current one reaches its expiry date or on the first business day of the notional contract month, whichever is sooner. As a robustness exercise, we consider other types of continuous futures series from Datastream. See Datastream (2010) for further details.

The "Type 4" data uses daily price returns from the near month contract to the index until the contract reaches its expiry date. At that point, it uses the price returns from the next contract month.

[17] The corresponding links are http://www-personal.umich.edu/~lkilian/reaupdate.txt, http://www.federalreserve.gov/releases/h15/data.htm , and http://www.eia.doe.gov/petroleum/data.cfm.

This effectively adjusts the index for the rolling yield, so that this series can be interpreted as an excess return index. Its shortcoming is that it is only available from 1995. Table 9 documents its DiD estimates, which are very similar to those in Table 6. The contribution of each channel to the post-2005 increase in oil correlation of agricultural commodities is also similar. Each channel seems to contribute around one-third for the total biofuels increase, with a slightly higher relevance of the biofuel channel after taking into account the controls. With residual correlations, the increments are 0.08, 0.14, and 0.25 for off-index agricultural commodities, indexed agricultural commodities, and biofuels respectively. With this numbers, we can decompose the 0.25 increase of biofuels into 0.08 from the cost channel, 0.06 from the financialization channel, and 0.11 from the biofuel channel. We conclude that our empirical evidence is not driven by the rolling yield adjustment.

`<<Table 9: Difference-in-differences analysis of daily oil correlations, using Datastream Type 4 futures series>>`

We also consider the Datastream "Type 3" and "Type 5" series, although they are only available since 2002 in many cases. The "Type 3" series roll-over to the second nearest contract when its volume is higher than the nearest contract. In this way, one uses the most active contract. The Tables are similar to the previous ones and available upon request. We conclude that the rolling method does not have an influence on the results.

`<<Table 10: Difference-in-differences analysis of monthly oil correlations, using Datastream Type 5 futures series>>`

The "Type 5" series consists of daily averages of the available maturities. Hence, they include long-term futures, where the micro fundamentals play a more important role than financial factors relative to short-term futures. Interestingly, Table 10 shows a significant biofuel channel at the monthly frequency with and without controls. The 2005 DiDs are significantly positive, and the 2009 DiDs are negative and non-significant. The 2005 DiD values are also much higher than in any of the previous tables. In addition, using these data, the biofuel and energy cost channels seem equally important for agricultural commodities, while the financialization channel does not seem relevant. With residual correlations that take into account the seven controls, the increments are 0.22, 0.17, and 0.48 for off-index agricultural commodities, indexed agricultural commodities, and biofuels respectively. With these numbers we can decompose the 0.48 increase of biofuels in two components: 0.22 from the cost channel, and 0.26 from the biofuel channel. The biofuels channel does not only have short-term implications, but also influences the evolution of commodity long-term futures.

V Equity market effects

We explore traces of correlations in equity markets with a double intention: one, to ascertain to what extent the biofuel channel influences the main financial markets; two, because they help us disentangle some causality in the oil-to-biofuels relationship. We look at the linkages between on the one hand, oil and corn prices and, on the other, stocks prices in the biofuels and oil exploration and production (E&P) sectors. These data are also from Datastream. However, it is difficult to compile a systematic index of biofuel-related firms because many of them are privately held (e.g. by Cargill), while others became public around or after 2005 (e.g., VeraSun Energy, listed in 2006). Such companies would not help us analyze the 2005 changes.

Therefore, we focus on the Archer Daniels Midland (ADM) stock price. According to *The New York Times*, ethanol could have made up to 40 percent of ADM's net income in fiscal 2007. ADM is also interesting because it is listed and has no oil operations. Hence, oil prices should influence its stock price mainly through the input costs channel unless there is also inter-fuel substitution. Finally, ADM is the market leader, and we think its activities are a valuable proxy for overall market exposure to biofuel input prices.[18]

We also analyze the correlations between corn and oil with the S&P oil E&P stock index. The E&P index is formed by hydrocarbons exploration and production specialist firms. Due to lack of data, we restrict our attention to the period dating from 2000. The E&P-to-oil correlations are expected to be strong, and can be interpreted as a rough reference of the maximum correlation one could achieve if ADM only operated in the biofuels industry. In addition, the E&P index also helps us ascertain the possibility of a reverse mechanism linking biofuels and oil stocks.

Table 11 presents the estimates. Raw correlations are not too insightful as they lack general stock market controls, so we focus the exposition on residual values. Pre-2005, ADM has a small correlation with corn (.0271) and negative with oil (-.0603, $p < .01$). The small size of the corn estimate could be due to ADM's product diversification. The negative oil estimate can reflect the relatively minor role that biofuels play in the period and, importantly, the fact that energy is a cost input in ADM's production. These results are therefore consistent with the returns of a well-diversified firm operating in the agricultural sector. Compare this to the pre-2005 E&P correlations. As one would expect, they are very strong with oil (.3993, $p < .01$) and meaningless with corn (.0179).

`<<Table 11: Stock market correlations with oil and corn>>`

[18] ADM has traditionally been a diversified company operating in the food, beverage, nutraceutical, industrial and animal feed markets worldwide. Traditional ADM products include soybeans oil, cottonseed, as well as corn germ, syrup, starch, glucose, sweeteners, ethyl alcohol, and wheat flour.

In 2005-2009, correlations are significative for ADM-corn (.0547, $p < .01$), E&P-oil (.5090) and E&P-corn (.2087), and only non-significant for ADM-oil (.0396). The non-significant ADM-oil correlation may appear because the cost and substitution mechanisms operate in different directions and can cancel out. As was the case in previous sections, we are specially interested in the differences between the pre- and post-break values. They are significant across commodities –ADM-oil (.0999) and E&P-corn (.1908), both $p < .01$. In contrast, the differences are not significative with the associated commodities (ADM-corn .0276 and E&P-oil .1097).

In the post-2009 period, the correlations of E&P with both oil and corn decrease, but they are still high and significant. Both the ADM correlations with oil and corn decrease slightly, but they were already low in 2005-2009. The differences are not significative.

To recapitulate, ADM has increased its correlation with oil from clearly negative to slightly positive. The E&P index has increased its correlation with corn from neutral to clearly positive. This is consistent with the emergence of a recent biofuels channel operating via inter-fuel substitution.

VI Concluding remarks

In this paper, we study how microeconomic fundamentals influence the relationships between commodity futures. We focus on recent developments in the biofuels industry, and whether they have shaped the co-movement between oil and agricultural futures. There is a plausible economic logic for an oil-food connection through biofuels, but non-biofuels have also increased their oil correlations. Popular reasons for a commodity-wide co-movement are the increasing commercialization of commodity index funds and the impact of energy costs.

We use US daily futures data from 1990 to mid-2011 to disentangle the substitution, cost, and financialization channels. We formalize the analysis in three stages: First, we estimate the time location of the structural breaks. Then, we run an extensive difference-in-differences (DiD) analysis between biofuels and non-biofuels. Third, we seek further evidence in the stock market.

Biofuel effects become statistically positive after 2005. They are particularly strong for soybean oil and far weaker for sugar and soybean meal. Soybean oil is a close gasoline substitute, and soybean meal has no energy value. Sugar is a fuel mainly in Brazil, outside the jurisdiction of the US legislation. The non-biofuel breaks are posterior and their magnitudes significantly smaller. These patterns do not disappear with the controls.

Biofuel correlations are higher than those one could attribute to the financialization and cost channels, and have not disappeared in recent years. The 2009 DiDs are not as high as their 2005 counterparts, but are still significant. Finally, the stock market analysis indicates that Archer Daniels

Midland has increased its correlation with oil from clearly negative to slightly positive, and the S&P oil exploration and production stock index has increased its correlation with corn from neutral to clearly positive.

Overall, our results make a strong case for a biofuels' channel with substantial bearing on commodity markets. With short-term futures and daily correlations, substitution accounts for about one-third of the correlation increase, with costs and financialization splitting the remaining two-thirds. With longer-term futures and monthly correlations, substitution accounts for about one-half of the correlation increase, with costs explaining the remaining half.

More generally, we contribute to the study of the linkage between microeconomic conditions and financial markets. This is important in several contexts, including the liquefied natural gas industry, the role of Asia in commodity markets and the use of gold in crisis periods. The importance of commodity futures inter-relationships is expected to grow in the future, as economic liberalization, technological advancements, global competition and environmental concerns induce firms to search for greener, lower-cost production methods which often cross conventional technological and national boundaries.

Runge and Senauer (2007) warn that "biofuels have tied oil and food prices together in ways that could profoundly upset the relationships between food producers, consumers, and nations in the years ahead, with potentially devastating implications for both global poverty and food security." Such an oil-food link is likely to have a large impact on human welfare and would exceed the possible importance of other cross-commodity correlations. This is an important issue deserving further research.

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Appendix I: Inter-fuel substitution model

Let us take corn as an example. The equilibrium ethanol quantity depends on the oil price and is a component of corn demand. The idea is to value corn by netting costs from the value of products in the biofuels' production process. Thus the netback price of a unit of corn is the gross product worth of ethanol, minus the costs incurred in transporting it, minus the production costs. The same logic can be applied to soybeans and sugar. We formalize this inter-fuel substitution in the following stylized model, which does not include other channels such as commodity production cost and financialization.

Ethanol producers account for the supply side in the market $q_e^S = a_e + b_e p_e$, and gasoline blenders for the demand $q_e^D = c_e - d_e p_e$. The demand intercept c_e depends positively on the price of crude oil p_o as the main driver of gasoline prices. The supply intercept a_e depends negatively on the corn price p_c as an input cost. This means that for a given p_e, q_e^D increases on p_o, while q_e^S decreases with p_c. For simplicity, we assume that a_e linearly depends on the corn price p_c

$$a_e = a_0 - a_1 p_c,$$

and c_e linearly depends on the gasoline price p_o

$$c_e = c_0 + c_1 p_o.$$

We can express the equilibrium quantity of ethanol ($q_e^S = q_e^D$) as

$$\begin{aligned} q_e &= \frac{b_e c_e + d_e a_e}{b_e + d_e} \\ &= \left(\frac{b_e c_0 + d_e a_0}{b_e + d_e}\right) + \left(\frac{b_e c_1}{b_e + d_e}\right) p_o - \left(\frac{d_e a_1}{b_e + d_e}\right) p_c = \phi + \phi_o p_o - \phi_c p_c, \end{aligned}$$

where ϕ_o and ϕ_c positively depend on c_1 and a_1

Let us move on to the corn market. The demand takes the form $q_c^D = c_c - d_c p_c$. We decompose it into demand for the ethanol market $q_{ethanol}^D$, which we normalize to $q_{ethanol}^D = q_e$, and demand for

other uses q^D_{other}. That is,

$$q^D_c = q^D_{other} + q^D_{ethanol} = (\varphi - \varphi_c p_c) + (\phi + \phi_o p_o - \phi_c p_c)$$
$$= (\varphi + \phi + \phi_o p_o) - (\varphi_c + \phi_c)\, p_c = c_c - d_c p_c.$$

Farmers supply $q^S_c = a_c + b_c p_c$. The equilibrium corn price ($q^S_c = q^D_c$) is

$$p_c = \frac{c_c - a_c}{b_c + d_c} = \frac{\varphi + \phi + \phi_o p_o - a_c}{b_c + \varphi_c + \phi_c}$$
$$= \left(\frac{\varphi + \phi - a_c}{b_c + \varphi_c + \phi_c}\right) + \left(\frac{\phi_o}{b_c + \varphi_c + \phi_c}\right) p_o = \alpha + \beta p_o.$$

Therefore, p_c is increasing in p_o since ϕ_o is part of β. Our empirical work uses price variations and hence focuses on β. This is linked to the relevant parameters by

$$\beta = \frac{\phi_o}{b_c + \varphi_c + \phi_c}, \text{ where } \phi_o = \frac{b_e c_1}{b_e + d_e} \text{ and } \phi_c = \frac{d_e a_1}{b_e + d_e}.$$

We find $\beta = 0$ when $\phi_o = 0$ because $b_c + \varphi_c + \phi_c < \infty$ due to, among other reasons, the existence of storage and export markets. Similarly, $\phi_o = 0$ when $c_1 = 0$ because $b_e \neq 0$ and $b_e + d_e < \infty$. Note that b_c, $d_c (= \varphi_c + \phi_c)$, b_e and d_e are the slopes of q^S_c, q^D_c, q^S_e, and q^D_e, respectively. We understand the case of $\beta > 0$ as $\phi_o > 0$, and thus $c_1 > 0$, i.e., a biofuel channel where q^D_e positively depends on p_o.

The existence of a current linkage would imply that $\beta > 0$. Our goal is to quantify whether/when β changed from 0 to a positive value, i.e., the start of a corn - crude oil connection, and any other later changes. A change from $c_1 = 0$ to $c_1 > 0$ may be due to policy changes or a more complex connection between q^D_e and p_o, e.g., it may contain a threshold effect such that $c_1 = 0$ if $p_o \leq p^*$ and $c_1 > 0$ otherwise.

Appendix II: Oil price threshold regression

The substitution channel assumes that there is a functioning biofuels industry. This is likely to be the case only if oil prices are above a certain level. The International Energy Agency (IEA) estimates that biofuels are not cost competitive unless oil trades at a minimum of US$40/barrel: oil prices below that threshold would not be "sufficiently" high to cause co-movement. The IEA estimate is consistent with official Congressional Budget Office documents suggesting that the ethanol break-even point is when the ratio of the corn and oil prices is around 0.9.

We condition the co-movement of oil and non-energy commodities on oil prices using the methodology in Hansen (2000). We test whether there is an oil price threshold that triggers the recent structural

linkage, and also estimate the threshold itself. Formally, we are interested in the regression

$$y_t = \mathbf{x}_t'\boldsymbol{\theta}_1 + u_t, \qquad q_t \leq \gamma,$$
$$y_t = \mathbf{x}_t'\boldsymbol{\theta}_2 + u_t, \qquad q_t > \gamma,$$

where $(\boldsymbol{\theta}_1, \boldsymbol{\theta}_2, \gamma)$ are the parameters to estimate (i.e., the threshold γ is unknown) and q_t is the variable that splits the sample in two regimes, the oil price in our case. We use the nominal oil price, as the daily real price is difficult to compute because the CPI is available on a monthly frequency. Yet, this should not cause important changes to the main results. We apply the heteroskedasticity–consistent Lagrange multiplier (LM) test (Hansen, 1996) to verify the existence of a threshold effect. We find clear evidence against a constant co-movement in all non-energy commodities except lean hogs and pork bellies, and also live cattle and orange juice when introducing controls.

`<<Table A1: Threshold regressions of non-energy commodities on crude oil>>`

Table A1 includes the estimates and 95% confidence intervals (C.I.) of the thresholds, and the below- and above-threshold OLS slopes. The results are similar with and without controls. Regarding biofuel-related commodities, the thresholds are around \$40/barrel with the exception of sugar, which is slightly lower (\$32.49/barrel). The corn, soybeans and soybean oil C.I. are narrow. They are substantially wider for soybean meal and sugar, but these products are not part of the US biofuels industry in any meaningful way. The below-threshold slopes are not significant, except (marginally) for corn. The above-threshold estimates are much higher and significant.

Regarding non-biofuels, grains display a similar threshold in general, but for instance Minnesota wheat shows a very high threshold with controls. Copper also displays a similar threshold, but the rest of metals are not that similar. The below-threshold slopes of non-biofuels are mostly non-significant, with the clearest exceptions of gold, platinum and silver. The above-threshold are much higher and strongly significant in all cases except feeder cattle and lumber.

Overall, the patterns that we find from conditioning the co-movement on oil prices and time are consistent as the oil price has been consistently higher than 40 since the end of 2004. Note also that the 2008 boom and bust in the oil price was such that between December 2008 and February 2009 there were several periods with oil prices below 40. Around those dates, we can see correlations decreasing in Figure 3. On the other hand, the methodology in Hansen (2000) is more restrictive than the B-P method, in the sense that it allows a single threshold while the latter allows several breaks.

	Code	Category	Data	Contracts	Exchange
BIOFUEL FEEDSTOCKS					
Corn	CC	Grains	02.01.79	Mar,May,Jul,Sep,Dec	CME Group including CBoT and CME
Soybean Meal	CSM	Grains	02.01.79	Jan,Mar,May,Jul, Aug,Sep,Oct,Dec	CME Group including CBoT and CME
Soybean Oil	CBO	Grains	02.01.79	Jan,Mar,May,Jul, Aug,Sep,Oct,Dec	CME Group including CBoT and CME
Soybeans	CS	Grains	02.01.79	Jan,Mar,May,Jul,Aug,Sep,Nov	CME Group including CBoT and CME
Sugar	NSB	Softs	02.01.79	Mar,May,Jul,Oct	New York Board of Trade (NYBOT)
OTHER COMMODITIES					
Chicago Wheat	CW	Grains	02.01.79	Mar,May,Jul,Sep,Dec	CME Group including CBoT and CME
Cocoa	NCC	Softs	02.01.79	Mar,May,Jul,Sep,Dec	New York Board of Trade (NYBOT)
Coffee	NKC	Softs	02.01.79	Mar,May,Jul,Sep,Dec	New York Board of Trade (NYBOT)
Copper	NHG	Metals	01.09.89	All	New York Mercantile Exchange including COMEX (NYM and CMX)
Cotton	NCT	Metals	02.01.79	Mar,May,Jul,Oct,Dec	New York Board of Trade (NYBOT)
Feeder Cattle	CFC	Livestock	02.01.79	Jan,Mar,Apr,May,Aug,Sep,	CME Group including CBoT and CME
Gold	NGC	Metals	02.01.79	All	New York Mercantile Exchange including COMEX (NYM and CMX)
Kansas Wheat	KKW	Grains	02.01.79	Mar,May,Jul,Sep,Dec	Kansas City Board of Trade (KCBT)
Lean Hogs	CLH	Livestock	02.01.79	Feb,Apr,Jun,Jul,Aug,Oct,Dec	CME Group including CBoT and CME
Live Cattle	CLC	Livestock	02.01.79	Feb,Apr,Jun,Aug,Oct,Dec	CME Group including CBoT and CME
Lumber	CLB	Softs	02.01.79	Jan,Mar,May,Jul,Sep,Nov	CME Group including CBoT and CME
Minnessota Wheat	MMW	Grains	02.01.79	Mar,May,Jul,Sep,Dec	Minneapolis Grain Exchange (MGE)
Oats	CO	Grains	02.01.79	Mar,May,Jul,Sep,Dec	CME Group including CBoT and CME
Orange Juice	NJO	Softs	02.01.79	Jan,Mar,May,Jul,Sep,Nov	New York Board of Trade (NYBOT)
Palladium	NPA	Metals	02.01.79	All	New York Mercantile Exchange including COMEX (NYM and CMX)
Platinum	NPL	Metals	02.01.79	All	New York Mercantile Exchange including COMEX (NYM and CMX)
Pork Bellies	CPB	Livestock	02.01.79	Feb,Mar,May,Jul,Aug	CME Group including CBoT and CME
Rice	CNR	Grains	07.01.00	Jan,Mar,May,Jul,Sep,Nov	CME Group including CBoT and CME
Silver	NSL	Metals	02.01.79	All	New York Mercantile Exchange including COMEX (NYM and CMX)
Natural Gas	NNG	Energy	03.04.90	All	New York Mercantile Exchange including COMEX (NYM and CMX)
Crude Oil	NCL	Energy	30.03.83	All	New York Mercantile Exchange including COMEX (NYM and CMX)

Table 1: Data description
Source Datastream.

	Break	Lower	Upper	Pre-break	Post-break	R^2
BIOFUEL FEEDSTOCKS						
Corn	17-Feb-05	13-Jul-04	20-Apr-05	0.0191**	0.2817***	0,057
Soybean Meal	21-Feb-05	29-Mar-04	9-Aug-05	0,0104	0.2006***	0,029
Soybean Oil	25-Jan-05	28-Sep-04	28-Feb-05	0,0073	0.3394***	0,104
Soybeans	21-Jan-05	23-Aug-04	21-Mar-05	0,01	0.2792***	0,069
Sugar	30-Dec-03	21-Sep-00	27-Apr-04	0,0023	0.2671***	0,019
OTHER COMMODITIES						
Chicago Wheat	3-Dec-04	18-Feb-03	7-Nov-05	0,0166	0.1462***	0,047
	28-Feb-08	14-Jul-05	22-Jan-09		0.3145***	
Cocoa	7-Feb-07	17-Feb-06	13-Aug-07	0,0003	0.226***	0,021
Coffee	1-Dec-03	17-Mar-03	20-Apr-05	-0,0113	0.1866***	0,014
Copper	6-Feb-06	12-Aug-05	20-Mar-06	0,0186	0.4196***	0,108
Cotton	1-Jun-04	16-Apr-03	9-Dec-04	0,0151	0.2094***	0,029
Feeder Cattle	9-Apr-08	12-Jul-07	25-Mar-09	-0,0018	0.0728***	0,011
Gold	24-Sep-93	5-Dec-91	6-Feb-98	0.1027***	0.0405***	0,076
	16-Sep-05	6-Jul-04	4-Jan-06		0.1742***	
Kansas Wheat	25-Apr-06	12-Jul-05	12-Jul-06	0.0176*	0.2589***	0,044
Lean Hogs						
Live Cattle	9-Apr-08	18-Apr-07	15-Jan-09	0,0044	0.0955***	0,013
Lumber	27-Dec-07	6-May-05	13-Oct-09	-0,0031	0.1094***	0,004
Minnessota Wheat	6-Mar-08	31-May-07	6-May-08	0.0198**	0.2527***	0,034
Oats	6-Aug-07	20-Jun-06	9-Apr-08	0.0274**	0.2392***	0,021
Orange Juice	2-Jan-04	20-Apr-99	27-Feb-07	0,0056	0.0893***	0,005
Palladium	16-Sep-05	2-Feb-05	24-Jan-06	0,009	0.2979***	0,04
Platinum	30-Nov-05	20-Sep-04	20-Apr-06	0.0387***	0.2286***	0,052
Pork Bellies						
Rice	17-Oct-07	30-Nov-06	22-Jan-09	0,0032	0.1535***	0,021
Silver	6-Feb-06	17-Mar-05	11-Abr-06	0.0776***	0.3596***	0,082
Natural Gas	16-Jan-01	9-Jun-00	18-Jun-01	0.1897***	0.6107***	0,064
	19-Mar-08	17-Aug-07	30-Jan-09		0.2611***	

Table 2: Structural break regressions of non-energy commodities, and natural gas, on crude oil

We estimate Bai-Perron (1998) regressions with daily log-price changes in %, where the dependent variable is each non-energy commodity and natural gas. The method estimates the number of breaking points (at 5%), their location, as well as provides 95% confidence intervals. For each commodity, we also provide the slope pre- and post-break (* sig. .10; ** sig. .05; ***.01) and R^2. There is no evidence of breaks for lean hog and pork bellies, and there is evidence of two in the case of coffee, Kansas wheat, Minnesota wheat and natural gas. Data from January 1990 to July 2011 with the exception of rice data starting on 2000.

	Break	Lower 95% C.I.	Upper 95% C.I.	Pre-break slope	Post-break slope	R^2
BIOFUEL FEEDSTOCKS						
Corn	17-Feb-05	21-Jun-04	1-Aug-05	0,0187	0.3281***	0,032
Soybean Meal	14-Apr-05	5-Apr-04	14-Mar-06	0,0056	0.2394***	0,017
Soybean Oil	12-Jan-05	22-Sep-04	11-Mar-05	-0,0029	0.4877***	0,073
Soybeans	21-Jan-05	20-Jul-04	17-May-05	0,0057	0.3693***	0,041
Sugar	30-Dec-03	29-Nov-02	16-Dec-04	0,0129	0.2136***	0,018
OTHER COMMODITIES						
Chicago Wheat	11-Dec-07	15-Nov-06	28-May-08	0.0354**	0.3359***	0,021
Cocoa	30-Jul-07	22-Jan-07	5-Mar-08	0,0042	0.2944***	0,016
Coffee	11-Sep-03	21-Dec-01	10-Oct-05	-0.0383**	0.1227***	0,024
	3-Jan-08	27-Mar-07	21-Jan-09		0.3362***	
Copper	6-Feb-06	8-Sep-05	15-May-06	0.0447***	0.4722***	0,059
Cotton	30-Nov-04	7-Jan-04	22-Sep-05	0,0239	0.2569***	0,02
Feeder Cattle	9-Apr-08	2-Feb-07	2-Jun-09	-0,0028	0.1889***	0,006
Gold	16-Sep-05	16-Mar-05	27-Oct-06	0.1329***	0.4143***	0,058
Kansas Wheat	29-Nov-04	14-Aug-02	3-Oct-06	0,0091	0.1443***	0,024
	28-Feb-08	29-Aug-06	17-Feb-09		0.3473***	
Lean Hogs						
Live Cattle	9-Apr-08	3-May-07	29-Jan-09	0,0142	0.2421***	0,01
Lumber	27-Dec-07	3-May-06	15-Oct-09	-0,0042	0.1561***	0,004
Minnessota Wheat	3-Dec-04	30-Apr-03	9-Mar-06	0,0014	0.1537***	0,023
	25-Feb-08	18-Dec-06	13-Mar-09		0.3218***	
Oats	6-Aug-07	1-Sep-06	26-Feb-08	0.0264*	0.3149***	0,019
Orange Juice	2-Jan-04	11-Aug-99	4-Sep-08	0,0114	0.1014***	0,004
Palladium	16-Sep-05	22-Dec-04	29-Dec-05	0.0270*	0.3830***	0,04
Platinum	30-Nov-05	22-Mar-05	22-Jun-06	0.0759***	0.3843***	0,042
Pork Bellies						
Rice	17-Oct-07	5-Dec-06	11-Jun-08	0,0149	0.2632***	0,022
Silver	6-Feb-06	19-Sep-05	14-Jul-06	0.1046***	0.4514***	0,06
Natural Gas	16-Jan-01	26-Jul-00	29-Aug-01	0.1475***	0.4215***	0,072
	31-Jul-06	12-May-04	2-Apr-08		0.2721***	

Table 3: Structural break regressions of non-energy commodities, and natural gas, on crude oil after controlling for GARCH effects

We estimate Bai-Perron (1998) regressions with daily log-price changes in % after standardizing them by their GARCH(1,1) volatility, where the dependent variable is each non-energy commodity and natural gas. The method estimates the number of breaking points (at 5%), their location, as well as provides 95% confidence intervals. For each commodity, we also provide the slope pre- and post-break (* sig. .10; ** sig. .05; ***.01) and R^2. There is no evidence of breaks for lean hog and pork bellies, and there is evidence of two in the case of coffee, Kansas wheat, Minnesota wheat and natural gas. Data from January 1990 to July 2011 with the exception of rice data starting on 2000.

	Break	Lower 95% C.I.	Upper 95% C.I.	Pre-break slope	Post-break slope	R2
BIOFUEL FEEDSTOCKS						
Corn	8-Feb-05	4-Nov-04	9-Aug-05	0.0195***	0.205***	0,078
Soybean Meal	7-Feb-05	10-Sep-03	16-Aug-05	0,0099	0.1483***	0,042
Soybean Oil	26-Jan-05	2-Dec-04	28-Mar-05	0,0075	0.2565***	0,131
Soybeans	21-Jan-05	26-Jul-04	4-Apr-05	0,0097	0.2118***	0,091
Sugar	2-Jan-04	15-Aug-03	12-Jul-04	-0,0007	0.2245***	0,027
	4-Oct-07	12-Jun-07	31-Dec-08		0.210***	
OTHER COMMODITIES						
Chicago Wheat	22-Nov-04	10-Apr-03	11-Oct-05	0.0191*	0.1303***	0,072
	12-Feb-08	12-Sep-07	8-Apr-09		0.1909***	
Cocoa	14-Jul-06	3-Oct-05	12-Sep-07	-0,0044	0.1078***	0,053
Coffee	14-Apr-03	22-Nov-02	16-Sep-04	-0,0161	***	0,027
Copper	2-Jan-04	30-May-03	24-Feb-04	0,0122	0.148***	0,192
	27-Dec-07	16-Jan-97	18-Jan-08		0.2584***	
Cotton	14-Feb-01	5-Jul-99	13-May-02	0,0062	0.1075***	0,045
Feeder Cattle	2-Apr-08	23-May-07	8-Dec-09	-0,0017	0.0291***	0,023
Gold	27-Jan-94	22-Feb-93	8-Feb-95	0.0842***	0.0279**	0,231
	14-02-00	20-Dec-99	7-Oct-05		0.0376***	
	2-Jan-04	18-Apr-03	23-Mar-04		0.0995***	
	19-11-07	4-Jul-07	14-May-08		0.1358***	
Kansas Wheat	27-Apr-06	23-Nov-05	19-Jul-06	0.0173**	0.1709***	0,067
Lean Hogs						
Live Cattle	14-Mar-08	17-May-07	24-Dec-09	0,0037	0.0515***	0,024
Lumber	11-Feb-00	Out	4-Dec-01	-0,0022	0,0074	0,018
Minnessota Wheat	3-Dec-04	Out	5-May-05	0,0063	0.103***	0,057
	6-Mar-08	18-Sep-07	Out		0,1583	
Oats	15-Nov-06	10-Nov-98	20-Dec-06	0.0247*	0.1343***	0,037
Orange Juice	2-Jan-04	13-Jul-98	2-Nov-07	0,0062	0.0534***	0,009
Palladium	25-Oct-95	Out	18-Feb-98	0.0321***	.-0.036***	0,109
	16-Apr-03	28-Mar-01	2-Jul-03		0.1088***	
Platinum	29-Oct-03	11-Aug-00	15-Apr-04	0.0331***	0.0951***	0,13
Pork Bellies						
Rice	30-Aug-07	23-Jul-07	28-Oct-10	-0,0007	0.0846**	0,039
Silver	14-Feb-96	25-Jul-95	5-Apr-04	0.098***	0.0373***	0,204
	2-Oct-03	23-May-02	8-Jan-04		0.1619***	
	13-Feb-04	25-Apr-06	10-Jun-09		0.2174***	
Natural Gas	16-Jan-01	12-Apr-00	1-Jun-01	0.1908***	0.6138***	0,066
	19-Mar-08	4-Sep-07	21-Nov-08		0.2097***	

Table 4: Structural break regressions of non-energy commodities, and natural gas, on crude oil and controls

We estimate Bai-Perron (1998) regressions with daily log-price changes in %, where the dependent variable is each non-energy commodity and natural gas. We use the following controls: an emerging markets equity index, the JP Morgan bonds index, S&P500 and the exchange rate between the US dollar and a currency basket. The method estimates the number of breaking points (at 5%), their location, as well as provides 95% confidence intervals. "Out" represents a confidence bound that lays outside of the sample period. For each commodity, we also provide the slope pre- and post-break (* sig. .10; ** sig. .05; ***.01) and R^2. There is no evidence of breaks for lean hog and pork bellies, and there is evidence of several breaks in the case of sugar, Chicago wheat, copper, gold, Minnesota wheat, palladium, silver and natural gas. Data from January 1990 to July 2011 with the exception of rice data starting on 2000.

	Total correlation			Residual correlation		
	Pre-2005	**2005-2009**	**Post-2009**	**Pre-2005**	**2005-2009**	**Post-2009**
BIOFUEL FEEDSTOCKS						
Corn	0.0324*	0.3275***	0.3381***	0.0330**	0.2450***	0.1989***
Soybean Meal	0,0189	0.2596***	0.2416***	0,0178	0.1848***	0.1426***
Soybean Oil	0,0124	0.5075***	0.5023***	0,0123	0.4100***	0.3183***
Soybeans	0,0188	0.4089***	0.3782***	0,0181	0.3144***	0.2285***
Sugar	0,0245	0.2573***	0.2421***	0,0236	0.1811***	0.1703***
OTHER COMMODITIES						
Chicago Wheat	0.0280*	0.2684***	0.3279***	0.0302*	0.1855***	0.1764***
Cocoa	-0,0049	0.2165***	0.3042***	-0,0073	0.0986***	0.1317***
Coffee	0,001	0.2099***	0.3098***	-0,0003	0.1223***	0.1623***
Copper	0,032	0.4001***	0.5009***	0.0390**	0.2754***	0.2397***
Cotton	0.0321*	0.3045***	0.2123***	0.0329*	0.2291***	0,0571
Feeder Cattle	-0,0018	0,0778	0.2391***	-0,0008	0,0199	0.1270***
Gold	0.1765***	0.3633***	0.2643***	0.1743***	0.2704***	0.2142***
Kansas Wheat	0,0261	0.2516***	0.3445***	0,0262	0.1696***	0.1961***
Lean Hogs	0,0195	0,0222	0.1143***	0,0191	0,0204	0,0485
Live Cattle	0,0111	0.1126**	0.2713***	0,0115	0,0538	0.1299***
Lumber	0,0014	0.0630*	0.1039**	0,0061	0,0071	-0,003
Minnessota Wheat	0,015	0.1985***	0.3307***	0,0138	0.1338***	0.1788***
Oats	0,0276	0.2002***	0.2841***	0.0286*	0.1299***	0.1168***
Orange Juice	0,0112	0.0961**	0.1306***	0,0132	0.0615*	0,0493
Palladium	0,0092	0.3114***	0.3449***	0,0069	0.1711***	0,0948
Platinum	0.0718***	0.3639***	0.3112***	0.0672***	0.2256***	0,0769
Pork Bellies	-0,0045	0,0448	0,046	-0,0064	0,0362	-0,0232
Silver	0.1271***	0.3713***	0.3560***	0.1254***	0.2376***	0.2114***
AVERAGES						
All biofuels	0.0214*	0.3521***	0.3404***	0.0209*	0.267***	0.2117***
Corn, Soya, Soyoil, Sugar	0.022*	0.3753***	0.3651***	0.0218*	0.2876***	0.229***
Corn, Soya, Sugar	0.0252**	0.3312***	0.3194***	0.0249**	0.2468***	0.1992***
Non-biofuels	0.0321***	0.2153***	0.2664***	0.0322***	0.136***	0.1214***
Indexed	0.0406***	0.2362***	0.295***	0.0409***	0.153***	0.154***
Off-index	0.0188**	0.1825***	0.2216***	0.0185**	0.1093***	0.0701**
Agricultural	0.0153*	0.201***	0.2609***	0.0159**	0.1264***	0.1184***
Indexed agricultural	0,0164	0.2502***	0.2997***	0.0163*	0.161***	0.1447***
Off-index agricultural	0,0138	0.1394***	0.2123***	0.0154*	0.0831***	0.0855***
Natural gas	0.1968***	0.3448***	0.1781***	0.1973***	0.3334***	0.0981***

Table 5: Oil correlations for non-energy commodities and natural gas
Correlations between daily log-price changes (* sig. .10; ** sig. .05; ***.01). We consider three separate periods: pre-2005, post-2009 and between 2005 and 2009. Residual correlations are calculated after extracting the effect of controls: an emerging markets equity index, the JP Morgan bonds index, S&P500 and the exchange rate between the US dollar and a currency basket. Data from January 1990 to July 2011.

	Total correlation		Residual correlation	
All biofuels				
	DiD 2005	**DiD 2009**	**DiD 2005**	**DiD 2009**
Non-biofuels	0.1476***	-0.0629**	0.1423***	-0,0407
Indexed	0.1352***	-0.0705***	0.1341***	-0.0564*
Agricultural	0.1451***	-0.0717***	0.1356***	-0,0473
Indexed agricultural	0.0970***	-0.0613**	0.1014***	-0,039
Off-index agricultural	0.2052***	-0.0847**	0.1784***	-0.0577*
Biofuels excluding soybean meal				
	DiD 2005	**DiD 2009**	**DiD 2005**	**DiD 2009**
Non-biofuels	0.1700***	-0.0612**	0.1620***	-0.0440*
Indexed	0.1576***	-0.0689***	0.1538***	-0.0596**
Agricultural	0.1676***	-0.0700***	0.1553***	-0.0506*
Indexed agricultural	0.1195***	-0.0597**	0.1212***	-0,0423
Off-index agricultural	0.2277***	-0.0831**	0.1982***	-0.0610*
Biofuels excluding soybean meal and soybean oil				
	DiD 2005	**DiD 2009**	**DiD 2005**	**DiD 2009**
Non-biofuels	0.1227***	-0.0629**	0.1181***	-0,0329
Indexed	0.1103***	-0.07055***	0.1098***	-0.0486*
Agricultural	0.1203***	-0.0717***	0.1114***	-0,0395
Indexed agricultural	0.0722***	-0.0613**	0.0772***	-0,0313
Off-index agricultural	0.1804***	-0.0847**	0.1543***	-0.0500

Table 6: Difference-in-differences analysis of daily oil correlations

DiD applied to correlations between daily log-price changes (* sig. .10; ** sig. .05; ***.01). We consider three separate periods: pre-2005, post-2009 and between 2005 and 2009. Residual correlations are calculated after extracting the effect of controls: an emerging markets equity index, the JP Morgan bonds index, S&P500 and the exchange rate between the US dollar and a currency basket. Data from January 1990 to July 2011.

	Goldman Sachs Commodity Index				Non-energy Goldman Sachs Commodity Index			
	Total correlation		Residual correlation		Total correlation		Residual correlation	
All biofuels								
	DiD 2005	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**
Non-biofuels	0.1329***	-0.0543*	0.1317***	-0,014	0,0279	-0,0056	0,0291	0,0471
Indexed	0.1206***	-0.0548*	0.1226***	-0,0221	0,0139	0,0094	0,0141	0,0599
Agricultural	0.1382***	-0.0588**	0.1315***	-0,0148	0.0564**	-0,0339	0.0486**	0,0159
Indexed agricultural	0.0875***	-0,0423	0.0941***	0,0022	0,0005	0,0033	-0,0005	0,0539
Off-index agricultural	0.2017***	-0.0795**	0.1783***	-0,0361	0.1264***	-0.0803**	0.1100***	-0,0316
Corn, Soya, Soyoil, Sugar								
	DiD 2005	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**
Non-biofuels	0.1568***	-0.0468*	0.1518***	-0.0088	0.0457*	0.0174	0.0405	0.0737**
Indexed	0.1444***	-0.0473*	0.1428***	-0.0169	0,0317	0.0325	0.0255	0.0865**
Agricultural	0.1621***	-0.0514*	0.1517***	-0.0096	0.0743***	-0.0108	0.0601**	0.0425
Indexed agricultural	0.1113***	-0,0348	0.1142***	0,0074	0,0183	0,0264	0,0109	0.0805**
Off-index agricultural	0.2255***	-0.0721**	0.1984***	-0,0309	0.1442***	-0.0573*	0.1215***	-0,005
Corn, Soya, Sugar								
	DiD 2005	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**
Non-biofuels	0.1105***	-0.0596**	0.1104***	-0.0140	0,0308	0.0115	0,0379	0.0737**
Indexed	0.0981***	-0.0601**	0.1014***	-0.0220	0,0168	0.0265	0,0229	0.0865**
Agricultural	0.1158***	-0.0642**	0.1103***	-0.0148	0.0593***	-0.0168	0.0574**	0.0425
Indexed agricultural	0.0651***	-0.0476*	0.0729***	0,0022	0,0034	0,0204	0,0083	0.0804**
Off-index agricultural	0.1792***	-0.0849**	0.1571***	-0,036	0.1293***	-0.0632*	0.1188***	-0,005

Table 7: Difference-in-differences analysis of daily correlations with two Goldman Sachs Commodity Indexes

DiD applied to correlations between daily log-price changes (* sig. .10; ** sig. .05; ***.01). We consider three separate periods: pre-2005, post-2009 and between 2005 and 2009. Residual correlations are calculated after extracting the effect of controls: an emerging markets equity index, the JP Morgan bonds index, S&P500 and the exchange rate between the US dollar and a currency basket. Data from January 1990 to July 2011.

	Weekly				Monthly					
	Total correlation		Residual correlation		Total correlation		Residual correlation		Additional controls	
All biofuels										
	DiD 2005	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**
Non-biofuels	0.1569***	-0,0086	0.1521**	0,0277	0,1301	-0,0181	0,1226	-0,0409	0,0544	0,0547
Indexed	0.1261**	0,0056	0.1289 *	0,0241	0,1475	0,0009	0,1534	-0,0539	0,0946	0,0204
Agricultural	0.1731***	-0,0339	0.1592***	0,0282	0,0858	-0,0188	0,0869	0,0913	0,0612	0,1561
Indexed agricultural	0.0908*	0,0132	0,0924	0,0641	0,1226	-0,0145	0,1484	0,087	0,1262	0,1406
Off-index agricultural	0.2760***	-0,0928	0.2427***	-0,0167	0,0399	-0,0242	0,0101	0,0966	-0,02	0,1755
Corn, Soya, Soyoil, Sugar										
	DiD 2005	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**
Non-biofuels	0.1812***	-0,0166	0.1728***	0,0157	0.1777***	-0,059	0.1572*	-0,1055	0,0918	-0,0222
Indexed	0.1501***	-0,0024	0.1496***	0,0122	0.1950**	-0,04	0.1880*	-0,1185	0,132	-0,0565
Agricultural	0.1974***	-0,0419	0.1799***	0,0163	0.1334*	-0,0598	0,1216	0,0266	0,0986	0,0792
Indexed agricultural	0.1151**	0,0052	0.1131**	0,0522	0.1701*	-0,0554	0.1830*	0,0223	0.1636*	0,0636
Off-index agricultural	0.3003***	-0,1007	0.2634***	-0,0286	0,0874	-0,0652	0,0447	0,032	0,0174	0,0986
Corn, Soya, Sugar										
	DiD 2005	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**
Non-biofuels	0.1260***	-0,0003	0.1268**	0,041	0,0985	-0,0529	0,1205	-0,1169	0,0703	-0,0558
Indexed	0.0952*	0,0014	0.1036*	0,0374	0,1159	-0,0339	0,1512	-0,1299	0,1105	-0,0901
Agricultural	0.1422***	-0,0256	0.1339***	0,0415	0,0542	-0,0537	0,0848	0,0152	0,0771	0,0456
Indexed agricultural	0,0599	0,0215	0,0671	0,0774	0,091	-0,0493	0,1463	0,0109	0,1421	0,03
Off-index agricultural	0.2451***	-0,0844	0.2174***	-0,0034	0,0082	-0,0591	0,008	0,0206	-0,0041	0,065

Table 8: Difference-in-differences analysis of weekly and monthly oil correlations

DiD applied to correlations between weekly and monthly log-price changes (* sig. .10; ** sig. .05; ***.01). We consider three separate periods: pre-2005, post-2009 and between 2005 and 2009. Residual correlations are calculated after extracting the effect of controls: an emerging markets equity index, the JP Morgan bonds index, S&P500 and the exchange rate between the US dollar and a currency basket. The last columns include additional monthly controls: Kilian's index of global real economic activity in industrial commodity markets, US core inflation from Federal Reserve price indexes, and EIA US oil reserves (excluding strategic reserves) .Data from January 1990 to July 2011.

	Total correlation		Residual correlation	
Corn, Soya, Soyoil, Sugar				
	DiD 2005	**DiD 2009**	**DiD 2005**	**DiD 2009**
Non-biofuels	0.1407***	-0.0518**	0.1331***	-0,0393
Indexed	0.1289***	-0.0612**	0.1240***	-0.0554*
Agricultural	0.1482***	-0.066**	0.1375***	-0,0453
Indexed agricultural	0.1105***	-0.0629**	0.1125***	-0,0424
Off-index agricultural	0.1952***	-0.0698**	0.1689***	-0.0488
Corn, Soya, Soyoil, Sugar				
	DiD 2005	**DiD 2009**	**DiD 2005**	**DiD 2009**
Non-biofuels	0.1687***	-0.0537**	0.1587***	-0,0412
Indexed	0.1569***	-0.0631**	0.1495***	-0.0574**
Agricultural	0.1762***	-0.0679***	0.1631***	-0.0472*
Indexed agricultural	0.1385***	-0.0648**	0.1380***	-0,0443
Off-index agricultural	0.2232***	-0.0718**	0.1944***	-0.0508
Corn, Soya, Sugar				
	DiD 2005	**DiD 2009**	**DiD 2005**	**DiD 2009**
Non-biofuels	0.1146***	-0.0558**	0.1075***	-0,0314
Indexed	0.1028***	-0.0652**	0.0983***	-0.0476*
Agricultural	0.1221***	-0.067***	0.1119***	-0,0374
Indexed agricultural	0.0844***	-0.0669**	0.0868***	-0,0346
Off-index agricultural	0.1691***	-0.0738**	0.1433***	-0.0410

Table 9: Difference-in-differences analysis of daily oil correlations, using Datastream Type 4 futures series

DiD applied to correlations between daily log-price changes (* sig. .10; ** sig. .05; ***.01). We consider three separate periods: pre-2005, post-2009 and between 2005 and 2009. Residual correlations are calculated after extracting the effect of controls: an emerging markets equity index, the JP Morgan bonds index, S&P500 and the exchange rate between the US dollar and a currency basket. Data from January 1995 to July 2011.

	Total correlation		Residual correlation		Additional controls	
Corn, Soya, Soyoil, Sugar						
	DiD 2005	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**
Non-biofuels	0.3537**	0,022	0.3306*	-0,0864	0.3417*	-0,0525
Indexed	0.3314**	0,0746	0,3202	-0,0534	0.3425*	-0,0362
Agricultural	0.2668**	0,002	0,2356	-0,0064	0.2906**	-0,0015
Indexed agricultural	0.2762**	0,0123	0.2544*	0,0186	0.3169 **	0,0237
Off-index agricultural	0.2551*	-0,011	0,2121	-0,0376	0.2577*	-0,0331
Corn, Soya, Soyoil, Sugar						
	DiD 2005	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**
Non-biofuels	0.379***	-0,0674	0.3465**	-0,1708	0.3568**	-0,1487
Indexed	0.3567***	-0,0148	0.336**	-0,1378	0.3576**	-0,1324
Agricultural	0.2921***	-0,0875	0.2514*	-0,0908	0.3057**	-0,0977
Indexed agricultural	0.3015**	-0,0771	0.2702*	-0,0659	0.3320**	-0,0725
Off-index agricultural	0.2804**	-0,1004	0,2279	-0,122	0.2728*	-0,1293
Corn, Soya, Sugar						
	DiD 2005	**DiD 2009**	**DiD 2005**	**DiD 2009**	**DiD 2005**	**DiD 2009**
Non-biofuels	0.2909***	-0,045	0.2775**	-0,1484	0.3014**	-0,1409
Indexed	0.2686**	0,0076	0.267*	-0,1155	0.3022*	-0,1246
Agricultural	0.204***	-0,065	0.1824*	-0,0685	0.2503*	-0,0899
Indexed agricultural	0.2134**	-0,0547	0.2012*	-0,0435	0.2766*	-0,0647
Off-index agricultural	0,1923	-0,078	0,1589	-0,0997	0,2174	-0,1214

Table 10: Difference-in-differences analysis of monthly oil correlations, using Datastream Type 5 futures series

DiD applied to correlations between monthly log-price changes (* sig. .10; ** sig. .05; ***.01). We consider three separate periods: pre-2005, post-2009 and between 2005 and 2009. Residual correlations are calculated after extracting the effect of controls: an emerging markets equity index, the JP Morgan bonds index, S&P500 and the exchange rate between the US dollar and a currency basket. The last columns include additional monthly controls: Kilian's index of global real economic activity in industrial commodity markets, US core inflation from Federal Reserve price indexes, and EIA US oil reserves (excluding strategic reserves). Data from January 2002 to July 2011.

	Total correlation			Residual correlation		
	Pre-2005	**2005-2009**	**Post-2009**	**Pre-2005**	**2005-2009**	**Post-2009**
-WITH OIL-						
ADM	-0.0714**	0.1797***	0.3299***	-0.0603**	0,0396	0,0355
Post-pre diff.		0.2511***	0.1502**		0.0999**	-0,0041
E&P	0.3576***	0.5066***	0.6379***	0.3993***	0.5090***	0.4450***
Post-pre diff.		0.1489*	0.1314		0,1097	-0,0641
-WITH CORN-						
ADM	0,0366	0.1458***	0.2115***	0.0271	0.0547*	0.0479
Post-pre diff.		0.1092**	0,0658		0.0276	-0.0068
E&P	0,035	0.2692***	0.3064***	0.0179	0.2087***	0.1129***
Post-pre diff.		0.2342***	0.0372		0.1908***	-0.0958*

Table 11: Stock market correlations with oil and corn

Correlations between daily log-price changes (* sig. .10; ** sig. .05; ***.01). ADM is Archer Daniels Midlands' stock and E&P is an S&P index of companies engaged in oil and natural gas exploration and production. We consider three separate periods: pre-2005, post-2009 and between 2005 and 2009. Residual correlations are calculated after extracting the effect of controls: an emerging markets equity index, the JP Morgan bonds index, S&P500 and the exchange rate between the US dollar and a currency basket. Data from January 2000 to July 2011.

	Regression on oil				Regression on oil and controls			
	Threshold	95%	Below	Above	Threshold	95%	Below	Above
BIOFUEL FEEDSTOCKS	estimate	conf. interval	slope	slope	estimate	conf. interval	slope	slope
Corn	39,08	[38.69, 40.78]	0.0195*	0.2866***	38,98	[37.83, 40.78]	0,017867	0.2152***
Soybean Meal	40,08	[37.21, 44.61]	0,0109	0.2099***	40,08	[37.28, 86.49]	0,009035	0.1628***
Soybean Oil	39,51	[38.95, 45.71]	0,0093	0.3458***	38,98	[38.89, 40.17]	0,007707	0.2647***
Soybeans	39,28	[38.95, 40.78]	0,0097	0.287***	38,98	[37.32, 40.78]	0,008023	0.2234***
Sugar	32,49	[32.00, 60.73]	0,0074	0.2224***	32,49	[20.92, 63.90]	0,004574	0.1695***
OTHER COMMODITIES								
Chicago Wheat	39,37	[37.09, 40.81]	0,018	0.2788***	40,15	[36.80, 40.81]	0.0209*	0.1984***
Cocoa	62,63	[34.93, 67.77]	0,022	0.2528***	38,67	[30.03, 62.63]	-0,0022	0.0871***
Coffee	35,88	[34.07, 41.77]	-0,0077	0.1870***	35,92	[22.30, 41.77]	-0,0097	0.1192***
Copper	38,98	[37.20, 39.50]	0,0179	0.3867***	37,31	[36.28, 38.98]	0,0162	0.2239***
Cotton	40,58	[37.20, 43.64]	0,0166	0.2369***	40,58	[36.60, 41.82]	0,0162	0.1726***
Feeder Cattle	45,46	[35.53, 48.54]	0,0003	0.0579***	17,81	[13.77, 48.54]	0.0329**	0,006
Gold	59,14	[53.62, 68.35]	0.0604***	0.2505***	26,44	[25.60, 26.98]	0.0315***	0.1055***
Kansas Wheat	39,28	[36.72, 40.81]	0,0157	0.2422***	40,15	[33.98, 40.81]	0,0167	0.1750***
Lean Hogs								
Live Cattle	44,61	[36.51, 48.54]	0,0049	0.0818***				
Lumber	70,82	[44.76, 77.03]	0,0054	0.1596***	23,27	[18.62, 97.70]	-0,0046	0,01
Minnessota Wheat	39,28	[37.20, 40.81]	0,01	0.2176***	100,88	100.59 , 101.58	0.0456***	0.1130***
Oats	39,37	[37.28, 58.75]	0,0176	0.2200***	56,31	[33.98, 69.29]	0.0308*	0.1688***
Orange Juice	68,81	[11.84, 83.45]	0,0168	0.1650***				
Palladium	52,64	[46.34, 62.55]	0,0202	0.3786***	49,9	[37.51, 53.57]	0,0098	0.1682***
Platinum	59,35	[49.64, 65.20]	0.0459***	0.3158***	47,37	[37.51, 65.20]	0.0332***	0.1305***
Pork Bellies								
Rice	78,23	.12, 95.67]	0.0365*	0.2443***	83,08	.88, 95.97]	0,0164	0.1625***
Silver	59,02	[58.24, 62.66]	0.0818***	0.5084***	47,37	[36.28, 49.92]	0.0688***	0.2503***

Table A1: Threshold regressions of non-energy commodities on crude oil and controls
We estimate Hansen (2000) regressions with daily log-price changes in %, where the dependent variable is each non-energy commodity, and the threshold variable is the oil price. We use the following controls: an emerging markets equity index, the JP Morgan bonds index, S&P500 and the exchange rate between the US dollar and a currency basket. The method estimates the threshold, as well as provides 95% confidence intervals. For each commodity, we also provide the slope below- and above-threshold (* sig. .10; ** sig. .05; ***.01) and R^2. There is no evidence of threshold effects for lean hogs and pork bellies, neither live cattle with controls. Data from January 1990 to July 2011 with the exception of rice data starting on 2000.

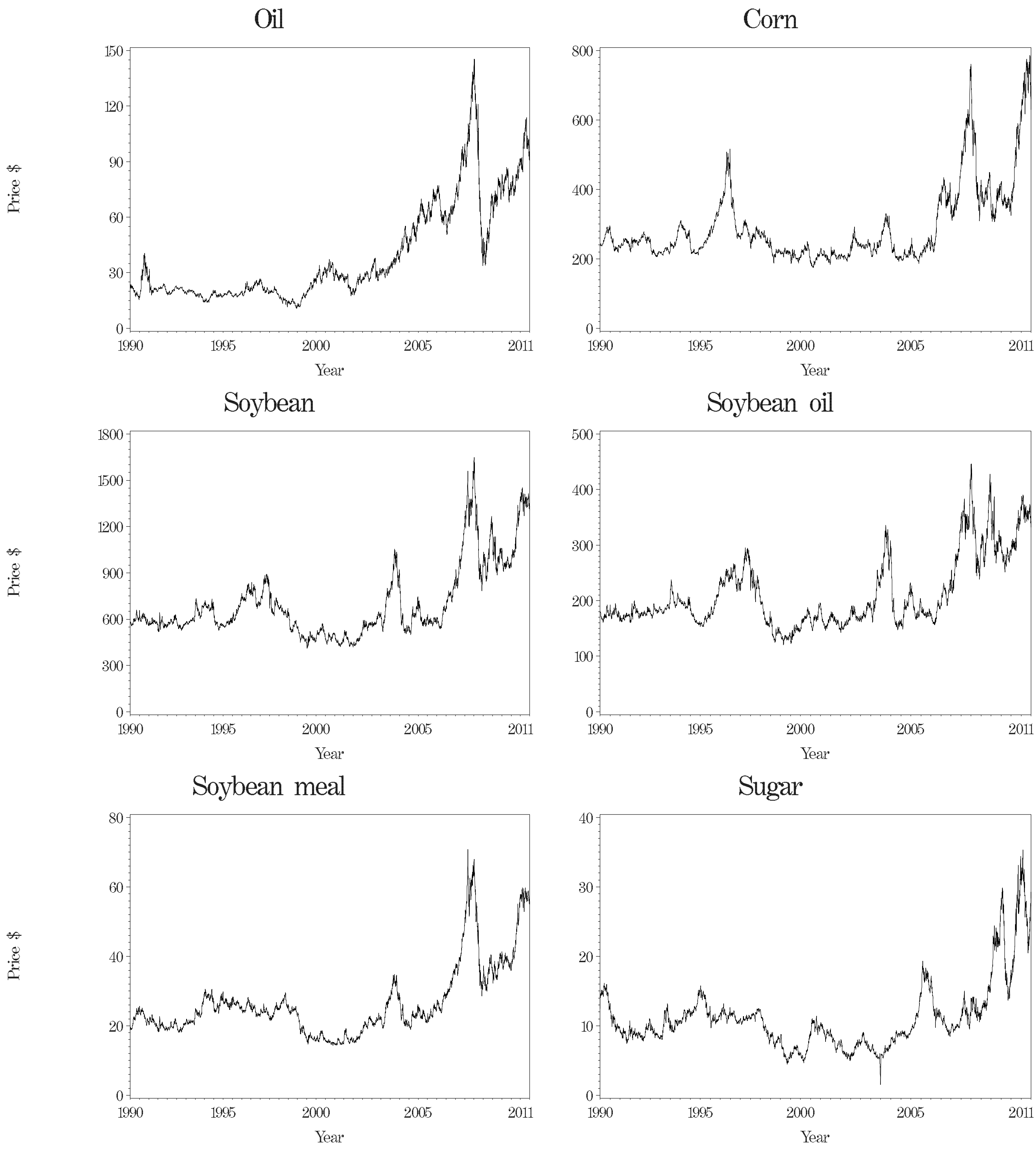

Figure 1: Daily prices for oil and biofuel feedstocks.

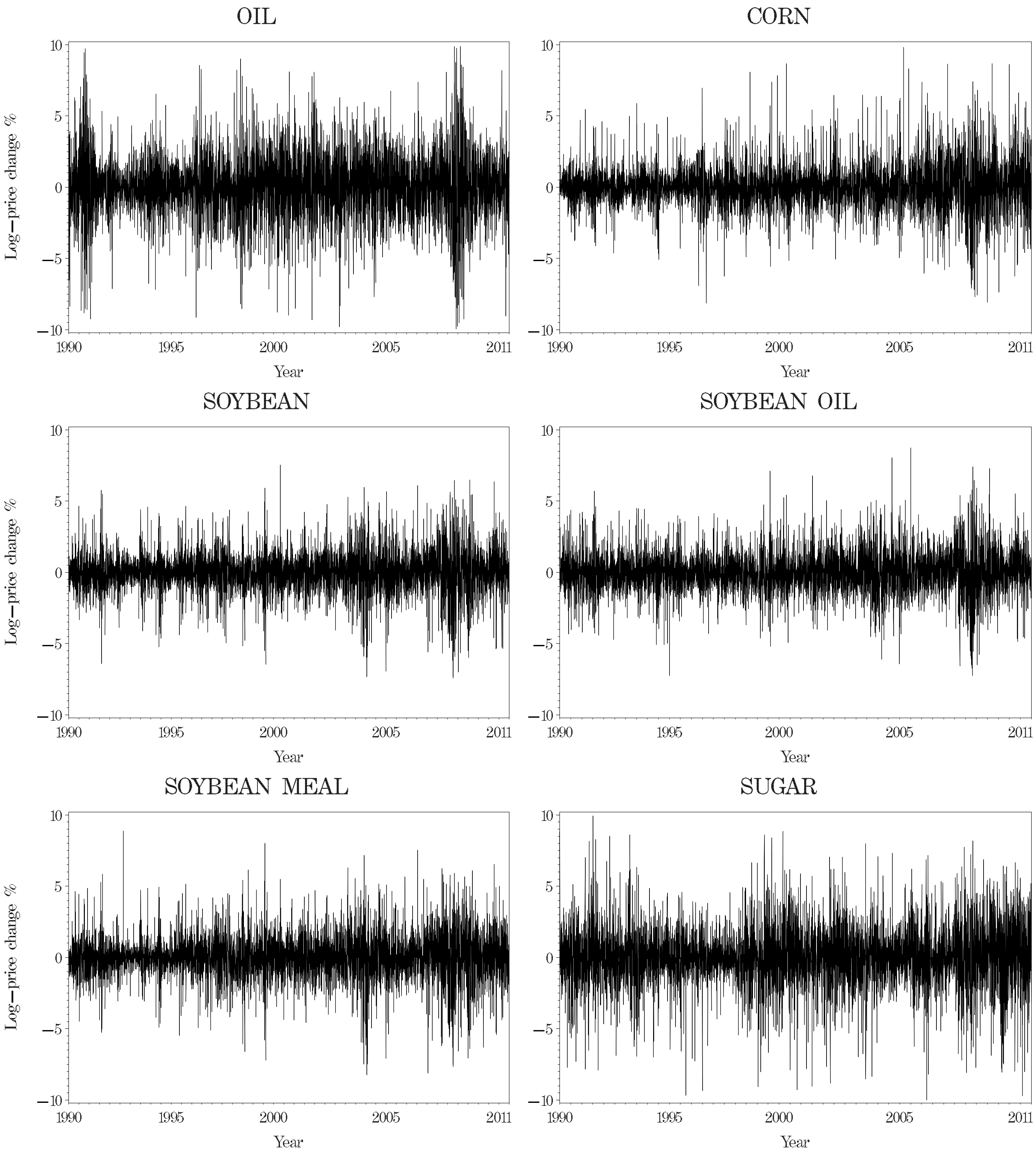

Figure 2: Daily log-price changes for oil and biofuel feedstocks.

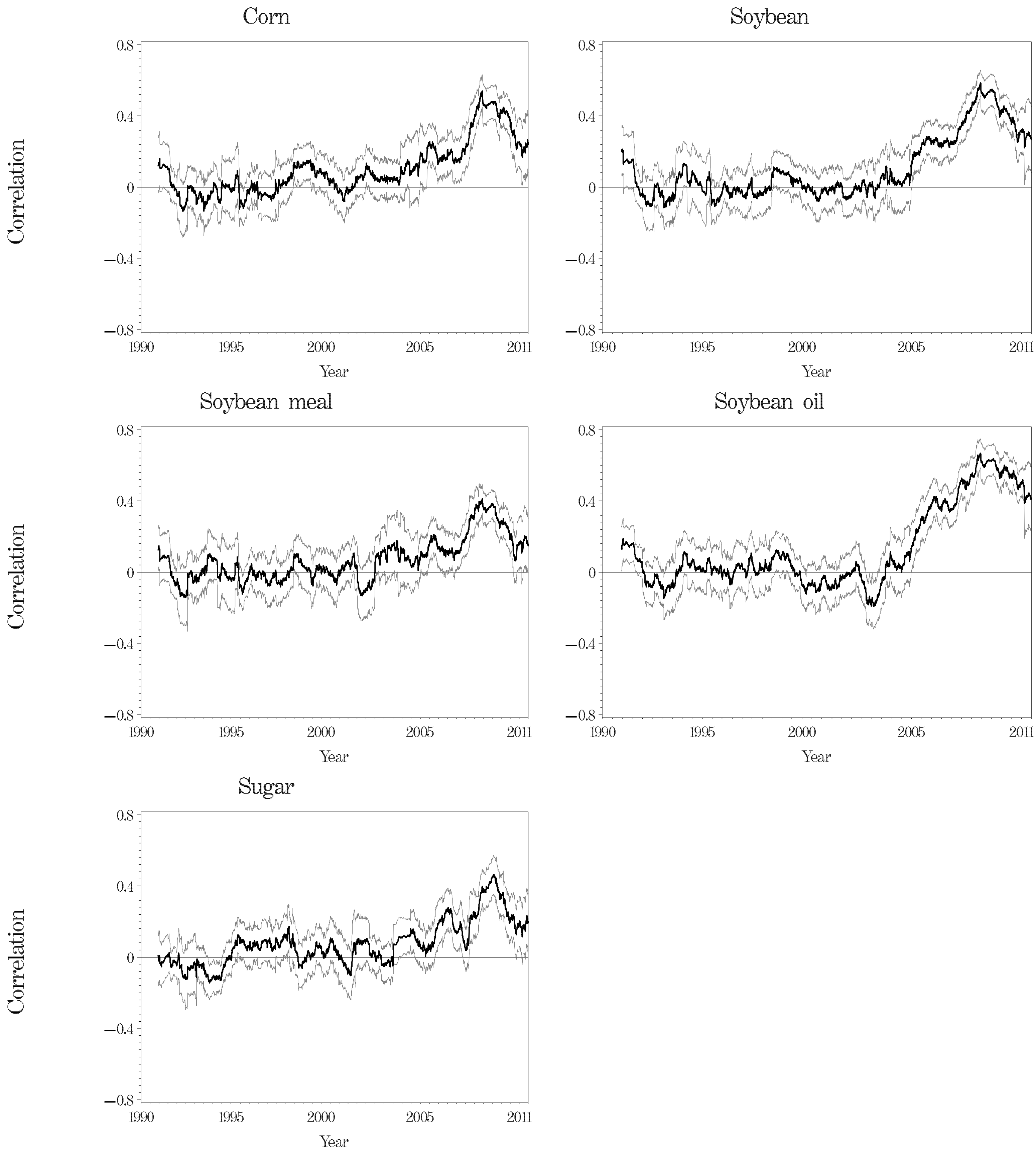

Figure 3: One-year rolling window correlations between log-price changes of oil and biofuel feedstocks (estimate and 95% CI).

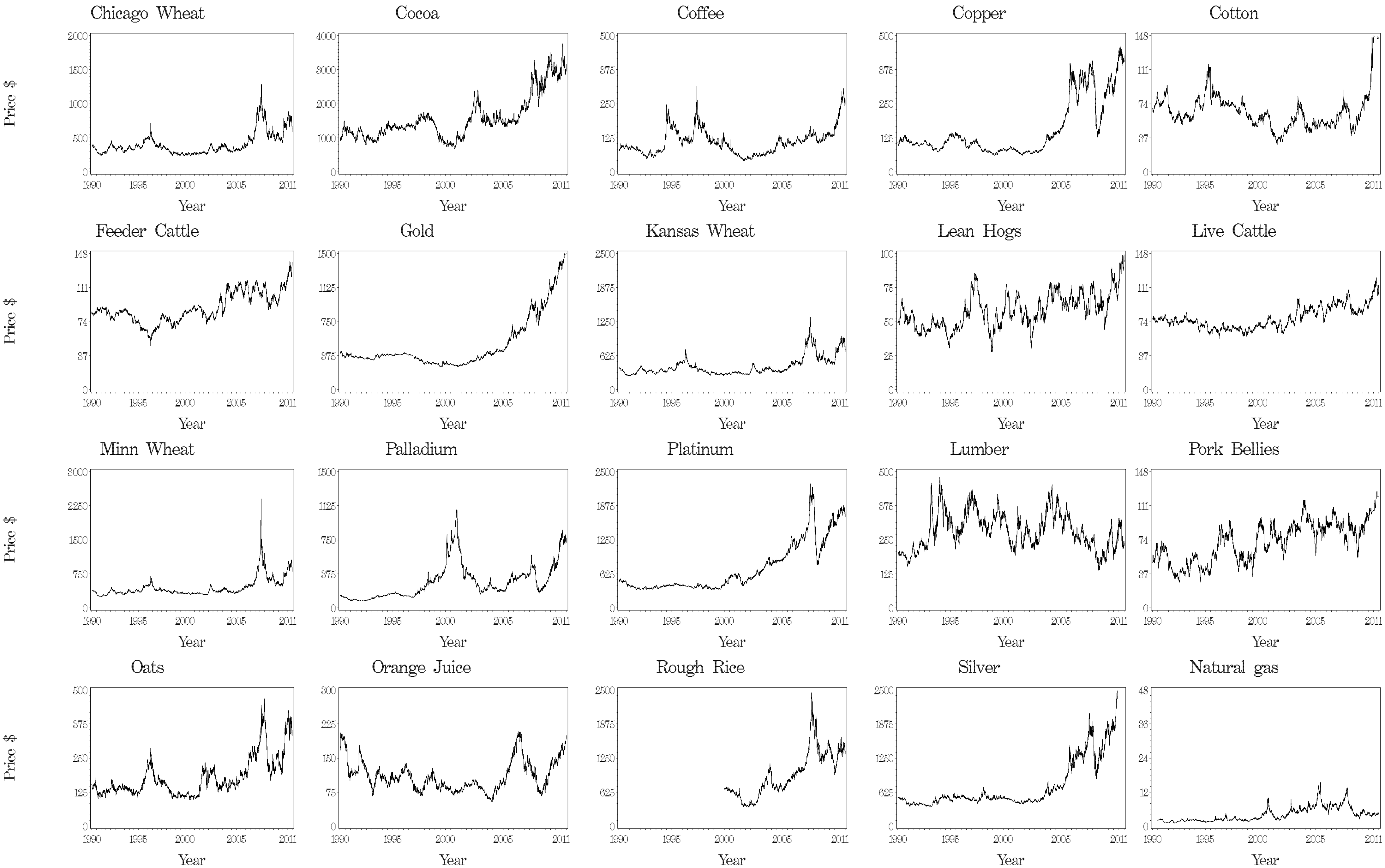

Figure 4: Non-biofuel daily prices.

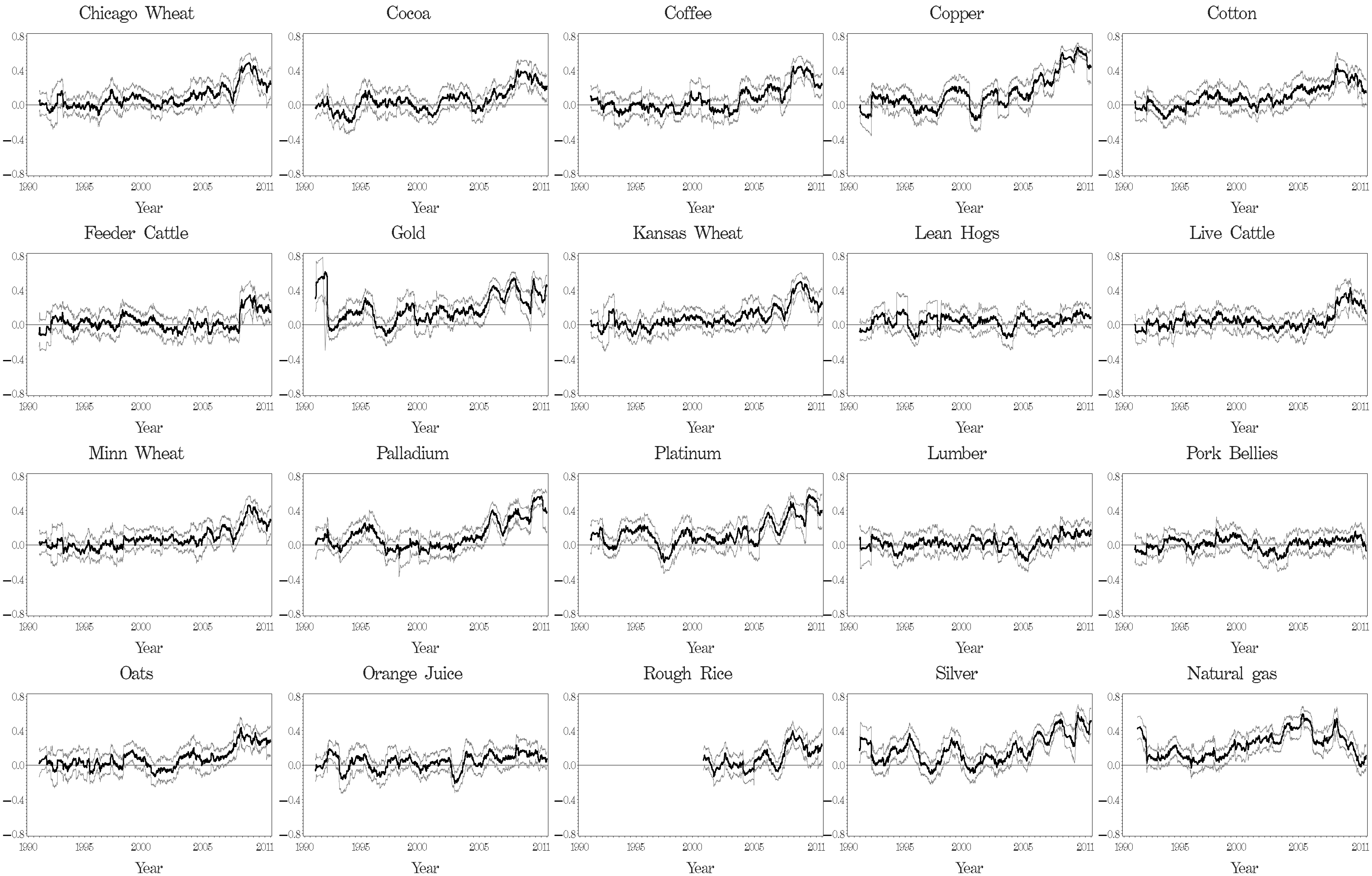

Figure 5: One-year rolling window correlations between log-price changes of oil and non-biofuel commodities (estimate and 95% CI).