Interdependencies in the Energy-Bioenergy-Food Price Systems:
A Cointegration Analysis[1]

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Abstract

The present paper studies the interdependencies between the energy, bioenergy and food prices. We develop a vertically integrated multi-input, multi-output model with two channels of price transmission: a direct biofuel channel and an indirect input channel. We test the theoretical hypothesis by applying time-series analytical mechanisms to nine major traded agricultural commodity prices, including corn, wheat, rice, sugar, soybeans, cotton, banana, sorghum and tea, along with one weighted average world crude oil price. The data consists of 783 weekly observations extending from January 1994 to December 2008. The empirical findings confirm the theoretical hypothesis that the prices for crude oil and agricultural commodity are interdependent: an increase in oil price by 1 dollar/barrel increases the agricultural commodity prices between 0.10 \$/tonne and 1.50 \$/tonne. Contrary to the theoretical predictions, the indirect input channel of price transmission is small and statistically insignificant.

Keywords: Energy, bioenergy, crude oil, prices, renewable fuels, cointegration.

JEL classification: C14, C22, C51, Q11, Q13, Q42.

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1 Introduction

In recent years the production of bioenergy has increased significantly around the world. The expansion of bioenergy was driven, among others, by rising energy prices, and environmental policies aimed at reducing harmful effects of conventional sources of energy on global climate changes.[1] Bioenergy has a direct effect on agricultural sector, because it uses biomass as input, which together with agricultural commodities are produced on a fixed area of agricultural land.[2] Because of price inelastic food demand and land supply, the price increase of agricultural commodities may be substantial. The positive price effect of bioenergy expansion may be reduced by two factors. First, new technological development may improve yields and lead to an offsetting effect in supply of agricultural commodities. Second, with rising agricultural profitability, unused fallow land may be brought into cultivation. However, because technological improvement is costly, and the fallow land brought into cultivation usually is less productive, these factors cannot fully offset the positive price effect of bioenergy (*Huber* 2007; *Nielsen, Oleskowicz-Popiel* and *Al Seadi* 2007).

The potential impact of bioenergy support policy on the recent food price increase has sparked a lively debate and controversy about the contribution of biofuels to the recent food commodity price developments particularly the impact of biofuels on the 2007-2008 food price rise. On the one hand, international organisations, such as the *World Bank* and the *IMF*, argue that biofuels were an important factor leading to higher food prices. According to the *World Bank*'s study, up to 75 percent of the increase in food commodity prices could be attributed to bioenergy expansion (*Mitchell* 2008). The IMF estimated that the increased demand for biofuels accounted for 70 percent of the increase in corn prices and 40 percent of the increase in soybean prices (*Lipsky* 2008). Similarly, also *FAO* (2008) and *OECD* (2009) argue that the expansion of biofuel production was a substantial factor leading to the recent food price rise.

On the other hand, the policy executives in the EU and US play down the importance of biofuels in the recent food price developments. The *USDA* agrees that the biomass demand for biofuels has an impact on food commodity prices, but argues that it is not a major factor. According to the *USDA*, only 3% of the 40% rise in

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[1] Throughout the paper we use terms (fossil) energy, crude oil and fuel as synonyms.

[2] The main input in bioenergy production is biomass. Biomass covers a wide range of plant sources, including those that are used for fuel directly (e.g. fuelwood), and those that are processed into biofuels (corn, soy, sugarcane, sugar beet, rapeseed, wheat, etc.). Main biofuel products include ethanol (alcohol), biodiesel, and biogas. Main crops used for ethanol production include maize, sugar cane, sugar beet and wheat. Main crops used for biodiesel production are rapeseed, soy, and palm oil. Biogas can be produced either from biodegradable waste materials or from energy crops.

global food prices can be attributed to biofuel production (*Reuters* 2008). Similarly, *European Commission* (2008) acknowledges that the energy prices affect food commodity prices through the indirect input channel by increasing the cost of inputs like nitrogen fertilisers and transport costs. However, the European Commission argues that the impact of bioenergy is likely very small: "*The European Union currently uses less than 1 percent of its cereal production to make ethanol. This is a drop in the ocean. So this is not something to shake the markets*" (*European Commission* 2008). Similarly, the German government (Germany being the Europe's largest biofuel producer) argues that other factors, e.g. changing eating habits in the developing countries, are primarily to blame for the recent rising food price rise, but not the biofuel production (*Reuters* 2008).

The simultaneous increase in price volatility on energy and agricultural commodity markets has generated a notable amount of scientific studies attempting to explain the linkages between the fossil energy and agricultural commodity prices. Three types of approaches have been followed in the literature. First, cointegration analysis are performed to estimate the long-run relationship between the fuel price and biomass prices (*Campiche et al* 2007; *Yu, Bessler* and *Fuller et al* 2006; *Hameed* and *Arshad* 2008 ; *Imai, Gaiha* and *Thapa* 2008). The main shortcomings of these reduced form empirical studies are that they do not provide theoretical basis for deriving an estimable model, and they do not identify the channels of price transmission. Second, theoretical models were developed to identify and understand the channels of adjustment between agricultural, bioenergy and energy markets (*Gardner* 2007; *de Gorter* and *Just* 2008, 2009, *Saitone, Sexton* and *Sexton* 2008). This strand of literature is relatively new and only few theoretical models exist to date. Third, partial and general equilibrium (CGE) models have been developed to simulate the interdependencies between the agricultural, bioenergy and energy markets (*Arndt et al* 2008; *Hayes et al* 2009; *Birur et al* 2008; *Hertel* and *Tyner* 2008; *Tokgoz* 2009). The main disadvantage of the CGE approach is that the simulated effects largely depend on the calibrated or arbitrary assumed price transmission elasticities. We are not aware of any work combining the theoretical underpinning with empirical evidence in a unified framework. This is the main purpose of this paper.

The objective of this paper is to investigate the interdependencies between the energy, bioenergy and agricultural markets both theoretically and empirically, and to support the empirical results by performing simulation analysis. Our theoretical model (section 2) builds on the models of *Gardner* (2007) and *de Gorter* and *Just* (2008, 2009), which develop a vertical integration model of ethanol, by-product, and corn markets to analyse the welfare effects of corn production subsidies and ethanol

subsidy in the US. In order to analyse bidirectional price interdependencies, we extend the existing models along several dimensions. First, we consider two (instead of one) agricultural commodities. Second, we consider price transmissions also through the input channel. Third, our model is not specific to the US, but is generally applicable for the world markets. Finally, we apply the model to analyse the interdependencies between the fuel and agricultural commodity prices, but not to analyse the welfare effects of biofuel/agricultural policies. The main theoretical model results are verified in a simulation analysis.

Our empirical approach (section 3) is based on the cointegration analysis (*Johansen* 1988; *Johansen* and *Juselius* 1990). We examine the existence of a long-run relationship between the crude oil and agricultural commodity prices by applying the error correction estimation procedure. In a first step, we test the ten price series for stationarity using the Augmented Dickey-Fuller and Phillips Perron tests. Based on the unit root test results, we test for the existence of cointegrating vectors among the nine agricultural commodity price series and crude oil. Finally, in order to identify a structural model and determine whether the estimated model is reasonable, we perform innovation accounting and causality tests on the estimated error-correction model.

In line with the theoretical predictions, our empirical estimates show that the main transmission between the oil price and agricultural commodity prices occurs through the biofuel channel. Contrary to the theoretical predictions, in empirical analysis the indirect input channel of price transmission is found to be small and statistically insignificant. The Granger causality test results suggest a long run unidirectional causality from oil price to agricultural commodity prices. However, the tests deny the presence of a similar relation in the opposite direction. These results are supported by the simulation analysis.

The paper has important policy implications, as it sheds light on the potential impact of bioenergy policies on agricultural prices. The exact relationship between the energy, bioenergy and food price systems is not fully understood yet (*IMF* 2008; *von Braun* 2008; *World Bank* 2008). Our findings provide important insights for a better understanding of whether biofuels exercise a long-run pressure on agricultural markets or whether it is a temporary phenomenon, and scientific support for shaping the bioenergy and food polices. Since most governments in developed countries have introduced policies to promote bioenergy production and use, the findings of this paper may indirectly indicate what effect the bioenergy support polices may have on agricultural prices and thus potentially affecting agricultural production, food consumption and the use of land resources.

2 Theoretical framework

2.1 Bioenergy models in the literature

Several models have been developed for studying the effect of biofuels on agricultural markets. *Gardner* (2007) develops a vertical integration model of ethanol, by-product, and corn markets to analyse the welfare effects of corn and ethanol subsidies in the US. The main shortcoming of this model is that it does not consider the aggregate fuel market (fossil fuel and biofuels such as ethanol). *Gardner* model the market for ethanol by assuming a downward sloping demand and an upward sloping supply of ethanol, which affects corn market through a derived demand for corn in ethanol production. This implies that the fossil fuel and ethanol are imperfect substitutes in consumption. The transmission between the fuel and corn prices depends on the assumptions about correlation of the fuel and ethanol prices.

De Gorter and *Just* (2008, 2009) develop a similar model to *Gardner* (2007) with one agricultural product (corn), ethanol market and by-product, and analyse the welfare effects of corn and ethanol subsidies in the US. They extend the *Gardner*'s model to aggregate fuel market, and consider perfect and imperfect substitutability in consumption between fossil fuel and ethanol. The price transmission between fuel and corn is effectuated through the demand for corn in ethanol production. The price transmission occurs, when the price for fuel is sufficiently high and/or when corn price is sufficiently low, ensuring that ethanol production from corn is profitable relative to the profitability of non-ethanol use of corn.[3]

Similarly, *Saitone*, *Sexton* and *Sexton* (2008) focus on the ethanol and corn sectors in the US, and analyse price and income distribution effects of ethanol subsidies. They consider seed seller market power upstream from the agricultural sector, and buyer market power downstream from the farm in the corn-processing sector. *Saitone*, *Sexton* and *Sexton* show that market power has implications for transmission of ethanol expansion due to the crop subsidy. Market power in the downstream corn-processing sector causes a smaller increase in corn price due to the ethanol subsidy, while the upstream seed suppliers' market power has an ambiguous effect on the corn price, because market power in the seed sector induces offsetting effects on corn prices.

In all four models of *Gardner* (2007), *de Gorter and Just* (2008, 2009), and *Saitone*, *Sexton* and *Sexton* (2008) the transmission of prices from fuel to agricultural markets is effectuated only through the demand for agricultural commodity in

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[3]For low fuel and/or high corn prices, price transmission will not occur. In this case the production of ethanol from corn is not competitive implying no ethanol production in equilibrium.

biofuel production. There is no price transmission through the indirect input channel. However, in reality, fuel is an important input in agricultural production, such as fuel, fertilisers, pesticides. Hence, changes in fuel price affect agricultural production costs and hence agricultural prices. Ignoring this effect may lead to upward biased estimates of biofuel expansion on agricultural prices. Second, all three models assume only one agricultural commodity. With multiple commodities the derived effects may change and fuel market may affect not only biomass crops, but also those commodities, which are not used in biofuel production.

2.2 The model

The present study builds on models of *Gardner* (2007) and of *de Gorter* and *Just* (2008, 2009) and introduces two important extensions. First, we assume two agricultural commodities: one suitable for biofuel production (referred to as "biomass")[4] and one not suitable for biofuel production (referred to as "food"). Second, we consider the transmission of prices also through the input channel. Both extensions improve the model predictions.[5]

The world economy consists of vertically integrated agricultural, biofuel, fossil fuel, by-product, and input markets (Figure 1). The representative farm can substitute between producing two agricultural commodities (biomass and food) using constant return to scale production functions of two substitutable inputs: fuel and other inputs (referred to as "land"). Agricultural output can be supplied to food market and to biofuel market. We assume fixed Leontief coefficient transformation function of biomass into biofuel and by-product from biofuel production. Further, we assume a downward sloping demand for food and by-product, and an upward sloping supply curve for land. The aggregate fuel supply is a sum of biofuel and fossil fuel supplies. The aggregate fuel demand is a sum of agricultural and non-agricultural fuel demand. The fossil fuel supply (non-agricultural fuel demand) is given by upward (downward) sloping functions of prices.

The representative agricultural farm maximises its profits according to: $\Pi = \sum_i p^i Q^i(N^i, K^i) - wN^i - rK^i$, which implies the following equilibrium conditions:

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[4] Note that we consider the case where the agricultural commodity suitable for biofuel production may be used for both food and biofuel production. We denote it as biomass to simplify the text.

[5] Compared to previous studies, also the scope of this paper is different. We do not focus on the US, but on the world biofuel market, and we use the model to analyse the interdependencies between fuel and agricultural commodity prices, instead of analysing the welfare effects of biofuel/agricultural policies.

$$p^i \frac{\partial Q^i}{\partial N^i} = w \tag{1}$$
$$\text{for } i = AB, AN$$

$$p^i \frac{Q^i}{\partial K^i} = r \tag{2}$$
$$\text{for } i = AB, AN$$

where N is non-fuel input (land), K is fuel input, p is farm output price, w is land rental price, and r is fuel price. AB is index for biomass, and AN is index for food commodity. Equations (1) and (2) are marginal conditions for land and fuel input, respectively, and determine input demand and output supply of agricultural commodities.

In Figure 2 the derived supplies of biomass, S^{AB}, and food commodity, S^{AN}, are shown as upward sloping curves (panels a and d, respectively).[6] The aggregate world food demand for biomass and food commodity is denoted by $D^{AB}(p^{AB})$ and $D^{AN}(p^{AN})$, and are shown in panels a and d, respectively. The world supply of land is given by $S^N(w)$ (not shown).

We assume constant Leontief transformation technology in biofuel sector with constant extraction coefficient denoted by β. Each unit of biomass results in β units of biofuel.[7] Additionally, biofuel production yields feed by-product, γ, units quantity per one unit of biomass. To simplify the analyses, we assume constant value of unit processing costs (adjusted for mark-up), c, incurred to biofuel production from one unit of biomass. This implies that biofuel supply, $S^B(r)$, and by-product supply, $S^O(p^O)$, represent the excess supply of biomass, $S^{AB} - D^{AB}$, adjusted by constant extraction coefficients: $S^B = \beta \left(S^{AB} - D^{AB} \right)$ and $S^O = \gamma \left(S^{AB} - D^{AB} \right)$, respectively, where p^O is the price for by-product. In Figure 2 biofuel supply, S^B, is shown in panel b.

The world supply of fossil fuel together with biofuel supply generates the aggregate fuel supply curve, $S^{TF}(r) = S^F + S^B$, where $S^F(r)$ is the world supply curve of fossil fuel (panel b in Figure 2). The aggregate fuel demand, $D^{TF}(r)$, is a sum of

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[6]In Figure 2 we show biomass market (panel a), fuel market (panel b) and food commodity market (panel d) (by-product and land markets are not shown). The effects sown in Figure 2 take into account adjustments in all markets.

[7]We assume that this coefficient also adjusts for quality differences between biofuel and fossil fuel. Hence it represents biofuel in equivalent of fossil fuel.

agricultural fuel demand, $K^{AB} + K^{NB}$, and non-agricultural fuel demand, $D^{NF}(r,t)$, where t is an exogenous parameter, which we use to derive the comparative static effects of fuel demand shocks (panel b in Figure 2). In order to simplify the analysis, we assume perfect substitutability between biofuel and fossil fuel in consumption.[8]

The equilibrium conditions for agricultural, input and fuel markets can be summarised in five equilibrium conditions. Food production from biomass with no biofuel production is given by:

$$\text{if} \quad p_o^{AB} \geq \beta r + \gamma p_o^O - c \quad \Rightarrow \quad S^B = S^O = 0 \quad \Rightarrow \quad D^{AB} = S^{AB} \tag{3a}$$

where p_o^{AB} is the equilibrium price for biomass in absence of biofuel production, p_o^O is by-product price in absence of production of by-product from biomass. Food and biofuel production from biomass is given by:

$$\begin{aligned} \text{if} \quad & p_o^{AB} < \beta r + \gamma p^O - c \quad \Rightarrow \quad S^B > 0, S^O > 0 \quad \Rightarrow \quad S^{AB} - D^{AB} > 0 \\ \text{and} \quad & p^{AB} = \beta r + \gamma p^O - c \end{aligned} \tag{3b}$$

Food commodity equilibrium:

$$S^{AN} = D^{AN} \tag{4}$$

Land market equilibrium:

$$N^{AB} + N^{AN} = S^N \tag{5}$$

By-product market equilibrium:

$$S^O = D^O \tag{6}$$

where $D^O(p^O)$ is by-product demand. Fuel market equilibrium:

$$S^{TF} = D^{TF} \tag{7}$$

Equation (3) determines the equilibrium condition for biomass. The unit return of biomass, if used to produce biofuels, is given by the adjusted fuel and by-product

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[8]In reality, fuel containing low share of biofuels (e.g. 10% or less in the case of ethanol) can be used in virtually all standard vehicles. However, fuel with high share of biofuels requires engine adaptation, which implies additional (fixed) costs to consumers. Hence, depending on the relative importance of these adjustment costs, the theoretical model may slightly overstate the impact of biofuels on agricultural prices.

prices net of processing costs c: $\beta r + \gamma p^O - c$. If the return from biofuel is smaller than the biomass equilibrium price in the absence of biofuel production, p_o^{AB}, then biofuel production is not profitable in equilibrium. In this case the equilibrium biomass price is determined by intersection of biomass demand and supply, $D^{AB} = S^{AB}$ (equation 3a). Biofuel production is in equilibrium, $S^B > 0$, when the unit return of biomass used for production of biofuels is higher than the biomass price, p_o^{AB}, on the food market: $\beta r + \gamma p^O - c > p_o^{AB}$. In this case the equilibrium biomass price is determined by the price for fuel and by-product: $p^{AB} = \beta r + \gamma p^O - c$ (equation 3b). Equation (4) represents the equilibrium condition for food commodity. Equations (5) and (6) determine the equilibrium on land and by-product markets, respectively. Equation (7) is clearing condition for the aggregate fuel market equilibrium, where $S^{TF} = S^F + S^B$ and $D^{TF} = D^{NF} + K^{AB} + K^{AN}$.

Figure 2 shows the equilibrium prices and quantities for biomass market (panel a), fuel market (panel b) and food commodity market (panel d). The equilibrium price and quantity for biomass is p_o^{AB}, Q^{AB}, and the equilibrium price and quantity for fuel is r, Q^F. There is no biofuel production in equilibrium, because the return from biomass for biofuel production would be lower than the price obtained if sold on the food market. With fuel price r, the unit return of biomass for biofuel production is given by p^{AB} ($= \beta r + \gamma p_o^O - c$), while the equilibrium food price is p_o^{AB}. As shown in panel a, food price is lower than the equilibrium price for biomass, $p^{AB} < p_o^{AB}$, implying no biofuel production in equilibrium.[9] Finally, the equilibrium price and quantity of food commodity is p^{AN}, Q^{AN}.[10]

2.3 Price interdependencies

In order to understand the channels of price transmission between the fuel and agricultural markets, we perform graphical analysis and numerical simulations.[11] In numerical simulations we use the world agricultural, biofuel and fuel market data for 2007 to calibrate the model. The share of biofuels in the total world fuel production is less than 1% using approximately 1.6% of world arable area. The share of agricultural fuel consumption and the share biomass output used for the biofuels is around 3.3%.[12] We analyse transmission of price signals in two scenarios. First, we assume no biofuel production. In this case, the model is calibrated to the world agricultural

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[9]Note that the fuel price r_o is equivalent to return from the biofuel production at price of biomass p_o^{AB}. Everything else equal, the biofuel production is profitable for fuel prices higher than r_o.

[10]As noted above, we assume that this commodity is used only for food production.

[11]In numerical simulations we assume Cobb-Douglas production function in agriculture and constant elasticity of substitution functions for supply and demand.

[12]A detailed overview of the data and their sources is shown in the Appendix.

and fuel data, with biofuel production set to zero. In a second scenario simulations are performed with biofuel production.[13]

Price transmission may occur in two directions: from fuel to agricultural prices and vice versa. In both directions price signals are transmitted through two channels: an indirect input channel and a direct bioenergy channel. First, fuel is used as input in agricultural production. Changes in fuel price will affect agricultural production costs and hence agricultural prices. Similarly, any changes in fuel use in agricultural production affects fuel demand inducing changes in fuel prices. Second, the direct channel of price transmission is effectuated through biofuel demand for agricultural commodities. Fuel price affects the profitability of biofuel production and hence it affects biofuel demand for agricultural commodities. The reverse price transmission from agricultural prices to fuel occurs through the direct channel because agricultural prices affect biofuel profitability, which affects biofuel supply on fuel market.

2.3.1 The transmission from the fuel price to agricultural prices

Adjustments on the fuel market have implications for agricultural markets, both on the supply and demand sides. The supply side adjustments include effects such as changes in productivity and technology, changes in oil reserves, etc. The demand side adjustments include, among others, the economic growth and the induced change in energy requirement, changes in consumption patterns (e.g. shift to more fuel-efficient cars), etc.

We start with a situation when oil price is low and biofuel production is not profitable, and study the channels of price transmission from fuel to agricultural prices by introducing a shock to the non-agricultural fuel demand. In initial equilibrium there is no biofuel production. In this case the transmission of price signals will occur only through the indirect input channel. This situation is shown in Figure 2: the initial equilibrium in the biomass market (panel a), the fuel market (panel b) and the food commodity market (panel d) is p_o^{AB}, Q^{AB}; r, Q^F; and p^{AN}, Q^{AN}, respectively. A positive shock introduced to the non-agricultural fuel demand shifts the aggregate fuel demand from D^{TF} to D_1^{TF}.[14] The new equilibrium sets are p_{1o}^{AB}, Q_1^{AB}; r_1, Q_1^F; and p_1^{AN}, Q_1^{AN}, for biomass (panel a), fuel (panel b) and food (panel d), respectively.[15] Fuel price rises from r to r_1 leading to higher agricultural production costs, which induces a leftward shift in the supply of agricultural commodities (form

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[13] As usual, for all scenarios we perform sensitivity analyses by varying model parameters.

[14] Note that the aggregate fuel demand is the sum of the non-agricultural fuel demand and the agricultural fuel demand.

[15] Note that these equilibria take into account adjustments in all markets including in by-product and land markets.

S^{AB} to S_1^{AB} for biomass and form S^{AN} to S_1^{AN} for food commodity). In equilibrium, the prices for both agricultural commodities rise. The price for biomass increases from p_o^{AB} to p_{1o}^{AB}. The price for food commodity increases from p^{AN} to p_1^{AN}.

Table 1 reports the calibrated transmission elasticities of agricultural prices with respect to changes in fuel price, with and without biofuel production (columns 9-12) and for different values of model parameters (columns 2-8). The calibrated elasticities in Table 1 are consistent with the graphical analysis.[16] The price transmission elasticity with no biofuel production is positive for both commodities (columns 9 and 11). Important factors affecting the transmission elasticities are agricultural production parameters, particularly the relative importance of fuel inputs in agricultural production (agricultural production elasticity of fuel). The transmission elasticities of both agricultural commodities in model 1 are equal (0.41), because we assumed the same weight of fuel input in agricultural production for both agricultural commodities (0.30). The price transmission elasticities decline with lower agricultural production elasticity of fuel (columns 9 and 11 in models 7 and 8), because the impact of higher fuel prices on agricultural production costs is smaller, when fuel is a relatively less important input in agricultural production. Models 2 and 3 show that the price transmission elasticity decreases in food demand elasticities (columns 9 and 11). This is because the price effect of lower food supply (caused by higher fuel costs) decreases in food demand elasticities. In a special case, when food demand is perfectly elastic, the price for agricultural commodities would not be affected by fuel price. Similarly, the price transmission elasticity decreases with land supply elasticity (model 6). A higher land supply elasticity implies higher availability of land, allowing the substitution of land for fuel, which partially offsets the fuel cost effect. Note that the price transmission elasticities are almost unaffected by the non-agricultural fuel demand and supply elasticities (columns 9 and 11 in models 4 and 5).

A further increase in non-agricultural fuel demand shifts the aggregate fuel demand further upward to D_2^{TF} (Figure 2). This in turn raises the biomass and food supplies to S_2^{AB} and S_2^{AN}, respectively. In Figure 2 the new equilibriums are p_2^{AB},

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[16] The elasticities in Table 1 are in line with *Hayes et al* (2009). *Hayes et al* use a partial equilibrium FAPRI model of the world agricultural sector to examine the impact of energy prices and policies on agricultural markets. They assume high energy price scenarios with and without biofuel policies and with and without biofuel demand growth constraints. The most comparable results are the scenarios where they assume an increase in energy price and no change in policies. Based on their reported price results for 14 agricultural commodities we have calculated the elasticities of agricultural commodities with respect to the crude oil price. The elasticities vary between -0.11 to 1.27. Only soybean oil price has a negative elasticity (-0.11). The most commodities have elasticity higher than 0.2. The most elastic is corn (between 0.49 with biofuel demand growth constraints and 1.27 without biofuel demand growth constraints), followed by soybeans (0.22 and 0.57) and wheat (0.23 and 0.52). The least elastic are prices of milk, cheese, beef and cotton (between 0.04 and 0.10).

Q_{2D}^{AB}, Q_{2S}^{AB}; r_2, Q_2^F; and p_2^{AN}, Q_2^{AN}, for biomass (panel a), fuel (panel b) and food (panel d), respectively. Note that now the price for fuel is sufficiently high making the biofuel production profitable. The supply of biofuel is given in panel b,[17] which is determined by the excess supply of biomass adjusted by a constant extraction coefficient: $S_2^B = \beta \left(S_2^{AB} - D^{AB} \right)$. The equilibrium quantity of biofuel is $Q_2^B = \beta \left(Q_{2S}^{AB} - Q_{2D}^{AB} \right)$. Now the price transmission occurs through both the direct biofuel channel and indirect input channel. First, because of higher fuel costs, the supply of both agricultural commodities is reduced. For example, everything else equal, without the production of biofuel, the price for biomass would increase from the initial equilibrium p_o^{AB} to p_{2o}^{AB} (panel a). However, the demand for biofuel pushes the price further up to p_2^{AB}. This second effect represents the direct biofuel channel of price transmission. The equilibrium price for food increases from p^{AN} to p_2^{AN} (Figure 2, panel d), because of higher fuel costs (the indirect channel), and because the use of biomass in biofuel production further increases all input prices and thus shifts the price for food further up (the direct channel). The correlation, e^{AN}, between prices for food and fuel is shown in panel c. The correlation is positive, implying a positive relationship between fuel and food prices. The same holds for biomass (not shown).

In summary, the impact of fuel price on agricultural prices is stronger with than without biofuel production. This is also confirmed by simulation results shown in Table 1. Price transmission elasticities are more than two times higher in the presence of biofuel production (columns 10 and 12) than without biofuel production (columns 9 and 11) for all considered models. With biofuel production (similar to the case of no biofuel production), the price transmission elasticities of both agricultural commodities decrease in food demand elasticities (columns 10 and 12 in models 2 and 3) and in land supply elasticity (model 6), while they increase in the relative importance of fuel in agricultural inputs (models 7 and 8). The price transmission elasticities decrease in non-agricultural fuel demand and supply elasticities (columns 10 and 12 in models 4 and 5).

2.3.2 The transmission from agricultural prices to fuel price

Reversely, changes in agricultural markets may induce adjustments in fuel markets. Such changes may concern both the supply side (e.g. weather effect, productivity change due to adoption of new technologies), or the demand side (e.g. change in consumption patterns due shifts in preferences, changes in consumption levels due

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[17]Note that the aggregate fuel supply shifts from $S^F S^F$ to $S^F S_2^{TF}$. For fuel prices higher than r_{2o}, the slope of the aggregate fuel supply changes because of biofuels. The horizontal difference between S_2^{TF} and S^F at fuel price r_2 is equal to biofuel production: $Q_2^B = S^{TF}(r_2) - S^F(r_2)$.

to income growth). As above, the transmission of prices may occur through the direct biofuel channel and/or the indirect input channel. The impact of a positive productivity shock to agricultural productivity for both agricultural commodities is shown in Figure 3 graphically and in Table 2 numerically.

The initial equilibriums on the biomass market (panel a), fuel market (panel b) and food market (panel d) are p_o^{AB}, Q^{AB}; r, Q^F; and p^{AN}, Q^{AN}, respectively. As above, in the initial equilibrium we assume no biofuel production. A positive agricultural productivity shock implies a rightward shift in agricultural commodity supply: in equilibrium the supply of biomass shifts from S^{AB} to S_1^{AB} (panel a), and the supply of food shifts from S^{AN} to S_1^{AN} (panel d). The impact of agricultural productivity increase on the fuel market depends on how the derived fuel demand in agriculture is affected by the productivity shift. This in turn depends on food demand elasticities.

Inelastic food demand leads to a large decline in agricultural commodity prices, when agricultural production increases. The productivity gain is offset by decreasing output prices, as a result of which, agricultural fuel demand declines. In panel b of Figure 3 the aggregate fuel demand shifts downward from D^{TF} to D_1^{TF}.[18] The new equilibrium on the fuel market is r_1, Q_1^F.

We can distinguish between the indirect input and the direct biofuel channels of price transmission, which can be further split into two sub-effects. First, everything else equal, the indirect input channel of price transmission (no biofuel production) reduces the aggregate fuel demand from the initial level D^{TF} to $D_1^{TF\prime}$. This aggregate fuel demand shift is driven by decreasing agricultural profitability due to a decrease in biomass and food prices from p_o^{AB} to p_{1o}^{AB} and from p^{AN} to $p_1^{AN\prime}$, respectively.[19] If agriculture would produce only food and no biomass was supplied for biofuel production, the two agricultural output prices would be, p_{1o}^{AB} and $p_1^{AN\prime}$. The indirect input channel reduces the price for fuel to r_1'.

Given that $r_1' > r_{1o}$, the production of biofuel is profitable. The second, direct biofuel effect, results in a final backward shift in the aggregate fuel demand from $D_1^{TF\prime}$ to D_1^{TF}. Everything else equal, the direct biofuel channel has two opposite effects on the fuel price. First, the effect of biofuels is a rise in fuel price from r_1' to r_1'', because of more agricultural demand for fuel induced by higher biomass production due to biofuel demand. Second, biofuels reduce fuel price from r_1'' to the equilibrium price

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[18] Note that the aggregate fuel demand is the sum of agricultural fuel demand and non-agricultural fuel demand. In Figure 3 the shift in the aggregate fuel demand is driven by changes in the agricultural fuel demand.

[19] Given by the shift of agricultural supplies to S_1^{AB} and to $S_1^{AN\prime}$ in panels b and d of Figure 3, respectively.

r_1, because biofuels increase fuel supply on the energy market, exerting a downward pressure on fuel price.[20][21] The equilibrium prices for biomass (panel a) and food (panel d) with inelastic food demands are p_1^{AB} and p_1^{AN}, respectively. The equilibrium biomass price p_1^{AB} is determined by biofuel profitability. Food price p_1^{AN} is affected by a final shift in supply from $S_1^{AN\prime}$ to S_1^{AN}, which is driven by higher agricultural input prices due to biofuel demand of biomass.

Thus, with inelastic food demand, the rise in agricultural productivity reduces fuel price through the indirect input channel (implying positive price transmission elasticity), while the direct biofuel channel may offset, weaken or strengthen the overall effect.

The transmission of prices is different, when the *demand for food is elastic*. In this case, higher agricultural productivity boosts the agricultural fuel demand, which shifts the aggregate fuel demand upwards. In equilibrium this corresponds to a shift in the aggregate fuel demand from D^{TF} to D_2^{TF} (Figure 3, panel b). The new equilibrium on the fuel market is r_2, Q_2^F. Again, we can distinguish between direct and indirect channels of price transmission. Further, the direct channel can be split into two sub-effects.

Everything else equal, the input channel of price transmission shifts the aggregate fuel demand from the initial level D^{TF} to $D_2^{TF\prime}$. The increase in the aggregate fuel demand is driven by higher agricultural profitability due a positive productivity shock, which however is less than offset by decreasing prices for biomass and food from p_o^{AB} to p_{1o}^{AB} and from p^{AN} to $p_2^{AN\prime}$, respectively,[22] in absence of biofuel production. With $D_2^{TF\prime}$, the price for fuel is r_2', implying that the indirect input channel has increased the price for fuel.

Everything else equal, the direct biofuel channel results in a further shift of the aggregate fuel demand from $D_2^{TF\prime}$ to D_2^{TF}.[23] First, biofuels rise the fuel price from r_2' to r_2'', because of higher agricultural demand for fuel. Second, biofuels reduce fuel price from r_2'' to r_2, because biofuels increase fuel supply, which exerts a downward

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[20]Note that if the second effect of biofuel channel is sufficiently high it could reduce the final equilibrium fuel price below or equal to r_1', with $r_1'' - r_1 \geq r_1'' - r_1'$. On the other hand, if the first effect of biofuel channel is sufficiently strong (i.e. if it more than offsets the second effect of biofuel channel and the indirect input channel), then the overall effect of agricultural productivity could lead to higher fuel price than the initial price r, which would imply a negative price transmission elasticity.

[21]Note that the aggregate fuel supply without biofuels is given by curve $S^F S^F$, and with biofuels by curve $S^F S_2^{TF}$.

[22]Given by the shift of agricultural supplies to S_1^{AB} and to $S_2^{AN\prime}$ in panels b and d of Figure 3, respectively.

[23]The fuel demand increases because of higher agricultural demand for fuel induced by biomass production for biofuels.

pressure on fuel price.[24] The equilibrium prices for biomass (panel a) and food (panel d) are p_2^{AB} and p_1^{AN}, respectively. The price for biomass, p_2^{AB}, is determined by biofuel profitability. The price for food, p_1^{AN}, is determined by a final shift in the supply from $S_2^{AN\prime}$ to S_1^{AN} (Figure 3). The equilibrium biofuel production equals to Q_2^B. Thus, with elastic food demand, the boost in agricultural productivity leads to a higher fuel price through the indirect input channel (implying a negative price transmission elasticity), while the direct biofuel channel may offset, weaken or strengthen the overall effect.

In summary, the total effect of price transmission from agricultural prices to fuel price is ambiguous. The indirect input channel implies positive price transmission elasticity with inelastic food demand, while negative with elastic food demand. Biofuels may offset, weaken or strengthen the overall effect. Panel c in Figure 3 shows the correlation between food and fuel prices. The correlation can be either positive, e_1^{AN}, or negative, e_2^{AN}. The same holds for biomass (not shown).

Table 2 reports the corresponding simulation results of price transmission effects from agricultural prices to fuel price. In all models with inelastic food demand for both agricultural commodities (models 1 and 4-8), price transmission elasticities are positive. Agricultural and fuel prices change in the same direction: a positive agricultural productivity shock increases agricultural production and reduces agricultural prices; and lower agricultural prices reduce agricultural fuel demand (the indirect input channel) and make biofuel more profitable (the direct biofuel channel). Both effects exert a downward pressure on fuel price. The price transmission elasticities are lower with than without biofuel production. The price transmission elasticities with biofuel production (columns 10 and 12; models 1 and 4-8) are driven by both direct and indirect channels of price transmission, while without biofuel production (columns 9 and 11; models 1 and 4-8) only by the indirect input channel. However, because the share of biofuel production and the share of agricultural fuel consumption on aggregate fuel are relatively low at around 0.8% and 3.3%, respectively, the transmission elasticities are relatively small.

The results in Table 2 show that the price transmission elasticities may be negative, if at least one agricultural product has elastic food demand (models 2 and 3). The calibrated price transmission elasticity becomes negative, if the demand for food is elastic (columns 9 and 11; model 3).[25] In these models the positive productivity

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[24] Note that now the second effect of biofuel channel, $r_2'' - r_2$, is higher than the first effect $r_2'' - r_2'$, so the final equilibrium fuel price, r_2, is below r_2'. Note that, if the second effect of biofuel channel is sufficiently high (if $r_2'' - r_2 > r_2'' - r$), then the overall effect of the productivity increase could reduce fuel price implying a positive transmission elasticity.

[25] This does not, however, hold in general. When food demands vary in terms of the relative

shock raises agricultural production, reduces agricultural prices and increases agricultural fuel demand, leading to a higher fuel price (indirect input channel). However, this is the case only when biofuel production is unprofitable (columns 9 and 11; model 3). In contrast, the price transmission elasticity is positive with positive biofuel production (columns 10 and 12; model 3). First, biofuels increase fuel price because of higher agricultural demand for fuel. Second, biofuels increase the aggregate fuel supply exerting a downward pressure on fuel price. The overall effect of the direct biofuel channel is a reduction of fuel price which more than offsets the price for fuel rise induced by the indirect input channel.[26]

3 Cointegration analysis

3.1 Econometric approach

Theoretical findings from the previous section suggest that the fossil energy prices affect agricultural commodity prices and, to a lesser extent, agricultural commodity prices may affect fossil energy prices. Hence, both fossil energy and agricultural commodity prices are endogenous. In standard regression models the endogeneity of all variables sharply violates the exogeneity assumption, placing particular variables on the right hand side of a regression equation. By specifying a Vector Autoregressive (VAR) model on a system of variables, this problem can be circumvented, because in VAR no such conditional factorisation is made a priori. Instead, variables can later be tested for exogeneity, and restricted to be exogenous then. These considerations motivate our choice of the VAR model for studying the interdependencies between related price series.

Stationary processes, which have time invariant expected values, variances, and covariances, i.e. the first and second moments of the random variables do not change over time, can be analysed using a simple VAR model. A m-variable VAR model of order n can be written as:

$$P_t = \sum_{i=1}^{n} \Gamma_i P_{t-i} + \mu + \varepsilon_t \qquad (8)$$

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magnitude of elasticities, the price transmission elasticities may be positive or negative depending, among others, on the ratio of elasticities and the relative market sizes between the elastic and inelastic food demands. This can be observed when comparing models 2 and 3 with assumption of no biofuel production (columns 9 and 11). The transmission elasticity is positive in model 2, where the biomass demand for food is elastic, and negative in model 3, where the demand for food is elastic.

[26]However, this does not hold in general. The price transmission elasticity could be positive or negative depending among others on the relative share of agricultural fuel demand and biofuel production in the aggregate fuel consumption.

where P is a $(M \times 1)$ vector of agricultural and fuel price series at time t, Γ_i is a $(M \times M)$ matrix of coefficients relating series changes at lagged i period to current changes in series, μ is a $(M \times 1)$ vector of constants, and ε_t is a $(M \times 1)$ vector of iid errors. According to VAR model (8), each of the M variables is a function of n lags of all M variables, including itself, a constant and a contemporaneous error term.

The estimation of VAR model (8) is subject to several econometric issues. First, in many cases prices series are nonstationary. According to *Engle* and *Granger* (1987), if some of the series in M are nonstationary, the VAR in differentiated data will be misspecified, implying that nonstationary processes have to be analysed differently than stationary processes. Second, according to *Engle* and *Granger*, even if each of the variables is nonstationary, a linear combination of them might be stationary. This linear combination, which is called the cointegrating equation, may be interpreted as a long-run equilibrium relationship among the variables. It is necessary to control for cointegration, because it affects the specification of the model used for causality testing. If the series are cointegrated, then causality testing should be based on a Vector Error Correction model (ECM) rather than on an unrestricted VAR model (*Johansen* 1988; *Johansen* and *Juselius* 1990). When cointegration is not modelled, evidence may vary significantly towards detecting causality between the predictor variables. Specifically, the absence of cointegration could mean the violation of the necessary condition for the simple efficiency hypothesis, which implies an absence of a long-run relationship between oil and agricultural commodity prices. Alternatively, based on the underlying conceptual framework (section 2), a failure to find cointegration may be attributed to the nonstationarity of the other components of the underlying relationship between crude oil and agricultural commodity prices, such as the non-fuel input prices in agriculture.

The ECM can be obtained by first differentiating (8) and adding a lagged error term:

$$\triangle P_t = \sum_{i=1}^{k-1} \Gamma_i \triangle P_{t-i} + \Pi P_{t-i} + \mu + \varepsilon_t \tag{9}$$

where P_{t-i} is the so called error correction term and Π is a $(M \times M)$ coefficient matrix containing response information of lagged levels of random variables to current changes.

Parameters in ECM (9) allow us to identify both the long-run and short-run interdependencies between the M series. The information on long-run relationship between the M variables is summarised in Π. When the rank of Π is a positive

number, r, and it is less than the number of series, M, then $\pi = \alpha\beta$ where α and β are $(M \times r)$ matrices. Matrix β contains the cointegration parameters, and matrix α includes information on the speed of adjustment. According to *Johansen* (1988) and *Johansen* and *Juselius* (1990), testing the hypothesis on β can provide information on long-run structure, while testing the hypothesis on α and Γ_i can identify the short-run relationships.

Cointegration as such does not say anything about the causality of series interdependencies, which however is a central question in our study. For example, one of the oil or agricultural commodities could be a price leader and the others price followers; or, alternatively, none of the commodities might be more important than the others. In the first case, the price of the leading commodity would be driving the prices of the other oil/agricultural commodities (be 'exogenous' to the other prices), and cointegration could be analysed from the equations for the other 'adjusting' prices, given the price of the leader. In the second case, all prices would be 'equilibrium adjusting' and, hence, all equations would contain information about the cointegration relationships. In order to identify the direction of causality, we perform Granger causality tests.

3.2 Data

Our data consists of weekly price observations for crude oil and nine major traded agricultural commodities: corn, wheat, rice, sugar, soybeans, cotton, banana, sorghum and tea for the period 1994-2008.[27] Crude oil prices are from the *Statistics of Norway* (1991-1996) and *Energy Information Administration* (1997-2009); agricultural output prices are from the *Food and Agriculture Organisation* (FAO).[28] Given that these prices are from markets located in major world trade centres, such as U.S. Gulf (maize, wheat, soybeans) or Bangkok (rice), they represent the world price. All prices are border prices, i.e. free on board (f.o.b.) or cost, insurance and freight (c.i.f.) prices in US dollars (USD).

In order to account for structural changes in the production, demand and policies of oil, bioenergy and agricultural commodities, we divide the price series into three equally sampled periods: 1994-1998, 1999-2003 and 2004-2008.[29] In each period there are 261×10 weekly observations, hence 783×10 observations in total. The segmentation of the sample corresponds roughly to structural breaks. The first break accounts

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[27] The weekly price data for wheat starts from 1998 and for sugar, banana and tea from 1997. For this period monthly sugar price data is used.

[28] See the Appendix for data description and main sources.

[29] A similar approach was followed by *Campiche et al* (2007).

for the reduction in OPEC spare capacity (defined as the difference between sustainable capacity and current OPEC crude oil production). The effect of this event on price dynamics is evident in the data, and it can be summarised in the accelerated rise of the average level of oil prices and in the increased volatility. The second break is related to increase in bioenergy policy support and hence production. In May 2003 European Commission adopted directive for promotion of biodiesel. As a result, from 2004 biofuel production increased considerably and its energy market share started to grow. The interdependencies between the fuel price and agricultural prices is expected to be stronger in particular in the third period, when biofuel production expanded significantly. Therefore, one may expect that both channels of price transmission are active in the third period, while in the first period only the indirect input channel is likely to affect agricultural prices.

3.3 Empirical results

We start with pretesting the ten price series for stationarity and determining lag length. The stationarity is tested using the Augmented Dickey-Fuller (ADF) and Phillips Perron tests (PP). Table 4 summarises the ADF test results and Table 5 summarises the PP test results on the level and first differences. In both tests the null hypothesis is a unit root for each variable. Both the ADF and PP tests fail to reject the null hypothesis of unit root suggesting that the levels of all ten prices are nonstationary (Tables 4 and 5, columns 2, 4 and 6). One way how to achieve the stationarity of the prices is to differentiate/detrend the series. Both the ADF and PP unit root tests of first differences rejects the null of a unit root for the ten prices (Tables 4 and 5, columns 3, 5 and 7). These results suggest that the nine agricultural commodity and crude oil prices in all three periods are integrated of order one, i.e. they are stationary in first differences.

Based on the unit root test results we proceed to determine the lag length, n. The most common procedure is to estimate a vector autoregression using the undifferenced data, and then to use the same lag length tests as in a traditional VAR. In STATA we determine the lag length using the Schwarz Information Criterion and Akaike Information Criterion. Both information criterions suggest the optimal lag length of one for all three periods (a maximum of 4 lags was considered).

In a second step, we examine whether there exist cointegrating vectors among the nine agricultural commodity price series and crude oil. We test for cointegration between world market prices for crude oil and each of the nine commodities using the likelihood ratio and trace tests, both of which determine the cointegration rank,

r. The obtained trace and Max-eigenvalue, $\lambda_{\max}$, statistics of the cointegration rank tests are reported in Tables 6-8. According to Table 6, the Johansen cointegration test results suggest that there are no cointegration relationships in the first period (1994-1998). Both the trace and Max-eigenvalue, $\lambda_{\max}$, statistics of the cointegration rank tests are lower than the critical values at 10% significance already at the first instance ($r = o$).

The test results are different for the second period (1999-2003), where both the trace and the likelihood ratio tests reject the absence of cointegration relation between crude oil and corn, and crude oil and soybeans price series at 10% significance level, which implies the presence of a cointegration relationship between prices for crude oil and corn, and crude oil and soybeans (Table 7). These results are in line with *Campiche et al* (2007), who find that corn prices and soybean prices were cointegrated with crude oil prices in the period 2006-2007. For the other seven agricultural commodities (wheat, rice, sugar, cotton, banana, sorghum and tea) both Johansen cointegration tests reject the presence of a cointegrating vector with crude oil. These results are consistent with findings of *Yu*, *Bessler* and *Fuller* (2006), who examined the relationship between crude oil prices and vegetable oils for biodiesel production (soybean, sunflower, rapeseed and palm oil), and found only one cointegrating vector among the four examined vegetable oil and crude oil prices for the period 1999-2005.

The cointegration test results are even more different for the third period (2004-2008). According to the likelihood ratio test statistics (Table 8), all nine agricultural commodity prices and crude oil prices contain a cointegrating vector. However, the trace test statistics in Table 8 rejects the presence of a cointegrating vector for rice, cotton and banana prices with crude oil prices at the 10% significance level. The presence of a cointegration relationship between the crude oil and agricultural commodities prices suggest that these series tend to move towards an equilibrium relationship in the long-run. These results are in line with *Hameed* and *Arshad* (2008), who investigate the long-term relationship between the prices for petroleum and vegetable oils prices (palm, soybean, sunflower and rapeseed oil), and find a long-run equilibrium relationship between the petroleum and palm, soybean, sunflower and rapeseed oil prices.

In general, the results reported in Tables 5-7 are perplexing. A higher significance of the price interdependencies in the third period compared to the first period indicate a presence of the direct biofuel channel of price transmission. Biofuel production expanded significantly in the last years, which has affected the inter-linkages between fuel and agricultural prices. These results are consistent with the theoretical results shown in tables 1 and 2, where the calibrated elasticities with biofuel production

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(columns 9 and 11) are higher than without (columns 10 and 12). However, the absence of price interdependencies in the first period (1994-1998) is perplexing. In this period, when the biofuel sector was relatively small and likely has not affected other markets, the fuel price and agricultural prices are expected to be interlinked only through the indirect input channel. The empirical results indicate that the indirect input channel of price transmission is small and statistically insignificant. This could be due to the fact that we analyse world agricultural prices which are also affected by production in less developed countries. These countries tend to use less fuel based inputs (e.g. machinery, fertilisers), but more labour intensive technologies. This is consistent with the underlying theoretical framework (Table 1, models 7 and 8), where price transmission elasticities decrease in the relative importance of fuel in agricultural inputs employed in agricultural production.

The fact that corn and soybeans, which are among the key agricultural commodities used for biofuel production, are cointegrated with oil in the second and third period (1999-2003) (Table 7), while the remaining commodities are cointegrated only in the third period (2004-2008) (Table 8), may indicate a delayed price transition particularly for non-biofuel agricultural commodities. As shown in section 2, biofuels affect non-biofuel agricultural commodities through prices for agricultural factors (e.g. land, labour). The expansion of biofuels induces higher production of biofuel agricultural commodities (e.g. corn, soybeans), which in turn increase agricultural factor prices. Higher factor prices then increase the prices of non-biofuel agricultural commodities. The delayed price transitions may be a result of various institutional and market rigidities present on rural factor markets (e.g. land rental contracts; constrained access to capital). First, biofuel agricultural commodities respond to biofuels, and then, after adjustments in the factor markets, other commodities follow.

Finally, in order to identify a structural model and determine whether the estimated model is reasonable, we perform innovation accounting and causality tests on the error-correction model of (9). The Granger causality tests suggest long run unidirectional causality from oil price to agricultural commodity prices. However, the tests deny the presence of a similar relation in the opposite direction. The coefficients of the error-correction term are highly significant, suggesting that the error-correction term acts as a significant force, which causes the integrated variables to return to their long run relation when they deviate from it in all the cases. Furthermore, the magnitudes of the error correction term indicate that it tends to correct the deviation at a low speed. Based on these results we cannot reject the underlying theoretical model (section 2).[30]

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[30] Apart from the conventional linear Granger test we apply a new nonparametric test for nonlinear

The impulse response functions are reported in Figure 4 4: impulse oil, response agricultural commodities, and Figure 5: impulse agricultural commodities, response oil. The impulse response results suggest that all agricultural commodity prices are affected by energy prices, including those that are not directly used for bioenergy production. Second, the impact of a positive oil price shock on agricultural commodities is considerably larger than vice versa. In nominal terms (changes in prices, USD) the largest long-run impact of a positive oil price shock (ca. 26 USD/barrel) is on soybeans prices (ca. 25 USD/tonne) (Figure 4). In value terms the impact is smaller on wheat, corn and rice markets (around 10 USD/tonne). The smallest response is estimated on the tea, banana, cotton, and sugar markets. These results are in line with the underlying conceptual framework (section 2)[31] and previous studies (*Campiche et al* 2007, *Hameed* and *Arshad* 2008, and *Yu, Bessler* and *Fuller* 2006. The oil price response on agricultural commodity price shocks is insignificant (Figure 5).

The impulse response analysis results allow us to calculate the long run (ca 3 years) price transmission elasticities (Table 9). Generally, the price elasticities of agricultural commodities with respect to oil (top panel) are larger than the elasticities of oil with respect to agricultural commodities (bottom panel). The transmission elasticity of agricultural commodities with respect to oil is strictly positive: fuel price increases all nine agricultural commodity prices. The size of the response depends, among others, on the size of biofuel demand for agricultural commodities and on the relative importance of fuel in agricultural cost input structure. Our findings suggest that the price transmission elasticity is higher for those agricultural goods, which are also used for bioenergy production (sugar, soybeans, corn and wheat). According to the underlying conceptual framework, this may occur due to differences in production technologies between agricultural commodities. The magnitude of the estimated elasticities ranges between 0.05 and 0.30 and is the same range as in *Rahim, Zariyawati* and *Shahwahid* (2008), who estimate the long-run price elasticities for rice and soybeans 0.16 and 0.32, respectively. Our estimated elasticities, although slightly higher, are also consistent with the elasticities found in simulation studies using the Computable General Equilibrium (CGE) models. For example, in the study of *Birur, Hertel* and *Tyner* (2008), the elasticities vary between 0.01 and 0.11. Grains, oilseeds

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causality by Diks and Panchenko after controlling for cointegration. In addition to the traditional pairwise analysis, we test for causality while correcting for the effects of the other variables. The results are similar and therefore not reported.

[31] The theoretical elasticities in tables 1 and 2 show relatively high values for the causality from oil price to agricultural commodity prices (table 1) and small values (close to zero) for the causality in reverse direction (table 2).

and sugar cane have the elasticity between 0.04 and 0.11. For other agricultural commodities, the elasticities range between 0.01 and 0.10. The simulation results of *Chantret* and *Gohin* (2009) suggest the elasticity for wheat between 0.01 and 0.03.[32] The estimated elasticities (Table 9) are also in line with the theoretically predicted elasticities (Table 1) in term of the sign but are lower in terms of the magnitude. In the theoretical model we assumed perfect market adjustments. In reality, however, market rigidities and market imperfections may reduce or delay price adjustments.[33] Therefore, the theoretical elasticities in Table 1 can be considered as an upper bound.

The estimated elasticities of oil price with respect to agricultural commodity prices are considerably smaller and for two products (cotton and tea) even negative (bottom panel in Table 9). Several reasons might be responsible for these results. First, because the share of agricultural fuel consumption and the biofuel production is relatively small in the total fuel consumption. Second, because the theoretical impact of agricultural prices on the price of fuel is ambiguous: the causality between agricultural prices and fuel price through both direct and indirect channels of price transmission could be positive or negative (section 2).

4   Conclusions

The present paper studies the interdependencies between the energy, bioenergy and food prices. First, we develop a vertically integrated partial equilibrium model to theoretically study the interdependencies between the fuel price and agricultural prices. The theoretical model builds on the previous work of *Gardner* (2007) and de *Gorter* and *Just* (2008, 2009). In contrast to previous studies, we model two channels of price transmission: a direct biofuel channel and an indirect input channel. Among others, we show that the impact of fuel price on agricultural prices is stronger with than without biofuel production. Second, we apply time-series analytical mechanisms to nine major traded agricultural commodity prices, including corn, wheat, rice, sugar, soybeans, cotton, banana, sorghum and tea, along with one weighted average world crude oil price for the period 1994-2008. In order to account for structural breaks, we segment the price series into three equally sampled periods: 1994-1998, 1999-2003 and 2004-2008. The main objective is to identify the indirect input channel and the direct biofuel channel of price transmission. The interdependencies between fuel price

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[32]Note that *Birur*, *Hertel* and *Tyner* (2008) and *Chantret* and *Gohin* (2009) do not report price elasticities. We have calculated the elasticities based on the reported percentage price changes for agricultural commodities and crude oil.

[33]For example, *Saitone*, *Sexton* and *Sexton* (2008) show that market power in the processing sector may reduce price adjustments on the agricultural markets.

and agricultural prices is expected to be stronger in particular in the third period due to the expansion biofuels in this period.

Our empirical findings confirm the theoretical hypothesis that energy prices do affect prices for agricultural commodities and the interdependencies between the energy and food markets are increasing over time. Whereas we did not find any cointegration relationships in the first period (1994-1998), in the second period (1999-2003), we found that out of nine agricultural commodity prices only corn, soybeans are cointegrated with crude oil prices. However, the co-integration is weaker (less present) than theoretically predicted, which indirectly indicates that the indirect input channel of price transmission is small and statistically insignificant. In the third period (2004-2008) we found that the prices for all nine agricultural commodities are cointegrated with crude oil prices indicating a presence of the direct biofuel channel. The causality tests suggest that there is a long-run Granger causality from oil to agricultural commodity prices, but not vice versa. Based on the innovation accounting results, we calculate the long-run prise transmission elasticities. The impulse response analysis results suggest that all agricultural commodity prices are affected by energy prices, including those that are not directly used for bioenergy production. The impact of a positive oil price shock on agricultural commodities is considerably larger than vice versa. The magnitude of the long-run price transmission elasticities varies between 0.05 and 0.30 (or the fuel price increase by 1 dollar/barrel increases agricultural commodity prices between 0.10 \$/tonne and 1.50 \$/tonne).

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5   Appendix

5.1   Model assumptions and parameter values

The data used to calibrate the model are shown in Table 3. We use two values (upper and lower bound) for each key parameter to analyse the sensitivity of the results. We proxy the *share of fuel on total farm costs* with the cost share of energy in total agricultural cost structure. The energy cost (e.g. fuel, electricity) share varies

significantly across regions. Particularly strong difference is between developed and developing countries. *OECD* (2000) estimates the cost share of energy for the US equal to 0.08. Based on the calculation from the *FADN* (2009) the energy cost share varies between 0.04 and 0.13 in EU Member States. The energy also enters indirectly in agriculture particularly through fertilisers and pesticides. *OECD* (2000) estimates the cost share of fertilisers and chemicals at 0.14 for EU and 0.17 for the US. According to *FADN* (2009) the share of fertilisers and crop protection inputs varies between 0.03 and 0.14 among EU Member States. We use the parameter equal to 0.15 as lower bound and 0.3 as upper bound in the model.

The most commonly used values for *food demand elasticities* in the literature vary between -0.1 and -0.7 (e.g. *Floyd* 1965; de *Crombrugghe*, *Palm*, and *Urbain* 1997; *OECD* 2000; *Ciaian* and *Swinnen* 2009). We use the elasticity -0.5 for the lower bound. The size of the elasticity in terms of whether the food demand is elastic or inelastic has important implication for the results. For this reason the upper value was set to -1.5. For the by-product demand elasticity we assume a value equal to -1.0. We do not perform sensitivity analyses with the by-product demand elasticity.

We use *land supply elasticity* of 0.2 and 1.5. In empirical studies the land supply elasticity is usually found to be rather low, mostly due to natural constraints. For example, based on an extensive literature review *Salhofer* (2001) concludes that a plausible range of land supply elasticity for the EU is between 0.1 and 0.4. Similarly, *Abler* (2001) finds a plausible range between 0.2 and 0.6 for the US, Canada and Mexico. However, *FAO* (2008) reports a substantial amount of additional land - up to 2 billion hectares - potentially suitable for crop production. *Fischer* (2008) estimates that between 250 and 800 million hectares are potentially available for expanded crop production after excluding forest land, protected areas and land needed to meet increased demand for food crops and livestock. We use relatively high upper value of the land supply elasticity (1.5) also because the land input is a proxy for all non-fuel inputs in our model. Supply elasticities of non-fuel and non-land inputs vary widely: between 0.1 and 3 (*Balcombe* and *Prakash* 2000; *Floyd* 1965; *OECD* 2000; *Thijssen* 1988), because it covers a wide range of inputs (e.g. fertilisers, labour), which have various reactions to prices.

We base our assumption regarding the *non-agricultural fuel demand elasticity* on the studies which estimate the demand elasticity for all sectors in the economy. Studies estimating the elasticity separately for non-agricultural fuel demand are not available. The estimated values lie between -2.0 to 0.3, but most studies place the this number between -1.0 and 0.0 (e.g. *Brons et al.* 2006; *Hemery* and *Rizet* 2007; *Krichene* 2002; *Greene*, *Jones* and *Leiby* 1995; *Pindyck* 1979). We use non-agricultural

fuel demand elasticity in the model equal to -0.5 and -1.5.

The estimates of the *fossil fuel supply elasticity* vary in the literature between -0.40 and 1.0 (*Krichene* 2002; *Greene*, *Jones* and *Leiby* 1995; *Ramcharran* 2002; *Reynolds* 2002). There is evidence that OPEC countries have negative elasticity explained by the target revenue hypothesis accompanying the backward-bending supply curve, while non-OPEC countries show positive supply elasticity (*Ramcharran* 2002). In general, the short-run elasticities of fossil fuel demand and supply are very small relative to their long-run elasticity. The long-run fuel market elasticities are about ten times greater than short-run elasticities (*Huntington* 1991; 1994; *Greene*, *Jones* and *Leiby* 1995; *Krichene* 2002). We use fossil fuel supply elasticity equal to 0.3 as lower bound and 1.00 as upper bound.

Table 1: Calibrated price transmission elasticities of agricultural prices with respect to fuel price

Model	Model assumptions (Parameters from the literature)							Calibrated elasticities			
								Fuel⇒Biomass		Fuel⇒Food	
	μ^{AB}	μ^{AN}	μ^{NF}	ε^F	ε^N	α^{AB}	α^{AN}	$S^B=0$	$S^B>0$	$S^B=0$	$S^B>0$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1	-0.50	-0.50	-0.50	0.30	0.20	0.30	0.30	0.41	1.29	0.41	1.29
2	**-1.50**	-0.50	-0.50	0.30	0.20	0.30	0.30	0.29	1.02	0.29	1.02
3	-0.50	**-1.50**	-0.50	0.30	0.20	0.30	0.30	0.29	1.00	0.29	1.00
4	-0.50	-0.50	**-1.50**	0.30	0.20	0.30	0.30	0.42	0.83	0.42	0.83
5	-0.50	-0.50	-0.50	**1.00**	0.20	0.30	0.30	0.42	0.90	0.42	0.90
6	-0.50	-0.50	-0.50	0.30	**1.50**	0.30	0.30	0.34	0.77	0.34	0.77
7	-0.50	-0.50	-0.50	0.30	0.20	**0.15**	0.30	0.25	0.93	0.38	0.94
8	-0.50	-0.50	-0.50	0.30	0.20	0.30	**0.15**	0.38	0.85	0.25	0.82

Notes: μ^{AB} - biomass demand elasticity; μ^{AN} - food demand elasticity; μ^{NF} - non-agricultural fuel demand elasticity, ε^F - fossil fuel supply elasticity, ε^N - land supply elasticity, α^{AB} - fuel elasticity in biomass production function, α^{AN} - fuel elasticity in food production function, S^B - biofuel production. Further model assumptions: share of biofuel production in total fuel production = 0.8%; share of agricultural fuel demand in total fuel demand = 3.3%; share of biomass used for biofuels in total biomass production = 3.3%; share of land used for biomass production in total land use = 48.5%; share of land used for biofuels in agricultural land use = 1.6%. See Appendix for literature sources of model parameters.

Table 2: Calibrated price transmission elasticities of fuel price with respect to agricultural prices

	Model assumptions							Calibrated elasticities			
	(Parameters from the literature)							Fuel⇒Biomass		Fuel⇒Food	
Model	μ^{AB}	μ^{AN}	μ^{NF}	ε^F	ε^N	α^{AB}	α^{AN}	$S^B = 0$	$S^B > 0$	$S^B = 0$	$S^B > 0$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1	-0.50	-0.50	-0.50	0.30	0.20	0.30	0.30	0.02	0.05	0.02	0.05
2	**-1.50**	-0.50	-0.50	0.30	0.20	0.30	0.30	0.00	0.04	0.00	0.04
3	-0.50	**-1.50**	-0.50	0.30	0.20	0.30	0.30	-0.001	0.03	-0.001	0.03
4	-0.50	-0.50	**-1.50**	0.30	0.20	0.30	0.30	0.01	0.03	0.01	0.03
5	-0.50	-0.50	-0.50	**1.00**	0.20	0.30	0.30	0.01	0.03	0.01	0.03
6	-0.50	-0.50	-0.50	0.30	**1.50**	0.30	0.30	0.02	0.05	0.02	0.05
7	-0.50	-0.50	-0.50	0.30	0.20	**0.15**	0.30	0.02	0.06	0.02	0.06
8	-0.50	-0.50	-0.50	0.30	0.20	0.30	**0.15**	0.02	0.06	0.02	0.06

Notes: μ^{AB} - biomass demand elasticity; μ^{AN} - food demand elasticity; μ^{NF} - non-agricultural fuel demand elasticity, ε^F - fossil fuel supply elasticity, ε^N - land supply elasticity, α^{AB} - fuel elasticity in biomass production function, α^{AN} - fuel elasticity in food production function, S^B - biofuel production. Further model assumptions: share of biofuel production in total fuel production = 0.8%; share of agricultural fuel demand in total fuel demand = 3.3%; share of biomass used for biofuels in total biomass production = 3.3%; share of land used for biomass production in total land use = 48.5%; share of land used for biofuels in agricultural land use = 1.6%. See Appendix for literature sources of model parameters.

Table 3: Data description and sources

Variable	Value	Unit	Coverage	Year	Source
Agricultural area	1411	Million ha	World	2007	FAOSTAT[1]
Land used for biomass crops	684	Million ha	World	2004	FAOSTAT[2]
Land used for biofuels	23	Million ha	World	2007	IEA (2006), OECD (2009)
Land used for food commodity	1046	Million ha	World	2007	Calculated[3]
Total agricultural production	2030	Billion USD	World	2007	UN[4]
Biomass production	983	Billion USD	World	2007	Calculated[5]
Biomass production in food use	951	Billion USD	World	2007	Calculated[6]
Biomass production in biofuel use	33	Billion USD	World	2007	Calculated[7]
Food commodity production	1046	Billion USD	World	2007	Calculated[8]
By-product production	10	Billion USD	World	2007	Calculated[9]
Fossil fuel supply	30390	Million barrels	World	2007	IEA (2009)[10]
Biofuel production	257	Oil equivalent	World	2007	FAO (2008)[11]
Agricultural fuel demand	1053	Million barrels	World	2007	Calculated[12]
Non-agricultural fuel demand	30594	Million barrels	World	2007	Calculated[13]
Biofuel extraction coefficient	7.8	Ratio	World	2007	Calibrated[14]
By-product extraction coefficient	17/56=0.30	Ratio	US	-	RFA (2008)[15]

Notes: [1]Agricultural area is proxied with the world arable area; [2]Total area of main biofuel crops; [3]Total agricultural area minus land used for biomass; [4]Proxied by the estimated value added of agriculture, hunting, forestry, fishing; [5]The share of land used for biomass crops multiplied by the total agricultural production; [6]The share of land used for biomass for food multiplied by the biomass production; [7]The share of land used for biofuels multiplied by the biomass production; [8]The share of land used for food commodity multiplied by the total agricultural production; [9]By-product extraction coefficient (0.3) multiplied by the biomass production used for biofuels; [10]Proxied with the total world oil demand in 2007 (36.12 Mtoe) with the barrel conversion factor (7.11); [11]The value was obtained by multiplying world biofuel production in 2007 by 365; [12]The share of the estimated value added of agriculture, hunting, forestry, fishing on total value added multiplied with total fuel; [13]The share of the estimated value added of the rest of the economy on total value added multiplied with total fuel; [14]Biofuel production multiplied by biomass production used for biofuels; [15]According to RFA (2008) each 56-pound bushel of corn processed by a dry mill results in approximately 17 pounds of distillers grains and 2.8 gallons of fuel ethanol.

Table 4: ADF unit root test results for prices of crude oil and agricultural commodities

Prices	1994-1998		1999-2003		2004-2008	
	Level	FD	Level	FD	Level	FD
Corn	-2.55	-9.08 †††	-2.16	-10.34 †††	-2.85	-9.91 †††
Wheat	-2.64	-9.56 †††	-2.11	-8.89 †††	-3.07	-9.74 †††
Rice	-2.35	-9.60 †††	-2.13	-10.43 †††	-2.80	-10.60 †††
Sugar	-1.55	-9.56 †††	-2.81	-10.41 †††	-2.28	-9.75 †††
Soybeans	-3.02	-10.42 †††	-2.03	-10.20 †††	-2.21	-10.25 †††
Cotton	-1.71	-9.86 †††	-2.95	-10.44 †††	-2.29	-9.97 †††
Banana	-2.12	-9.04 †††	-2.33	-9.79 †††	-3.00	-9.83 †††
Sorghum	-2.39	-9.95 †††	-1.61	-9.97 †††	-2.54	-10.96 †††
Tea	-1.67	-9.75 †††	-1.67	-9.55 †††	-1.91	-9.66 †††
Crude oil	-1.93	-12.66 †††	-1.57	-15.06 †††	-1.56	-15.36 †††

Notes: Augmented Dickey-Fuller test results, ††† significant at 1% level. Critical Values: -4.00 (1%), -3.43 (5%), -3.14 (10%). FD: First Differences.

Table 5: PP unit root test results for prices of crude oil and agricultural commodities

Prices	1994-1998		1999-2003		2004-2008	
	Level	FD	Level	FD	Level	FD
Corn	-3.06	-9.12 †††	-2.25	-10.98 †††	-1.95	-10.64 †††
Wheat	-2.65	-10.37 †††	-2.73	-10.89 †††	-2.68	-9.31 †††
Rice	-1.86	-10.69 †††	-2.21	-8.75 †††	-2.09	-9.97 †††
Sugar	-2.11	-10.03 †††	-1.52	-8.76 †††	-1.69	-9.30 †††
Soybeans	-1.51	-8.88 †††	-1.70	-8.97 †††	-2.61	-9.71 †††
Cotton	-2.80	-9.97 †††	-3.02	-10.57 †††	-2.91	-9.81 †††
Banana	-2.06	-9.05 †††	-1.89	-9.52 †††	-1.74	-10.62 †††
Sorghum	-3.05	-9.55 †††	-1.82	-10.86 †††	-1.47	-10.05 †††
Tea	-1.76	-10.61 †††	-2.16	-10.46 †††	-1.76	-9.14 †††
Crude oil	-2.35	-10.88 †††	-2.31	-12.95 †††	-1.45	-13.94 †††

Notes: Phillips Perron test results, ††† significant at 1% level. Critical Values: -4.10 (1%), -3.43 (5%), -3.17 (10%). FD: First Differences.

Table 6: Johansen cointegration test results for crude oil and food prices, 1994 - 1998

		L-max Test			Trace Test	
	$H_o:$	$r=0$	$r=1$	$H_o:$	$r=0$	$r=1$
Corn - crude oil		$4.70^{\dagger}$	2.56		$6.46^{\dagger}$	2.05
		(0.051)	(0.006)		(0.037)	(0.005)
Wheat - crude oil		$4.13^{\dagger}$	2.08		$5.72^{\dagger}$	1.67
		(0.010)	(0.010)		(0.071)	(0.011)
Rice - crude oil		$7.02^{\dagger}$	1.44		$7.10^{\dagger}$	2.37
		(0.020)	(0.015)		(0.118)	(0.010)
Sugar - crude oil		$4.41^{\dagger}$	2.03		$6.15^{\dagger}$	2.17
		(0.035)	(0.009)		(0.055)	(0.009)
Soybeans - crude oil		$7.02^{\dagger}$	1.48		$5.98^{\dagger}$	1.42
		(0.035)	(0.006)		(0.025)	(0.005)
Cotton - crude oil		$7.04^{\dagger}$	2.05		$7.54^{\dagger}$	2.58
		(0.020)	(0.005)		(0.059)	(0.009)
Banana - crude oil		$6.33^{\dagger}$	2.72		$6.01^{\dagger}$	2.80
		(0.023)	(0.013)		(0.050)	(0.009)
Sorghum - crude oil		$5.42^{\dagger}$	1.59		$8.58^{\dagger}$	1.82
		(0.017)	(0.008)		(0.023)	(0.006)
Tea - crude oil		$5.91^{\dagger}$	1.73		$6.44^{\dagger}$	1.62
		(0.035)	(0.006)		(0.019)	(0.004)

Notes: Johansen (1988, 1991) L-max and Trace test statistics. r=0 - no cointegration relationship; r=1 - at most one cointegration relationship. Critical values at 10% significance level are 10.60 (r=0) and 2.71 (r=1) for the L-max test and 13.31 (r=0) and 2.71 (r=1) for the Trace test. Asymptotic significance level (p-values) in parenthesis. † denotes failure to reject the hypothesis at the 10% level.

Table 7: Johansen cointegration test results for crude oil and food prices, 1999 - 2003

		L-max Test			Trace Test	
	$H_o:$	$r = 0$	$r = 1$	$H_o:$	$r = 0$	$r = 1$
Corn - crude oil		12.78	$1.41^{\dagger}$		14.13	$1.76^{\dagger}$
		(0.060)	(0.014)		(0.038)	(0.004)
Wheat - crude oil		$7.40^{\dagger}$	2.25		$6.17^{\dagger}$	1.45
		(0.019)	(0.005)		(0.015)	(0.009)
Rice - crude oil		$6.31^{\dagger}$	2.01		$6.58^{\dagger}$	1.64
		(0.025)	(0.011)		(0.016)	(0.025)
Sugar - crude oil		$7.26^{\dagger}$	1.94		$6.17^{\dagger}$	2.34
		(0.034)	(0.019)		(0.018)	(0.028)
Soybeans - crude oil		12.50	$2.05^{\dagger}$		13.51	$2.39^{\dagger}$
		(0.070)	(0.006)		(0.040)	(0.013)
Cotton - crude oil		$7.85^{\dagger}$	2.29		$6.18^{\dagger}$	1.89
		(0.080)	(0.008)		(0.030)	(0.005)
Banana - crude oil		$7.16^{\dagger}$	1.56		$7.07^{\dagger}$	1.46
		(0.024)	(0.019)		(0.027)	(0.017)
Sorghum - crude oil		$5.88^{\dagger}$	1.80		$6.75^{\dagger}$	2.17
		(0.022)	(0.011)		(0.101)	(0.043)
Tea - crude oil		$5.92^{\dagger}$	1.92		$7.15^{\dagger}$	2.27
		(0.015)	(0.006)		(0.083)	(0.014)

Notes: Johansen (1988, 1991) L-max and Trace test statistics. r=0 - no cointegration relationship; r=1 - at most one cointegration relationship. Critical values at 10% significance level are 10.60 (r=0) and 2.71 (r=1) for the L-max test and 13.31 (r=0) and 2.71 (r=1) for the Trace test. Asymptotic significance level (p-values) in parenthesis. † denotes failure to reject the hypothesis at the 10% level.

Table 8: Johansen cointegration test results for crude oil and food prices, 2004 - 2008

		L-max Test			Trace Test	
$H_o:$		$r = 0$	$r = 1$	$H_o:$	$r = 0$	$r = 1$
Corn - crude oil		16.03	$1.43^{\dagger}$		16.21	$1.63^{\dagger}$
		(0.056)	(0.004)		(0.040)	(0.005)
Wheat - crude oil		15.44	$1.62^{\dagger}$		14.31	$1.82^{\dagger}$
		(0.039)	(0.008)		(0.064)	(0.007)
Rice - crude oil		13.18	$1.29^{\dagger}$		$13.09^{\dagger}$	1.62
		(0.055)	(0.005)		(0.040)	(0.008)
Sugar - crude oil		14.52	$1.44^{\dagger}$		15.71	$1.57^{\dagger}$
		(0.094)	(0.004)		(0.047)	(0.004)
Soybeans - crude oil		14.60	$1.92^{\dagger}$		15.96	$1.17^{\dagger}$
		(0.071)	(0.027)		(0.039)	(0.004)
Cotton - crude oil		12.18	$1.90^{\dagger}$		$12.99^{\dagger}$	1.37
		(0.078)	(0.033)		(0.180)	(0.016)
Banana - crude oil		12.75	$1.00^{\dagger}$		$12.92^{\dagger}$	1.69
		(0.107)	(0.003)		(0.034)	(0.008)
Sorghum - crude oil		12.35	$1.22^{\dagger}$		13.93	$1.64^{\dagger}$
		(0.060)	(0.022)		(0.125)	(0.011)
Tea - crude oil		12.01	$1.47^{\dagger}$		13.74	$1.60^{\dagger}$
		(0.054)	(0.011)		(0.138)	(0.008)

Notes: Johansen (1988, 1991) L-max and Trace test statistics. r=0 - no cointegration relationship; r=1 - at most one cointegration relationship. Critical values at 10% significance level are 10.60 (r=0) and 2.71 (r=1) for the L-max test and 13.31 (r=0) and 2.71 (r=1) for the Trace test. Asymptotic significance level (p-values) in parenthesis. † denotes failure to reject the hypothesis at the 10% level.

Table 9: Estimated long-run price transmission elasticities

Agricultural commodities with respect to oil

	Oil	Corn	Wheat	Rice	Sugar	Soybeans	Cotton	Banana	Sorghum	Tea
Average price, USD	47.834	126.610	164.737	306.882	218.500	272.583	1251.961	597.194	129.655	1662.241
Impulse, USD	26.112									
Response, USD		10.176	12.155	7.951	32.773	25.770	39.131	13.301	2.785	47.841
Unit response, USD		0.390	0.466	0.304	1.255	0.987	1.499	0.509	0.107	1.832
Elasticity		0.147	0.135	0.047	0.275	0.173	0.057	0.041	0.039	0.053

Oil with respect to agricultural commodities

	Oil	Corn	Wheat	Rice	Sugar	Soybeans	Cotton	Banana	Sorghum	Tea
Average price, USD	47.834	126.610	164.737	306.882	218.500	272.583	1251.961	597.194	129.655	1662.241
Impulse, USD		40.413	60.364	142.343	70.866	87.220	237.623	176.791	39.673	319.744
Response, USD		0.920	0.938	1.913	0.063	0.864	-0.191	0.120	0.925	-0.006
Unit response, USD		0.023	0.016	0.013	0.001	0.010	-0.001	0.001	0.023	0.000
Elasticity		0.060	0.053	0.086	0.004	0.056	-0.021	0.008	0.063	-0.001

Notes: Top panel - Impulse: Positive shock in oil price (one standard deviation) in USD/barell; response: changes in agricultural commodity prices in USD/tonne. Bottom panel - Impulse: Positive shock in agricultural prices (one standard deviation) in USD/tonne; response: changes in oil prices in USD/barell. Impulse in week 0, response in week 150.
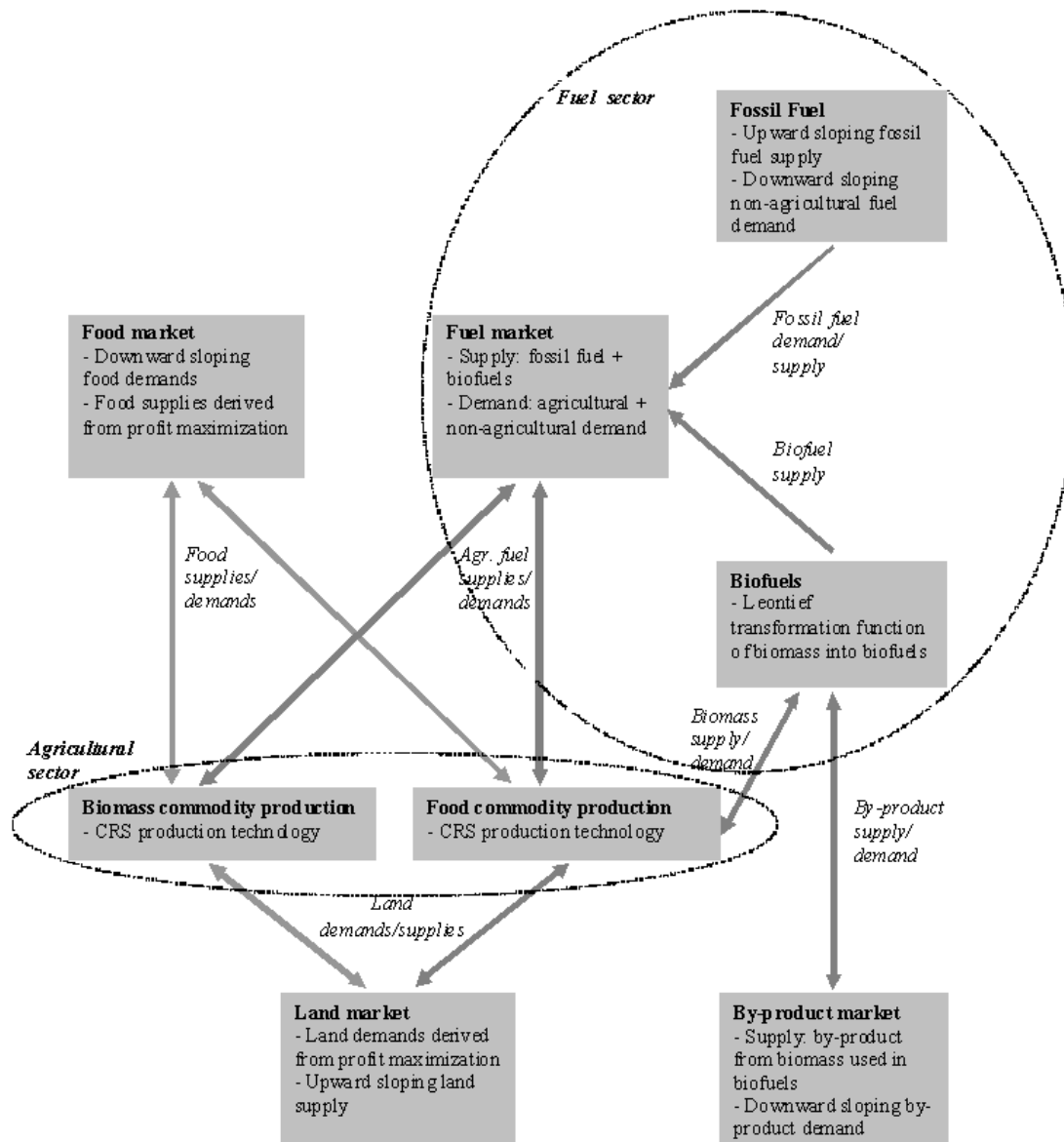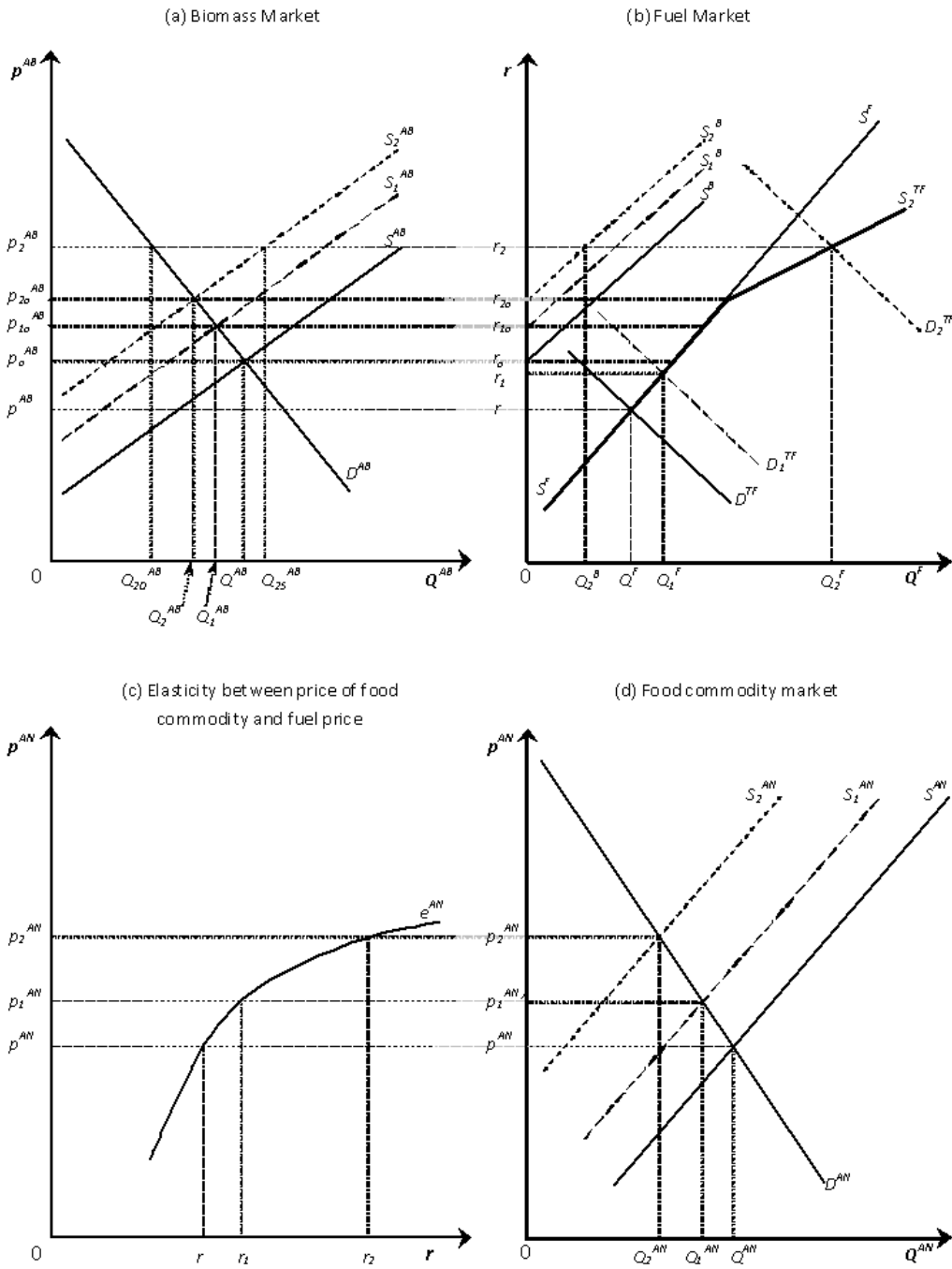
Figure 1: The structure of the model

(a) Biomass Market   (b) Fuel Market

(c) Elasticity between price of food commodity and fuel price   (d) Food commodity market

Figure 2: The effect of the non-agricultural fuel demand expansion

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(a) Biomass Market

(b) Fuel Market

(c) Elasticity between price of food commodity and fuel price

(d) Food commodity market
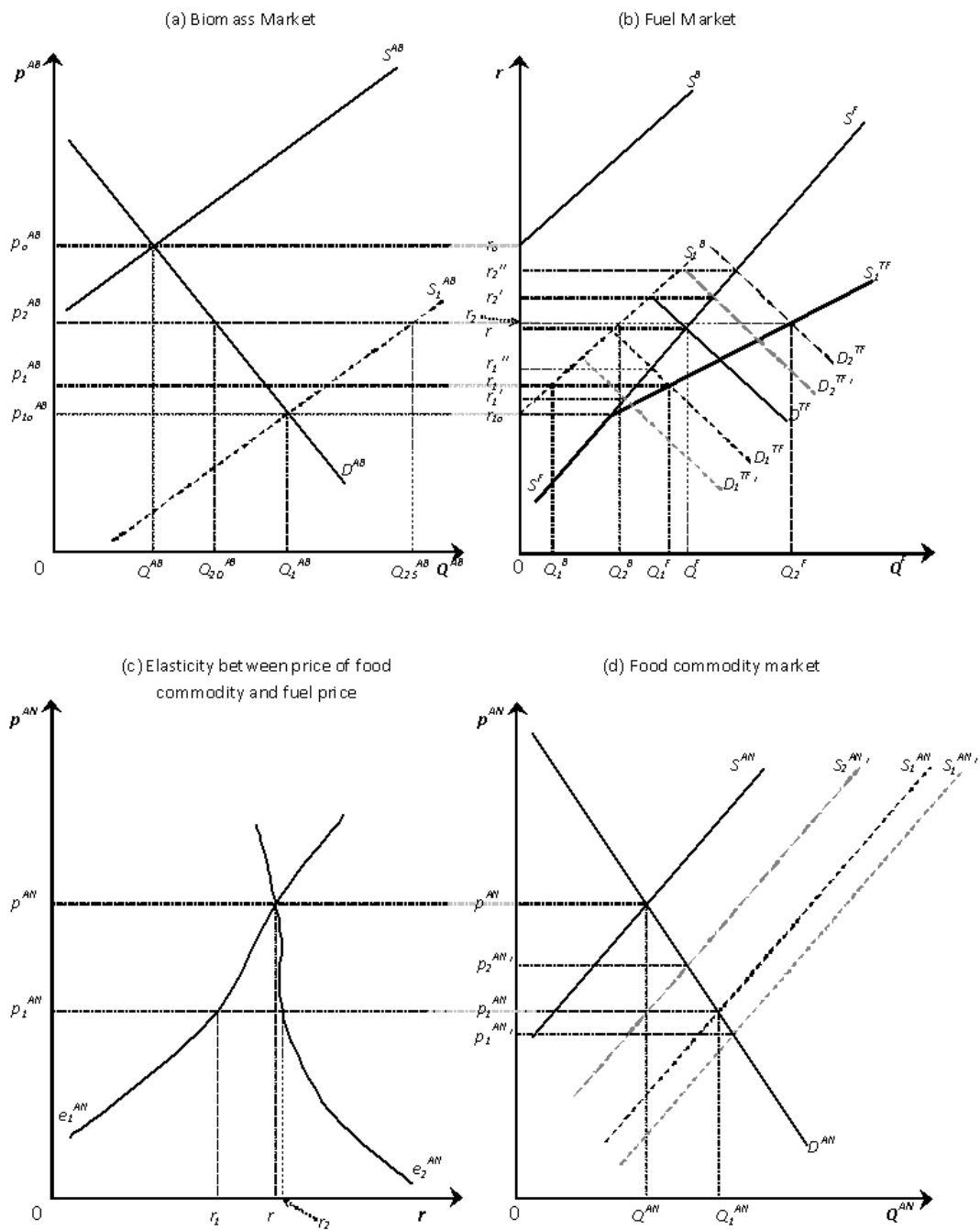
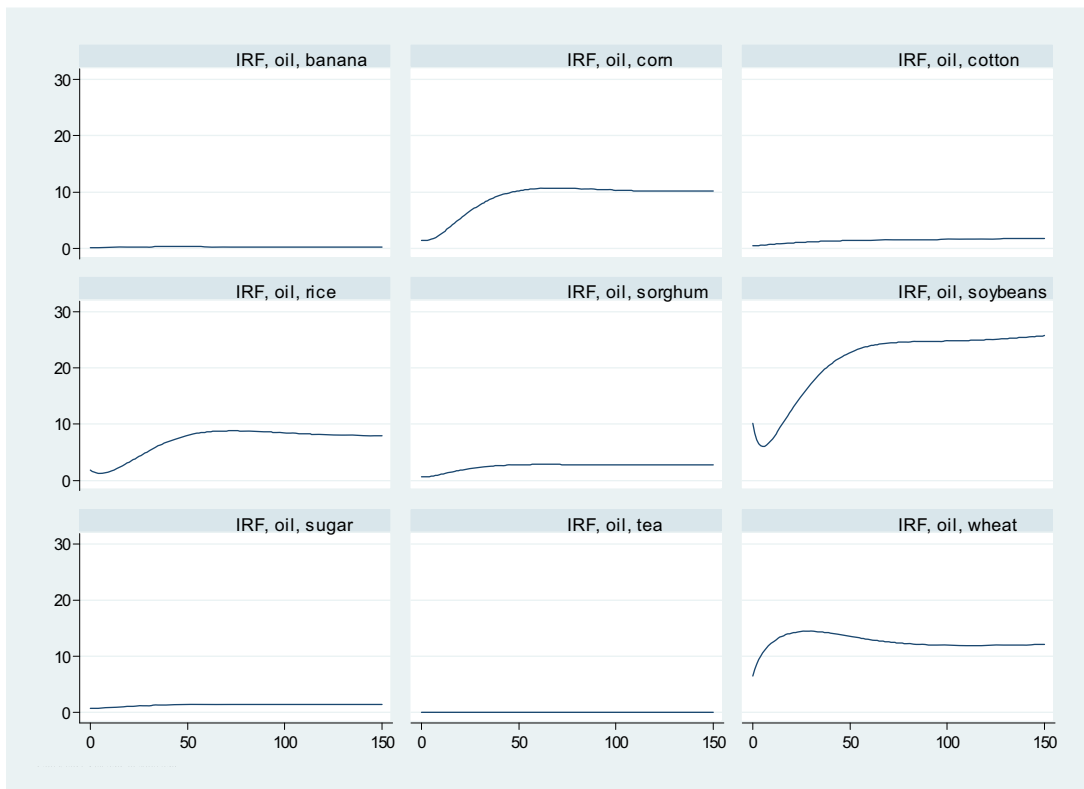Figure 3: The effect of a positive agricultural production shock

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Figure 4: Impulse response function (IRF) by agricultural commodity. Notes: Impulse: positive oil price shock (1 STD) in USD; response: changes in commodity prices over 150 weeks in USD
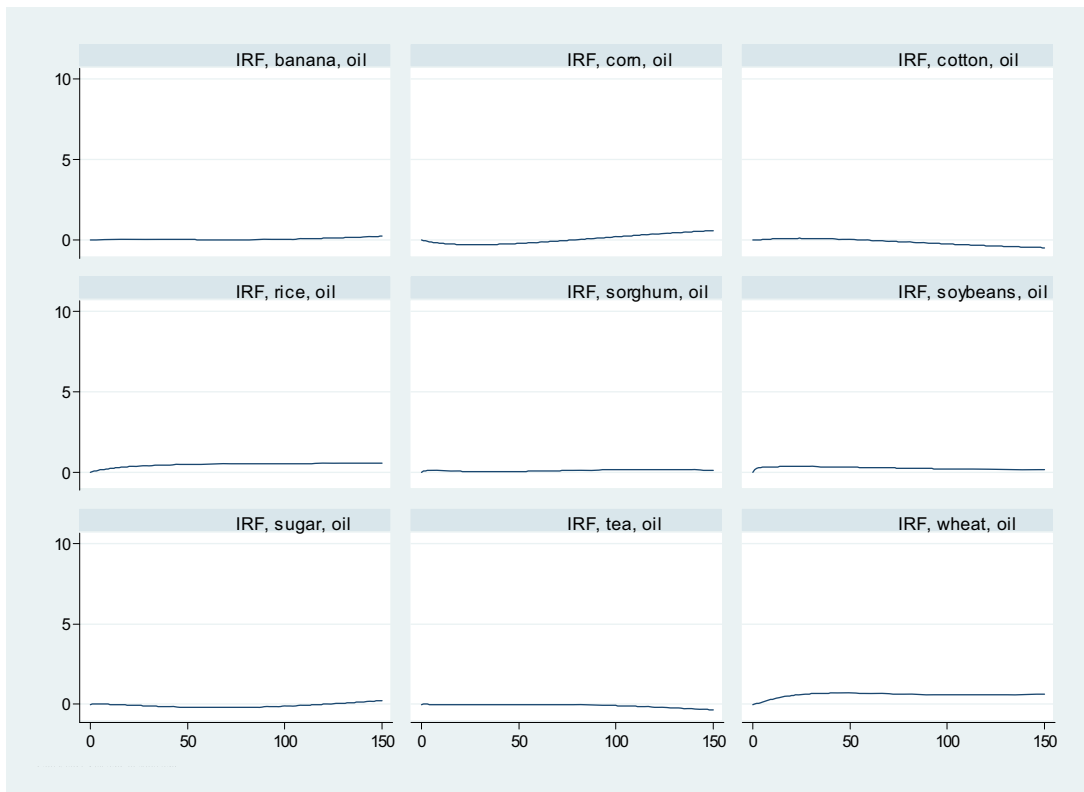
Figure 5: Impulse response function (IRF) by agricultural commodity. Notes: Impulse: positive agricultural price shock (1 STD) in USD; response: changes in oil prices over 150 weeks in USD