Impact of Multiple Volatilities in Bioenergy Investments

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Abstract

The paper investigates the effect of the output and input market volatilities on irreversible bioenergy investments in the absence of policy support schemes. The effects of different volatility sources on investment trigger are studied in a partial equilibrium model which represents the interplay of the global energy market and the local bioenergy and food markets. Volatilities are assumed to stem from normally distributed stochastic shocks to the global energy price and the local food demand. Bioenergy producers are assumed to have the possibility to suspend production if business conditions worsen. The equilibrium investment trigger of the aggregated bioenergy producer is derived in stochastic simulations in the framework of the real options approach. The results demonstrate that the positive correlation between the volatility and investment trigger, as known from the real options theory and financial markets, does not necessarily hold for real irreversible investment decisions which are simultaneously influenced by multiple volatilities. This is especially pronounced if the volatility on the input market is significantly higher than that on the output market or if both volatilities are high. Declining investment trigger indicates that in the case of high expected volatility investors may realize very high contribution margins which cover all investment cost in only few periods. In the following periods initial investments may be followed only by reinvestments or by no investments. The findings suggest that the more the energy and food markets are correlated, the more unpredictable the impact of rising volatility on investment decisions might be.

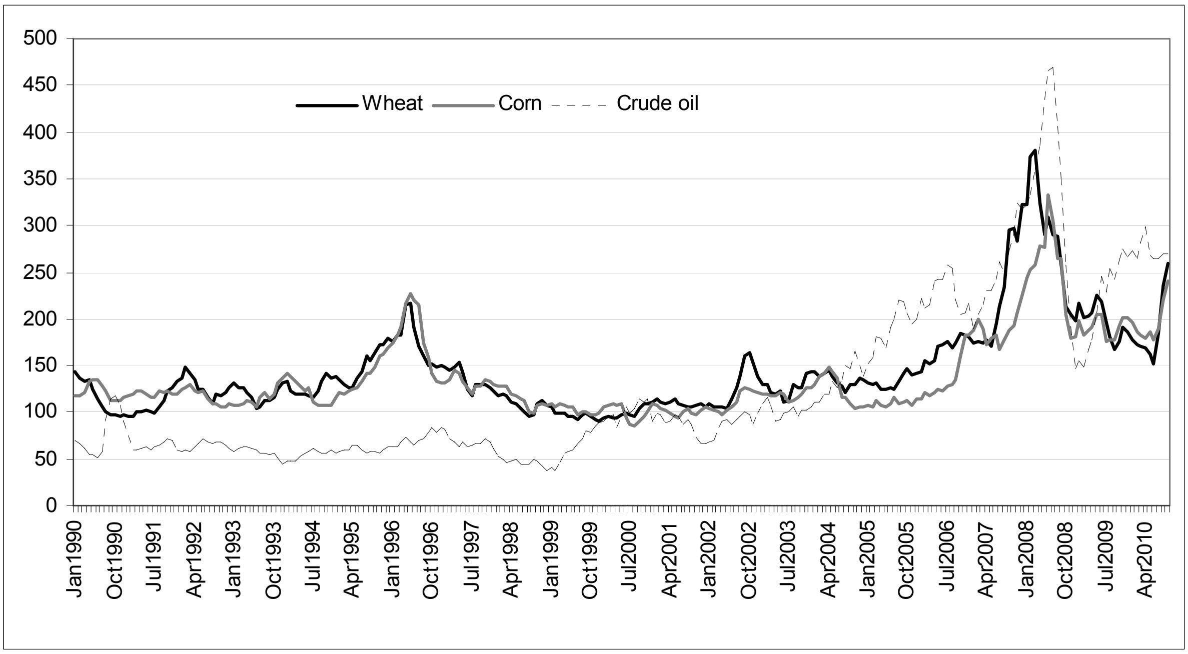
Keywords: bioenergy, uncertainty, real options approach, stochastic simulation

JEL Classification: D40, D81, Q41, Q42, Q48.

1. Introduction

The participation of agricultural sector in energy production has changed the interrelation between the energy and agricultural sector in a fundamental way. Until recently, energy and agricultural commodity prices used to have relatively low or even negative correlation (Tyner 2009)[1]. With the boost of bioenergy production in the years 2000-2005, prices for wheat, corn and many other agricultural goods reveal a strong correlation with energy prices (Gohin/Chantret 2010, Du et al. 2009, Rosegrant 2008). Indeed, as Figure 1 shows, the close link between crude oil prices and wheat and corn prices is a relatively recent phenomenon, and coincides with the start of the political promotion of bioenergy production in the USA and EU.

Figure 1: Price indices for wheat, corn and crude oil, 1960 – 2010, (2000=100)



Source: UNCTAD, UNCTADstat: Free market commodity price indices, monthly, January 1960 - September 2010.

Note: The year 2000 marks the beginning of politically promoted bioenergy production in the most participating countries. The agricultural commodity price peak of 2007/2008 is rather an unusual surge and owes mainly to the global macroeconomic factors (as e.g. depreciation of the US dollar and high growth rates in developing countries).

The increasing utilization of corn and wheat for bioenergy (bioethanol and biomethane) production has displaced the use of these crops for other purposes and enhanced the scarcity of agricultural land devoted to other crops. Such rededication of agricultural crops along with orientation of bioenergy producers on conventional energy prices has tightened the linkage

[1] Tyner (2009) demonstrates for the US ethanol market that the correlation between annual crude oil and corn prices, which used to be negative (-0.26) in the period 1988-2005, reached a positive value of 0.80 during the 2006-2008.

between energy and agricultural markets. It is therefore not surprising that the OECD/FAO Agricultural Outlook 2010-2019 considers this linkage as the most pronounced one among the new sources of agricultural price volatility[2].

Because of its relevance for agriculture, the issue of intersectoral volatility transmission has recently attracted much agricultural research. McPhail/Babcock (2008) found that the gasoline price volatility of 25% entails the volatility in the corn price of 17.5%. In a similar study Thompson et al. (2009) demonstrate that a 1%-increase in the crude oil price leads to a 0.31%-increase in the corn price. The significant part of the relevant literature is concerned with the effects of promoted bioenergy production on food prices. Hertel/Beckman (2010) arrive at the conclusion that in the presence of the renewable fuel standards (RFS) and binding blend quotas world price volatility is boosted by 25%, and the US coarse grains price volatility in response to corn supply shocks is 57% higher than in the absence of the RFS and blend quotas[3]. Similarly, Rosegrant (2008) estimates the impact of increasing bioenergy promotion to account for 30% of the increase in weighted average grain prices in 2007 compared to a hypothetical scenario without bioenergy promotion programs, whereat the biggest impact was on corn price (39%). As a direct effect of energy price volatility on bioenergy production, Hertel et al. (2010) estimate for the EU that increase in crude oil price during the period 2001-2006 accounted for about 2/5 of the expansion in biofuel production. This cursory overview of the recent studies suggests that price volatility of agricultural products, particularly those used for bioenergy feedstock, critically depends on the amount of bioenergy production. However, the simultaneous effect of oil price and feedstock volatilities on bioenergy investments (Serra et. al 2010) and effect of the latter on food prices in the absence of any policy support programs (as it is planned for the next decades) are less studied[4].

There are, therefore, at least two pressing reasons to closely study the effects of volatility transmissions on the interrelated markets. First, because of the prominence of food and energy in household budgets, large unpredicted shocks may entail economic crisis on the national and global levels. As most agricultural commodities are traded globally, the price and volatility transmission from the international to domestic markets became inevitable. Second, as bioen-

[2] OECD/FAO (2010), p. 54.

[3] The Renewable Fuel Standard (RFS) program from 2005 established the first binding renewable fuel volume in the United States. According to this standard, 7.5 billion gallons of renewable fuel are to be blended into gasoline by 2012.

[4] The urgency of answering these questions is reflected e.g. by the agenda of the Europe's largest biofuels congress *World Biofuels Markets* in 2011, where the impact of energy price and feedstock volatilities on biofuel production was one of the central topics (http://www.worldbiofuelsmarkets.com/bioenergy_finance_investment.html).

ergy production has already established new interdependences between the energy, bioenergy and food markets, it is likely to have a lasting grip on the food market after the liberalization of the bioenergy market.

2. Objectives of the study

The issue of the intersectoral price fluctuations and transmission is unquestionably manifold. In this paper we limit its examination to the questions of (1) how strategic investment decisions of bioenergy producers are influenced by the volatilities on the energy (output) market and the food (input) market, and (2) whether initial conditions on the interrelated markets have decisive impact on investment decisions. For this purpose we take irreversible cost-intensive investments in bioenergy in the absence of policy support programs as example.

To approach the formulated objectives, we employ a partial equilibrium model of the interplay of the global energy market and local bioenergy and food markets. The effect of changing volatilities on the input and output markets on investments in bioenergy is examined by using stochastic simulations in the framework of the real options approach (ROA). Volatilities are assumed to stem from normally distributed stochastic shocks to the global energy price and to food (proxied by corn) demand parameter.

The paper proceeds as follows. In the following section the general assumptions and the formal framework of the partial equilibrium model are presented; then section 4 introduces methodologies employed in the study, and section 5 discusses the simulation results. The reminder of the paper concludes with main findings and further research implications.

3. The model

3.1 General assumptions

The impact of intersectoral volatility transmissions on bioenergy investment decisions is analyzed in a partial equilibrium model. The model represents the interplay of three markets: the global energy market and the local bioenergy and food markets. The food market is represented by corn production. On the bioenergy market, there is an aggregate bioenergy producer representing the total number of bioenergy producers under perfect competition. The central assumption of the model is that bioenergy producers have the option to temporary suspend production and investments if business conditions worsen, and the suspension incurs no additional cost. Bioenergy production is based on using corn as the only substrate. We assume an absence of any support programs for bioenergy sector, so that bioenergy price is determined by the world energy price, which in turn is exogenous and varies stochastically. Bioenergy plants are subject to depreciation, so that reinvestments are needed to keep the production capacity constant; additional investments can increase production capacity. Investment outlays $Inv_{(t)}$ are irreversible (i.e. disinvestments are not possible) and variable. At the end of the period $t=0$, there is an initial investment which is based on the expected corn price and expected food demand in the next period. Bioenergy production starts in the period $t=1$. Plant size, investment outlay and production are proportional. For ease of exposition, we consider corn price as the only variable cost component of bioenergy production. Further we assume constant returns to scale in bioenergy production and market clearing on the bioenergy and corn markets. The direct energy use in bioenergy production neglected.

3.2 Food market

For the purpose of the model, corn production is seen as aggregated and limited by its maximum capacity (determined e.g. by the amount of arable land). The total corn supply $Q^S_{(t)c}$ is, therefore, exogenous and constant. Corn demand consists of two parts: corn demand for biomass (i.e. as input for bioenergy production) $Q^D_{(t)b}$ and corn demand for other uses $Q^D_{(t)f}$ (food and feed production):

$$Q^S_{(t)c} = Q^D_{(t)c} = Q^D_{(t)b} + Q^D_{(t)f} \tag{1}$$

$$\text{with } \; Q^D_{(t)f} = \frac{\varphi_{(t)}}{{p_{(t)c}}^{-\eta}} \tag{2}$$

where $\varphi_{(t)}$ is demand parameter, η demand elasticity, and $p_{(t)c}$ corn price.

The demand parameter $\varphi_{(t)}$ follows a geometric Brownian motion[5]. Assuming discrete time, the demand parameter can be modelled as:

$$\varphi_{(t)} = \varphi_{(t-\Delta t)} \cdot exp\left[(\mu_\varphi - \frac{\sigma_\varphi^2}{2}) \cdot \Delta t + \sigma_\varphi \cdot \varepsilon_{(t)\varphi} \cdot \sqrt{\Delta t}\right]. \tag{3}$$

with $\varphi_{(t)}$ as the expected demand parameter $\hat{\varphi}_{\,(t+\Delta t)}$, a drift rate μ_φ, volatility σ_φ, a normally distributed random number $\varepsilon_{(t)\varphi}$ and a time step length Δt. Time step Δt equals one period, and the drift is assumed to be zero. Such dynamic of the demand parameter implies that after the investment decisions are made, corn price will depend on the behavior of $\varphi_{(t)}$.

[5] The GBM is a process that describes the probability distribution of the future value of stochastic variables. The GBM assumes that over a longer period of time the relative (therefore *geometric*) time-discrete logarithmic changes (i.e. *motions*) in the value of the stochastic variable are normally distributed. The future changes of such variables are determined by present conditions alone and are independent of past movements (i.e. they follow a random walk). The present conditions consist of the drift (e.g. expected returns) of the variable and random shocks added to (or subtracted from) the drift.

3.3 Energy market

The energy market is represented by the exogenous energy price $p_{(t)e}$. We assume that energy price follows the geometrical Brownian motion (GBM) with no drift ($\mu_e = 0$):

$$p_{(t)e} = p_{(t-\Delta t)e} \cdot exp\left[(\mu_e - \frac{\sigma_e^2}{2}) \cdot \Delta t + \sigma_e \cdot \varepsilon_{(t)e} \cdot \sqrt{\Delta t}\right]. \quad (4)$$

The energy market is not influenced by the bioenergy or food production. However, we assume that evolution of corn and energy demand is correlated (e.g. through the income effect). This correlation can be expressed by variation of the normally distributed random number $\varepsilon_{(t)}$ (equations (3) and (4)), which scales the standard deviation of a random shock in the GBM process. For this aim we decompose the random number $\varepsilon_{(t)}$ in a variable specific component $z'_{(t)}$ and a non-specific component $z_{(t)k}$:

$$\varepsilon_{(t)\varphi} = \alpha z_{(t)k} + (1-\alpha) z'_{(t)\varphi} \quad (5)$$

$$\varepsilon_{(t)e} = \alpha z_{(t)k} + (1-\alpha) z'_{(t)e} \quad (6)$$

with the correlation parameter α.

Correlation parameter $\alpha = 1$ would yield the same random numbers for all variables that follows the GBM. In case it is zero there is no correlation between the evolutions of corn and energy demand. Within the range zero to one the correlation can be varied[6].

3.4 Bioenergy market

The bioenergy market is assumed to be considerably smaller than the energy market, so that the latter is not influenced by investment decisions of the bioenergy sector. Bioenergy demand is unlimited and the sector is able to absorb all available corn by adjusting its production decisions. By substituting equation (2) into (1) and taking into account the identity of demand and supply, the corn supply for bioenergy sector can be presented as the residual of the total corn supply and the corn demand for food:

$$Q^D_{(t)b} = Q^S_{(t)c} - \frac{\varphi_{(t)}}{p_{(t)c}{}^{-\eta}}. \quad (7)$$

This however is only possible, if the bioenergy sector has no production constraints. Since such constraints exist, three situations for sector's corn demand in a period (t) should be distinguished. In the first situation, the sector does not demand any corn if the expected corn

[6] The perfect correlation (expressed by α=1), which denotes equal randomness of both stochastic processes, is also used as a part of sensitivity analysis in order to exclude the influence of different white noise processes.

price $p_{(t)c}$ is higher than the expected energy price $p_{(t)e}$. If the corn price equals the energy price and the current production capacity $q_{(t)b}^{\max}$ is not reached, the amount of corn demanded by the bioenergy sector is the difference of the total corn supply and the corn demanded for other than bioenergy uses. And finally, if the corn price is lower than then energy price bioenergy sector can adjust its production up to the production capacity. The amount of bioenergy produced in a given period $q_{(t)b}$ equals then the amount of corn demanded by the sector $Q_{(t)b}^{D}$ in terms of corn's energetic value:

$$q_{(t)b} = Q_{(t)b}^{D} = \begin{cases} MIN\left[Q_{(t)c}^{S} - \frac{\varphi_{(t)}}{p_{(t)c}{}^{-\eta}}\ ,\ q_{(t)b}^{max}\right], if \quad p_{(t)e} \geq p_{(t)c} \\ 0 \quad otherwise. \end{cases} \tag{8}$$

Bioenergy production is, hence, determined by its capacity and the available amount of corn. As equations (8) shows bioenergy is produced only in case, if the expected contribution margin $cm_{(t)}$ (i.e. the difference of the expected energy and corn prices) is not negative[7].

Since bioenergy production competes for corn with food production, corn price is determined by corn demand on the food and bioenergy markets, and the energy price development:

$$p_{(t)c} \quad = \begin{cases} \left(\frac{\varphi_{(t)}}{Q_{(t)c}^{S}}\right)^{-\frac{1}{\eta}}, if\ p_{(t)e} < p_{(t)c} \\ MIN\left[\left(\frac{\varphi_{(t)}}{Q_{(t)c}^{S} - q_{(t)b}^{max}}\right)^{-\frac{1}{\eta}};\ p_{(t)e}\right] \ otherwise. \end{cases} \tag{9}$$

In equation (9), energy price $p_{(t)e}$ is the shadow price of the energetic use of corn[8]. It indicates the additional contribution margin which could be obtained if the current production capacity would be extended by one unit. Since such capacity increase is not possible in the same period[9], bioenergy production can influence the corn price while running up to its production limit. As consequence, the corn price (in case of bioenergy production) is the minimum of the shadow price and the price at which bioenergy production is run at its current capacity. Equation (9) also points up that after production capacity has been determined (namely by the investment decisions of the previous period), corn price will depend only on the stochastic behavior of demand parameter $\varphi_{(t)}$ and the energy price $p_{(t)e}$.

[7] The contribution margin per unit is defined as the difference of the output price and the variable cost per unit.
[8] Note, that the energy price $p_{(t)e}$ is the multiple of the market price of crude oil.
[9] Investments made in the current period are effective in the next period.

3.5 Investment decision

In our model we further assume that in every period the asset (bioenergy plants) depreciates geometrically with the rate λ, i.e. its productivity declines to $(1-\lambda)^{\Delta t}$ of the previous period's output. In order to keep the production capacity constant or to increase it, investments and reinvestments are needed[10]. This implies that production capacity of the next period is determined by the upper production limit and investment volume of a given period:

$$q_{(t)b}^{max} = q_{(t-\Delta t)b}^{max} \cdot (1-\lambda)^{\Delta t} + \frac{Inv_{(t-\Delta t)}}{inv} \tag{10}$$

where inv denotes investment costs per unit.

Since we explicitly assume no disinvestments (because of irreversible investment outlays), investments $Inv_{(t)}$ are made only, if the expected energy price is higher than the expected equilibrium investment trigger cm^*:

$$Inv_{(t)} = \begin{cases} MAX\left[0;\ (Q_{(t)c}^{S} - q_{(t)b}^{max} \cdot (1-\lambda)^{\Delta t} - \frac{\varphi_{(t)}}{(p_{(t)e}-cm^*)^{-\eta}}) \cdot inv\right],\ if\ p_{(t)e} > \ cm^* \\ 0,\ otherwise. \end{cases} \tag{11}$$

As assumed at the outset of the model, the bioenergy sector is considered as an aggregated producer consisting of many competing producers. In a perfectly competitive market, market entry by new firms prevents that contribution margin of producers exceeds a certain trigger level. Thus, in a long run, investors can prevent their average losses by choosing an equilibrium investment trigger at which the expected cash flows cover all production costs[11]. In case of irreversible investments, high sunk investment outlays force the sector to accept operative losses and maintain its production until at least a part of fix cost is covered[12]. Therefore, when choosing an investment trigger $cm*$, the bioenergy sector (as an aggregated investor) aims to meet the zero-profit condition in terms of the expected net present value of the cash flows at the end of the investment's lifetime. Formally, sector's goal can be formulated as:

$$E[NPV(cm^*)] = E[\textstyle\sum_{t=0}^{T} CF_t(1+r)^{-t} + RV_T] \equiv 0 \tag{12}$$

[10] If the sector does not invest or reinvest, asset's productivity declines over time, and the total output of the bioenergy sector declines as well. This implies that if no reinvestments are made the lifetime of the investment option is limited. The term $(1-\lambda)^{\Delta t}$ can, therefore, be interpreted as survival probability of the aggregated bioenergy producer.

[11] Triggers below the optimal trigger provide inferior solutions, and triggers above - if they allow exercising the investment option - may entail temporary profits, but they do not fulfill the essential equilibrium condition for competitive markets, namely the zero-profit rule.

[12] In case of high sunk cost of irreversible investments, considering investment under competition leads to the zero-profit optimization assumption. As shown by Dixit/Pindyck (1994), when assuming an infinite lifetime of options, investment trigger for options under competition is the same as for exclusive options.

with $RV_T = q_T^{max} \cdot \left[\frac{\sum_{t=T-10}^{T} cm_t}{T} \div \left(\frac{1+r}{1-\lambda} - 1\right)\right] \cdot (1+r)^{-T}$ (13)

where RV_T denotes the residual value of production, which arises if production capacity at (T) is higher than zero, r the interest rate, and CF_t the cash flow in (t).

The cash flow $CF_{(t)}$ is the difference of the total contribution margin of a given period and the investment amount made in the same period:

$$CF_{(t)} = CM_{(t)} - Inv_{(t)} \tag{14}$$

with $CM_{(t)}$ as the total contribution margin in a given period.

Taking into account equations (11) and (14), equation (12) shows that the expected NPV of investment decision also depends on the investment trigger.

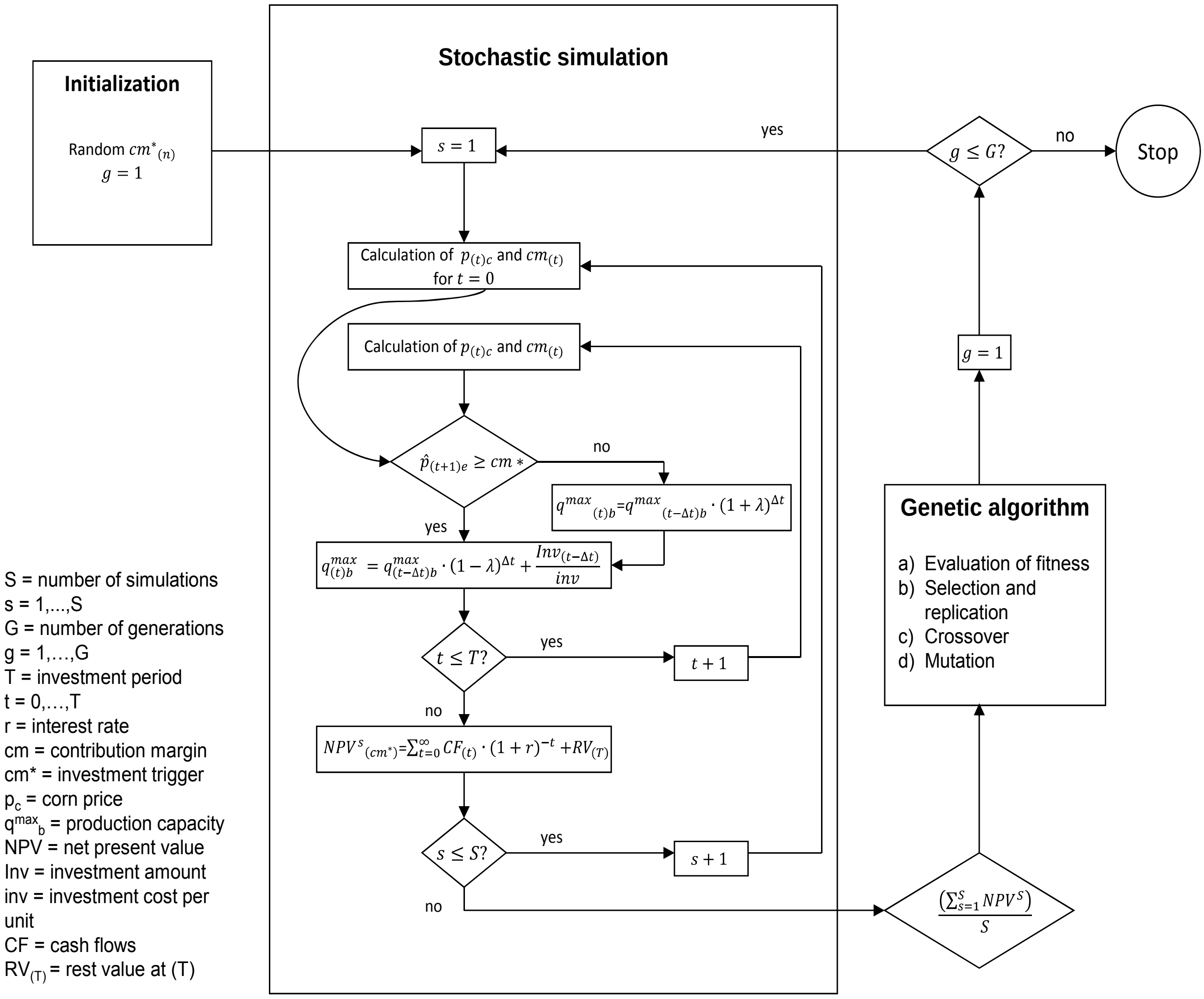
The questions now are: what is the equilibrium trigger at which the sector invests, and how the investment trigger is affected by the intersectoral price transmissions?

4. The methodologies

In our model we assume that energy price (i.e. the output price) and food demand parameter follow the geometrical Brownian motion[13]. The corn and energy markets however influence investment decisions simultaneously. An analytical solution of their overlapping impact is mathematically problematic. For this reason we resort to a real-options-based stochastic simulation in combination with genetic algorithm as approximation technique to identify an equilibrium investment trigger and to study how it is affected by the intersectoral price and volatility transmissions. In the first simulation step, a predefined number of investment strategies for a given period of time are simulated. In the second step, these strategies are optimized in search for an equilibrium solution by the genetic algorithm technique. The flow chart of the simulation is shown in Figure 2.

[13] For validation of this assumption see section 5.3.

Figure 2: Flow chart of the simulation approach



Source: Own presentation.

4.1 Real options approach

Investments in bioenergy are characterized by uncertain returns and high sunk costs, i.e. investments are at least partially irreversible. Uncertainty of irreversible investments can be reduced to some degree by waiting for new information, which may limit the downside risk of losses and concurrently capture the upside potential associated with different choices. The presence of optionality in investment decisions - to invest or not, or to invest later - means that valuing cost-intensive irreversible investments can be done by using real option theory.

Real options approach to investment in tangible, i.e. *real*, assets (Henry 1974, McDonald/Siegel 1986, Pindyck, 1991) is based on the option valuation technique developed for financial markets by Black, Scholes and Merton (1973). The opportunity to invest in a real asset can be compared with a call option on financial markets: like the owner of a call option, the investor has the right but not the obligation to pay a fixed sum (investment cost) and to receive revenues (stochastic cash flows) with an expected discounted value. Real options approach demonstrated that for uncertain and at the same time irreversible and flexible investments it is not necessarily optimal to invest if the expected present value of the future returns covers the investment outlays, i.e. according to the Net Present Value (NPV) criterion. The NPV reflects only the intrinsic value of the option to invest, but not its time value[14], which is the discounted value of the expected appreciation of the option. Consequently, in the presence of optionality the NPV method can lead to underestimation of investment trigger. The real options method incorporates the time value into valuation of investment decisions and shows that the option should only be exercised if the intrinsic value exceeds the time value. The *real* value of a real option, hence, results from the mathematically guided act of choosing a 'right' time for exercising an investment.

4.2 The application of genetic algorithm

Genetic algorithm (GA) is a heuristic optimization and search technique developed in analogy to the processes of natural evolution (cf. Goldberg 1998). In this study we apply this technique to search for a single value, namely the equilibrium investment trigger of the bioenergy sector. For this aim, each possible investment strategy is specified as a string of genes on one or more genotypes (or genomes). In our model, every genome is represented by one value, namely the investments trigger. We set the maximum population of genomes $N=10$ which are directly independent. Every genome can be interpreted as the variation of investment strategy of the sector. That means that the investment trigger of a single strategy is represented by one genome within the genome population. The number of iterations can vary depending on the problem at hand; for our study 10,000 iterations are applied.

The initial population is generated randomly, covering the range of possible solutions. In order to bring new genetic varieties into the genomes population, genetic operators such as *selection* and *replication*, *crossover*, and *mutation* are applied in this fixed sequence. This procedure is designed to gradually adjust the obtained solutions to the model's requirements (e.g. market equilibrium). Before the operators are applied to each successive generation of genomes, the *fitness* of every genome, i.e. the capability of the genome to solve the given problem, is tested. In our application, the fitness value is derived from the average expected NPV

[14] Time value is also referred to as flexibility of continuation value of an option.

of every strategy, stochastically simulated in 10,000 runs. The closer the average NPV is to zero, the fitter is the corresponding genome. The fitter solutions, as valuated by the fitness function, determine a selection of genetic material to be reproduced in the following generation. The rate of survival for selection and replication operator is defined here to be 5 of the better adapted genomes; the next 3 genomes are replaced with a defined probability by the same amount of the most profitable genomes from the last simulation series. The least 2 successful genomes are replaced by the 2 most fit genomes. New genetic varieties are further obtained by the crossover of parts of coded strings between two genomes. Every pair of genomes is chosen randomly with a certain probability and split at a random (but the same for both genomes) digit. The split sub-strings are then exchanged which leads to a new pair of genomes. In order to avoid a permanent fixation of a population on an inferior genotype, and, hence, to prevent the loss of genetic information (i.e. combinations of coded strings) that was sorted out in previous generations, a further operator, mutation, is used. Here every solution from previous operators is multiplied with a predefined small likelihood of a random number, enabling new variations in string pattern. The generation of new genomes in the preset sequence is repeated until the fixed number of iterations has been reached.

5. Results

5.1 Main findings

The results of the real options based stochastic simulation as presented in Table 1 demonstrate that the positive correlation between the price volatility and investment trigger, as known from the financial market, does not necessarily hold for real investment decisions which are simultaneously influenced by multiple volatilities. As seen from Table 1 [a], this is especially pronounced if the volatility on the input market significantly exceeds this on the output market or if both volatilities are very high. If the volatility of the energy price is kept constant, the trigger responds positively to increasing volatility on the food market mostly if the latter is less than 10%. If in turn the volatility of the food demand parameter is held constant, the impact of increasing energy price volatility on investment trigger is positive if the volatility of the food market is less th1n 20%. For equal volatilities up to 10% the correlation is also positive. In case of the perfect correlation, and of no correlation of both stochastic processes (Table 1 [b] and [c]) investment trigger positively responds to increasing volatilities on both markets only if those are small (up to a value between 5% and 10%). In all other cases the equilibrium trigger declines, often reaching values below the periodic investment cost.

Table 1: Investment trigger under variation of σ_φ, σ_e and α (r=10%, η=-0.7, $\varphi_{(t=0)}$= 70%)

[a] α=0.5

volatility of energy price, σ_e	volatility of food demand parameter, σ_φ				
	0%	2.5%	5%	10%	20%
0%	1.0000	1.0681	1.2027	1.1210	0.8364
2.5%	1.0522	1.0764	1.1825	1.1499	0.7396
5%	1.2357	1.1839	1.2440	1.1846	0.8006
10%	1.4546	1.4756	1.4413	1.2879	0.6638
20%	1.7548	1.8162	1.8473	1.6544	0.9199
30%	1.8689	1.9273	1.9706	2.0569	1.1765

[b] α=0

volatility of energy price, σ_e	volatility of food demand parameter, σ_φ				
	0%	2.5%	5%	10%	20%
0%	1.0000	1.1711	1.2769	0.9915	0.7888
2.5%	1.1410	1.2503	1.3173	0.9645	0.7386
5%	1.2814	1.3298	1.2915	0.9037	0.7316
10%	1.2471	1.2060	1.0536	0.7732	0.6556
20%	0.8745	0.7299	0.7041	0.6667	0.5692
30%	0.6822	0.6626	0.6412	0.5740	0.4642

[c] α=1

volatility of energy price, σ_e	volatility of food demand parameter, σ_φ				
	0%	2.5%	5%	10%	20%
0%	1.0000	1.1604	1.2715	0.9939	0.7793
2.5%	1.1471	1.0099	1.2455	1.1867	0.7513
5%	1.2891	1.0702	1.0734	1.2578	0.7078
10%	1.2304	1.4372	1.3117	1.2035	0.8972
20%	0.7648	0.7397	0.8248	1.7319	1.2858
30%	0.7494	0.6368	0.6243	0.5647	2.2917

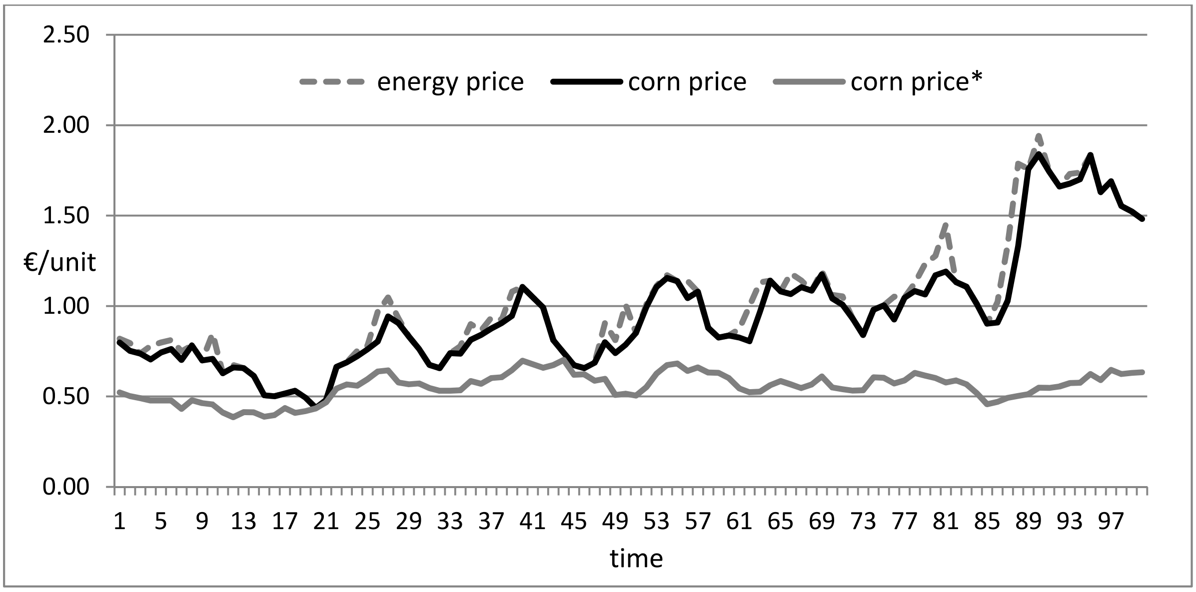
Source: Own calculations.
Note: Trigger values are normalized to periodic investment costs; $\varphi_{(t=0)}$ denotes the initial share of food demand in the total corn supply.

Declining investment trigger indicates that in the case of high expected volatility investors may realize very high contribution margins which could cover all investment cost in just few periods. In the following periods initial investments are followed only by reinvestments or by no investments at all. This can be explained by the fact that due to the option to suspend, firms' losses are bounded in bad states while there is no corresponding upward limit in good states. As a consequence, high price volatilities induce a chance for very high profits whereas losses are limited to the fixed costs through the option to suspend.

The negative response of investment trigger to rising volatility, hence, marks the threshold at which disinvestments would be the optimal strategy. Similar observations have been made by a number of studies dealing with the impact of two volatilities or uncertainties on the optimal trigger for switching between different operation modes, e.g. in a general model of uncertain investments (Bertola 1988), for heavy crude oil field production (Adkins/Paxson 2011), or for interpersonal relationships (Strobel, 2003). In the studies by McDonald/Siegel (1985) and Brennan/Schwartz (1985), in which only one volatility source (output price) is assumed, both positive and negative impact of rising volatility on investment trigger were observed. The results of these studies reinforce our finding that for uncertain irreversible investments with high sunk costs and little (if any) resale value investment trigger may decrease in response to increasing volatilities, sometimes falling below the Marshallian trigger. Prohibitively high costs of capital decumulation create a ratchet for disinvestments. For this reason, investments and production are not necessarily suspended, if the expected operating revenues are lower than expected operating costs. Accepting transitory losses seems to be efficient as this accurately reflects the underlying economics of volatile markets where expected gains and losses are based upon expected spikes of stochastic parameters. However, an analytical determination of the exact values at which the trigger declines is not possible as this depends not only on the individual combination of many initial parameters (Tables 2-7), but also decisively on the randomness of the underlying stochastic processes.

The simulated corn and energy price trends, as presented in Figure 3, further show that bioenergy production from agricultural crops leads to price convergence on the food and energy markets.

Figure 3: Exemplary corn and energy price development with and without bioenergy production (σ_e=0.2, σ_φ=0.1, α=0.5, η=-0.7)



Note: 'corn price*' denotes corn price in the case of no crop-based bioenergy production.

This result is in line with the empirical evidence for crude oil, wheat and corn prices shown in Figure 1.

5.2 Sensitivity analysis

The robustness of the model was tested by a sensitivity analysis varying several model parameters: food demand elasticity (η), initial demand parameter ($\varphi_{(t=0)}$), asset's depreciation rate (λ), and interest rate (r). As shown in Table 2, the impact of the increasing food demand elasticity on the equilibrium investment trigger is positive only if the volatility on the output market is less than 20%.

However, even for the elasticity η=-1, the trigger may decline if the volatility on the input market is higher than 10%. Also for different variations of the initial demand parameter (Table 3 and Table 1 [a]) similar conclusion can be made: the higher the share of food demand in the total corn supply, the higher in most cases the investment trigger. Nevertheless, also in this case for high volatility on the input market the trigger drops below the periodic investment costs. It also reveals a negative response to increasing volatility on the output market if the share of food demand in the total corn supply is either very low or very high.

Table 2: Investment trigger under variation of σ_φ, σ_e and η (r=10%, α=0.5, $\varphi_{(t=0)}$= 70%)

volatility of energy price, σ_e	food demand elasticity, η	volatility of food demand parameter, σ_φ: 0%	2.5%	5%	10%	20%
0%	-0.7	1.0000	1.0681	1.2027	1.1210	0.8364
	-1	1.0000	1.1101	1.2284	1.2310	0.8223
2.5%	-0.7	1.0522	1.0764	1.1825	1.1499	0.7396
	-1	1.1368	1.1485	1.2171	1.2181	0.7836
5%	-0.7	1.2357	1.1839	1.2440	1.1846	0.8006
	-1	1.2910	1.3422	1.3103	1.2450	0.8240
10%	-0.7	1.4546	1.4756	1.4413	1.2879	0.6638
	-1	1.4629	1.5687	1.5573	1.4100	0.9292
20%	-0.7	1.7548	1.8162	1.8473	1.6544	0.9199
	-1	1.6861	1.7462	1.7891	1.7687	1.1094
30%	-0.7	1.8689	1.9273	1.9706	2.0569	1.1765
	-1	1.6023	1.7473	1.7544	1.7838	1.5655

Source: Own calculations.
Note: Same as for Table1.

Table 3: Investment trigger under variation of σ_φ, σ_e and $\varphi_{(t=0)}$ (r=10%, η=-0.7, α=0.5)

volatility of energy price, σ_e	share of food demand in total corn supply, $\varphi_{(t=0)}$	volatility of food demand parameter, σ_φ: 0%	2.5%	5%	10%	20%
0%	10%	1.0000	1.0047	0.9661	0.8548	0.7682
	50%	1.0000	1.0000	1.0160	0.9286	0.7715
	100%	1.0000	1.1890	1.2432	1.1595	0.7680
2.5%	10%	1.0038	1.0006	0.9788	0.8365	0.7514
	50%	1.0043	1.0013	1.0182	0.9490	0.7506
	100%	1.1066	1.2180	1.2857	1.2040	0.7406
5%	10%	1.0011	1.0069	0.9882	0.9882	0.7343
	50%	1.0341	1.0200	1.0258	0.9720	0.7999
	100%	1.2946	1.3559	1.3259	1.2192	0.7305
10%	10%	0.9769	0.9997	0.9772	0.8445	0.6822
	50%	1.1708	1.1466	1.1370	1.0454	0.6722
	100%	1.4910	1.5633	1.5469	1.3100	0.6776
20%	10%	0.7964	0.8469	0.8753	0.8541	0.5792
	50%	1.4250	1.4810	1.4869	1.3828	0.7329
	100%	1.4010	1.5623	1.4796	1.4962	0.9503
30%	10%	0.7351	0.7141	0.7982	0.7382	0.4858
	50%	1.7093	1.8228	1.7983	1.7707	1.0999
	100%	0.9785	1.1566	1.0806	1.1207	1.0871

Source: Own calculations.
Note: Same as for Table1.

Variations of depreciation rate (Tables 4 and 5) reveal a strong impact on investment trigger as well. As seen from Table 4 (values in italic font), in case of zero volatility on both markets, the equilibrium trigger growth with increasing depreciation.

Table 4: Investment trigger under variation of λ and σ_e (σ_φ=10%, r=10%, α=0.5, η=-0.7, $\varphi_{(t=0)}$=70%)

volatility of energy price, σ_e	depreciation rate, λ						
	0%	5%	10%	20%	40%	50%	99%
0%	1.4953 *0.0342**	1.1284 *0.0514**	1.0550 *0.0685**	1.0200 *0.1027**	1.0039 *0.1712**	0.9952 *0.2055**	0.9947 *0.3733**
10%	1.8777	1.2827	1.1052	1.0754	1.0247	1.0240	1.0039
20%	2.4303	1.6880	1.4238	1.2290	1.0928	1.0679	1.0389
30%	2.7048	2.0074	1.5950	1.3531	1.1658	1.1356	1.0865

Source: Own calculations.
Note: Note: Same as for Table1; * values for $\sigma_e = \sigma_\varphi = 0\%$.

However, in the presence of volatility on both markets, the impact is opposite in most cases, especially for variation of energy price volatility and constant food demand volatility. If conversely the volatility of food demand is varied and the volatility of the energy price is kept constant (Table 5), the effect of increasing depreciation rate is not that clear, and the equilibrium trigger erratically declines, sometimes even below the periodic investment costs.

Table 5: Investment trigger under variation of λ and σ_φ (σ_e=20%, r=10%, α=0.5, η=-0.7, $\varphi_{(t=0)}$=70%)

volatility of food demand parameter, σ_φ	depreciation rate, λ						
	0%	5%	10%	20%	40%	50%	99%
0%	1.9922	1.7604	1.4768	1.2493	1.1025	1.0906	1.1011
5%	2.1320	1.8482	1.5154	1.2771	1.1242	1.0893	1.0440
10%	2.4692	1.6625	1.4357	1.2431	1.0930	1.0685	1.0382
20%	1.2200	0.9051	0.9351	1.0000	0.9918	1.0279	1.0332

Source: Own calculations.
Note: Same as for Table1.

The variation of the interest rate (Table 6) shows further irregularities: the impact of growing interest rate on the equilibrium investment trigger is negative only for relatively small volatilities on both markets. This impact becomes irregular (values in italic) when the volatility on the input market exceeds 2.5% and this on the output market is higher than 10%.

Table 6: Investment trigger under variation of σ_φ, σ_e and r (α=0.5, η=-0.7, $\varphi_{(t=0)}$=70%)

		volatility of food demand parameter, σ_φ				
volatility of energy price, σ_e	interest rate, *r*	0%	2.5%	5%	10%	20%
0%	5%	1.0000	1.1025	1.1788	0.8742	0.7578
	10%	1.0000	1.0681	*1.2027*	*1.1210*	*0.8364*
	50%	1.0000	1.0275	1.0503	1.0807	*1.0749*
2.5%	5%	1.0681	1.0941	1.1727	0.8834	0.7365
	10%	1.0522	1.0764	*1.1825*	*1.1499*	*0.7396*
	50%	1.0281	1.0227	1.0456	1.0733	*1.0667*
5%	5%	1.2771	1.2265	1.2375	0.9617	0.7340
	10%	1.2357	1.1839	*1.2440*	*1.1846*	*0.8006*
	50%	1.0568	1.0544	1.0585	*1.0775*	*1.0658*
10%	5%	1.4721	1.5258	1.4592	1.1061	0.8010
	10%	1.4546	1.4756	1.4413	*1.2879*	0.6638
	50%	1.1340	1.1303	1.1187	*1.1324*	*1.0909*
20%	5%	1.5411	1.6993	1.7539	1.4374	0.5736
	10%	*1.7548*	*1.8162*	*1.8473*	*1.6544*	*0.9199*
	50%	1.0909	1.3263	1.3161	1.2667	*2.8848*
30%	5%	1.2148	1.6448	1.8951	1.8492	0.9101
	10%	*1.8689*	*1.9273*	*1.9706*	*2.0569*	*1.1765*
	50%	1.4866	1.4859	1.4843	1.4743	*1.3560*

Source: Own calculations.
Note: Same as for Table1.

These observations, showing that the correlation between the volatility and equilibrium investment trigger is not necessarily positive, imply that the more the input and output markets are correlated, the more unpredictable the impact of rising volatility on bioenergy investment decisions might be.

5.3 Stationarity tests

As presented by equations (3) and (4), the energy price and corn demand parameter follow a geometric Brownian motion. This assumption however can only be made if both time series follow a random walk. Existence of random walk, i.e. of non-stationarity of time series, is usually tested by unit root tests. Table 7 and Table 8 summarize the results of 3 tests, namely the Augmented Dickey-Fuller test (ADF), Phillips-Perron test (PPerron) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) for the simulated energy price and food demand parameter.

Table 7: Percentile rejection of the unit root hypothesis for energy price using Augmented Dickey-Fuller test (ADF), Phillips-Perron test (PPerron) and Kwiatkowski-Phillips-Schmidt-Shin test (KPSS); sample size: 200 observations, 1000 simulations.

	ADF test		PPerron test		KPSS test (lag order 14)
significance level	average p-value	share of simulations with rejected H_0	average p-value	share of simulations with rejected H_0	share of simulations with rejected H_1
1%	0.2213	31.7%	0.2219	32.8%	32.4%
5%	0.2213	40.4%	0.2219	42.3%	42.1%
10%	0.2213	47.9%	0.2219	48.5%	45.2%

Source: Own calculations (in STATA).
Note: The presence of the unit root is expressed in the ADF and PPerron tests by the null hypothesis (H_0), and in the KPSS test by an alternative hypothesis (H_1).

Table 8: Percentile rejection of the unit root hypothesis for food demand parameter using Augmented Dickey-Fuller test (ADF), Phillips-Perron test (PPerron) and Kwiatkowski-Phillips-Schmidt-Shin test (KPSS); sample size: 200 observations, 1000 simulations

	ADF test		PPerron test		KPSS test (lag order 14)
significance level	average p-value	share of simulations with rejected H_0	average p-value	share of simulations with rejected H_0	share of simulations with rejected H_1
1%	0.3289	17.7%	0.3281	18.5%	25.6%
5%	0.3289	25.5%	0.3281	26.6%	38.5%
10%	0.3289	32.4%	0.3281	32.6%	43.4%

Source: Own calculations (in STATA).
Note: Same as for Table 7.

The ADF and the PPerron procedures are used for testing the null hypothesis (H_0) against an alternative hypothesis (H_1). The null hypothesis in this case is that time series is non-stationary around a deterministic trend i.e. that it has a unit root. Accordingly, the alternative hypothesis rejects the unit root assumption. The KPSS test, in contrast, assumes stationarity as a null hypothesis, and tests for absence of unit root. The KPSS is used as a conformity test since the ADF and PPerron tests do not provide accurate information about how close (or how far) the values are to (from) zero.

As seen from the Table 7 and Table 8, the assumption of unit root cannot be rejected in most cases (over 50% of simulations), and the results of different tests are congruent[15] (for energy price) or at least not contradictory (for food demand parameter). For further justification of applicability of the GBM to these two parameters, augmented Dickey-Fuller unit root test with additive outliers were conducted with the empirical data for the energy price (proxied by the crude oil price for the period 1990-2009) and the corn price (as a proxy for food demand parameter[16] for the period 1990-2010) under variation of time steps. The results as presented in Table 9 and Table 10 approve that the GBM cannot be rejected for energy price and food demand parameter.

Table 9: Augmented Dickey-Fuller unit root test with additive outliers (DFAO) for empirical energy price; sample size: 20 years

	time step, Δt		
	0.1	0.25	0.5
number of observations	240	80	40
1.Test for the presence of the additive outliers:			
τ_τ	-3.45	-3.50	-3.60
φ_3	2.38 (<6.49)	2.99 (<6.73)	2.71 (<7.24)
t-statistic	-2.057	1.108	-0.780
5% critical value	-3.375	-3.406	-3.519
p-value	0.5709	0.9274	0.9678
2.Test for the presence of the trend:			
τ_μ	-2.89	-2.93	-3.00
φ_2	0.61 (<4.88)	0.51 (<5.13)	3.39 (<5.68)
t-statistic	-0.588	-0.213	1.259
5% critical value	-2.833	-2.836	-2.927
p-value	0.8753	0.9375	0.9939
3. Test for the presence of the drift:			
τ	-1.95	-1.95	-1.95
φ_1	0.20 (<4.71)	0.50 (<4.86)	*6.93 (>5.18)*
t-statistic	0.445	0.709	2.632
5% critical value	-1.919	-1.920	-1.960
H_0 hypothesis rejected?	no	no	no

Source: Own calculations (in STATA) based on EIA (2010) data for Europe Brent spot price.
Note: Test statistics φ (values in the brackets) and τ are based on their empirical distributions as calculated Dickey/ Fuller (1979), Fuller (1976), and reproduced by Enders (2004).

[15] The small differences in the results are due to different distribution assumptions for the ADF, PPerron and KPSS tests.

[16] As seen from equation (9), for situations when the corn price does not equal the energy price after the investment and production decisions have been made the corn price depends solely on the expected corn demand parameter.

Table 10: Augmented Dickey-Fuller unit root test with additive outliers (DFAO) for empirical corn price; sample size: 21 years

	time step, Δt		
	0.1	0.25	0.5
number of observations	252	84	42
1.Test for the presence of the additive outliers:			
τ_τ	-3.45	-3.50	-3.60
φ_3	4.11 (<6.34)	4.43 (<6.73)	*14.84 (>7.24)*
t-statistic	-2.835	-2.937	-0.492
5% critical value	-3.423	-3.462	-3.440
p-value	0.1843	0.1506	0.9848
2.Test for the presence of the trend:			
τ_μ	-2.88	-2.93	-3.00
φ_2	3.42 (<4.75)	3.62 (<5.13)	2.19 (<5.68)
t-statistic	-2.599	-2.665	-2.069
5% critical value	-2.868	-2.893	-2.858
p-value	0.0931	0.0803	0.2573
3. Test for the presence of the drift:			
τ	-1.95	-1.95	-1.95
φ_1	0.78 (<4.63)	0.87 (<4.86)	0.32 (<5.18)
t-statistic	-0.882	-0.932	-0.565
5% critical value	-1.936	-1.948	-1.929
H_0 hypothesis rejected?	no	no	yes

Source: Own calculations (in STATA) based on EUROSTAT (2010) data for corn prices.
Note: Same as for Table 9.

6. Summary and conclusions

The paper applies the real options framework to study the effect of multiple uncertainties on irreversible investments in bioenergy. The equilibrium investment trigger of the bioenergy sector is derived in repeated stochastic simulations in combination with the genetic algorithm technique. The results reveal a high complexity of investment decisions in the context of increasing markets interrelations, and indicate several questions to be further investigated.

The results gained in stochastic simulations demonstrate that the positive correlation between the volatility and investment trigger does not necessarily hold for real investment decisions which are simultaneously influenced by different volatilities. Particularly this is true for firms which have the possibility to limit their losses in bad states by temporary production suspension. In the case of irreversible crops-based energy production, which takes place at the intersection of the agricultural and industrial sectors, the complexity of investment decision is amplified by the fact that production adjustment is conditioned - among others – by the input market specifics (e.g. limited supply or natural growth rates). Therefore, the assessment of bioenergy investment strategies in the liberalized energy market only by performance figures of the output market or the stock market may lead to wrong expectations of production and adjustment capabilities of the bioenergy and food markets. Because of the reciprocal effects of the involved markets, the magnitude of which is decisively contingent upon initial conditions on these markets, it cannot be generalized for real investments that increasing uncertainty of input or output prices necessarily leads to the increasing investment trigger.

It should also be noted that since our results are based on numerical simulation experiments, further research that analytically show the impact of the option to suspend and multiple volatilities would be beneficial. In this connection, the impact of initial investment conditions also requires a detailed investigation. Further, because changes in price dynamics have significant implications for resource allocation and, hence, for food and energy security, a sound understanding of the mechanism of price and volatility spillovers is of equal importance for risk management of irreversible cost-intensive investment projects and for assessment of macroeconomic policy decisions. Therefore, other influences as for instance the effect of the total corn supply shock on bioenergy investments and food price also deserve a closer look.

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