Institute of Economic Studies, Faculty of Social Sciences
Charles University in Prague

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Pavla Blahova
Karel Janda
Ladislav Kristoufek

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Institute of Economic Studies,
Faculty of Social Sciences,
Charles University in Prague

[UK FSV – IES]

Opletalova 26
CZ-110 00, Prague
E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

Institut ekonomických studií
Fakulta sociálních věd
Univerzita Karlova v Praze

Opletalova 26
110 00 Praha 1

E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

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The Perspectives for Genetically Modified Cellulosic Ethanol in the Czech Republic

Pavla Blahova[a]
Karel Janda[a,b]
Ladislav Kristoufek[a,c]

[a]IES, Charles University Prague
E-mail: PBlahova@email.cz

[b] University of Economics, Prague
E-mail: karel-janda@seznam.cz
corresponding author

[c] Institute of Information Theory and Automation, Academy of Sciences of the Czech Republic
E-mail: kristoufek@ies-prague.org

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Abstract:

This paper connects the biofuels literature with genetic modifications literature by considering the potential of genetic modifications for increasing the efficiency of cellulosic biofuels production. This is done for one particular case through analyzing the effect of genetically modified corn adoption on overall yields of corn for silage. Our econometric model confirms that the use of genetically modified corn with inserted MON810 gene increases the overall corn biomass yield in the production and environmental conditions of the Central Europe, in particular in the Czech Republic.

Keywords: Cellulosic Biofuels; Genetic Modifications

JEL: C23; Q16; Q42

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Contact Address: Karel Janda, Department of Microeconomics and Mathematical Methods, Institute of Economic Studies, Charles University, Opletalova 26, 110 00 Prague, Czech Republic
Tel.:(+420) 222 112 316, Fax: (+420) 222 112 304, e-mail: Karel-Janda@seznam.cz

1. Introduction

The main objective of this paper is to connect the biofuels literature, for a recent representative review see Janda et al. (2012), with genetic modifications (GM) literature by considering the potential of GM for increasing the efficiency of biofuels production. This is done for one particular case through analyzing the effect of GM corn adoption on overall yields of corn for silage. Because cellulose based biofuels can be produced from the corn for silage or corn stover, the increase in corn yields due to the GM may contribute to better perspectives for biofuels in Central Europe. GM technology is also associated with lower costs of planting and could result in lower cost of biofuels production.

Analytical part of this work deals with the question whether the use of genetically modified corn with inserted MON810 gene increases the overall corn biomass yield in the production and environmental conditions of the Central Europe, in particular in the Czech Republic. Answering such question brings us closer to exploring the possibilities of biofuels in the context of Central Europe since the GM modified biomass is a very natural promising feedstock for the production of advanced biofuels.

The current status of GM crops in Europe, see Wesseler (2012), is very different from that in the USA, where many GM crops are grown (corn, soybean, cotton etc.). Nolan and Santos (2012) investigated the effect of genetic modifications on corn for grain yields in the USA using data from experimental field trials. Results of their analysis suggest that yield of GM corn is $1.4-1.5$ times higher than the yield of regular corn. Another important outcome of their analysis is that Bt corn is associated with increase in corn yields but HT corn seems to be yield neutral. Bt corn is an insect resistant crop which contains a gene of soil bacterium called Bacillus thuringiensis (hence Bt crops) while HT stands for herbicide-tolerant GM technology. This result of Nolan and Santos (2012) has an important implication for our analysis since the only GM corn hybrids grown in the Czech Republic have inserted MON810 gene resulting in Bt modification. In our analysis, we would like to confirm the assumption of positive effect of Bt corn on overall corn for silage yields in the Czech Republic. An important difference between Nolan and Santos (2012) and our research is that while Nolan and Santos (2012) examine influence of GM on grain yield, we are interested in overall biomass yield. While the results of Nolan and Santos (2012) are therefore directly relevant for first generation conventional biofuels produced from corn grain, our results are directly relevant for second generation advanced biofuels production.

The potential of GM crops in EU is decreased by conservative legislation (Beckmann et al. (2006) and Groeneveld et al. (2013)) which results in too little effort put into GM research. Therefore in Europe, we do not have field trial data comparable with the USA ones. However, not having data on field trials is not an unbeatable obstacle. Another paper investigating the yield gains from GM corn for grain in USA by Xu et al. (2010) analyzed the effect of GM corn on corn for grain yields using weather conditions as control variables. They came to similar conclusion as Nolan and Santos (2012). We therefore base our analysis on controlling for weather conditions as well.

Both above mentioned studies investigate the effect of GM modifications on corn for grain yields. We based our decision to use corn for silage in our analysis on the following grounds.

In the Czech Republic, regulations on further manipulation with GM product are rigorous and result in GM corn being grown almost exclusively for silage. If certain GM crop is allowed to be grown in the Czech Republic, it does not mean that all further manipulation is allowed (animal feed, human consumption etc.). Therefore, investigating the effect of GM corn on corn for grain yields in Czech Republic is not feasible.

In the Czech Republic, if produced from corn, ethanol is produced through the food crop based procedure. With the technological improvements in the cellulose based biofuels production, ethanol could be produced also from the corn for silage or corn stover. Refineries producing cellulose based ethanol are already available in Crescentino (Italy) on commercial scale and in a number of pilot plans in the USA and Europe, like for example pilot refinery of DuPont in Nevada, Iowa (USA). This DuPont refinery focuses its production process on corn stover, which is the part of plant remaining after harvesting the grain. As opposed to stover, silage is made from the whole plant. Increased yields can reduce the cost of production, boost the produced volume of ethanol, and the land occupied by crops dedicated for ethanol production would be smaller.

While the references mentioned in the previous paragraphs were concerned primarily with GM crops, there is also a very sizable literature dealing with use of corn as feedstock for biofuels. In this literature many economic modeling techniques are used to model the impact of corn based ethanol from different points of view. Basic distinction may be made between structural and reduced form models. Structural models are based on economic theory complemented with some technological assumptions. Reduced form models are usually concerned only with statistical properties of time series and do not take the economic or technological factors which generated those time series explicitly into account.

The structural approach is used for example by Chakravorty et al. (2011) or by Beckman at al. (2011) in the context of CGE modeling or by de Gorter et al. (2013) in the partial equilibrium models. Detailed taxonomy of structural models and their results with respect to economics of corn ethanol biofuels is provided by Rajagopal and Zilberman (2007) and their comparison with reduced form models is given by Zilberman et al. (2012).

The reduced form models of corn ethanol usually focus on relationships among prices of relevant commodities. In a pair of papers focusing on the co-integration of prices for oil, ethanol and feedstocks, Serra, Zilberman and co-authors study the US (Serra, Zilberman, Gil, and Goodwin, 2011) and Brazilian (Serra, Zilberman, and Gill, 2011) ethanol markets, where Brazilian case is dealing with sugar cane ethanol. Zhang et al. (2008, 2009, 2010) investigated volatility in ethanol and commodity prices and other features of prices relationships among corn ethanol and related commodities. Recently, Bastianin et al. (2014, 2013, 2012, 2011, 2009) in a series of papers starting already in 2009 or Carter et al. (2012) investigated relations among prices of corn and other biofuels related commodities using US data. Nazlioglu and Soytas (2011, 2012) investigate these questions in the context of emerging markets and in relation to the financial markets determinants of biofuels. An extensive recent survey of reduced form econometric models of corn ethanol and other biofuels is provided by Serra and Zilberman (2013).

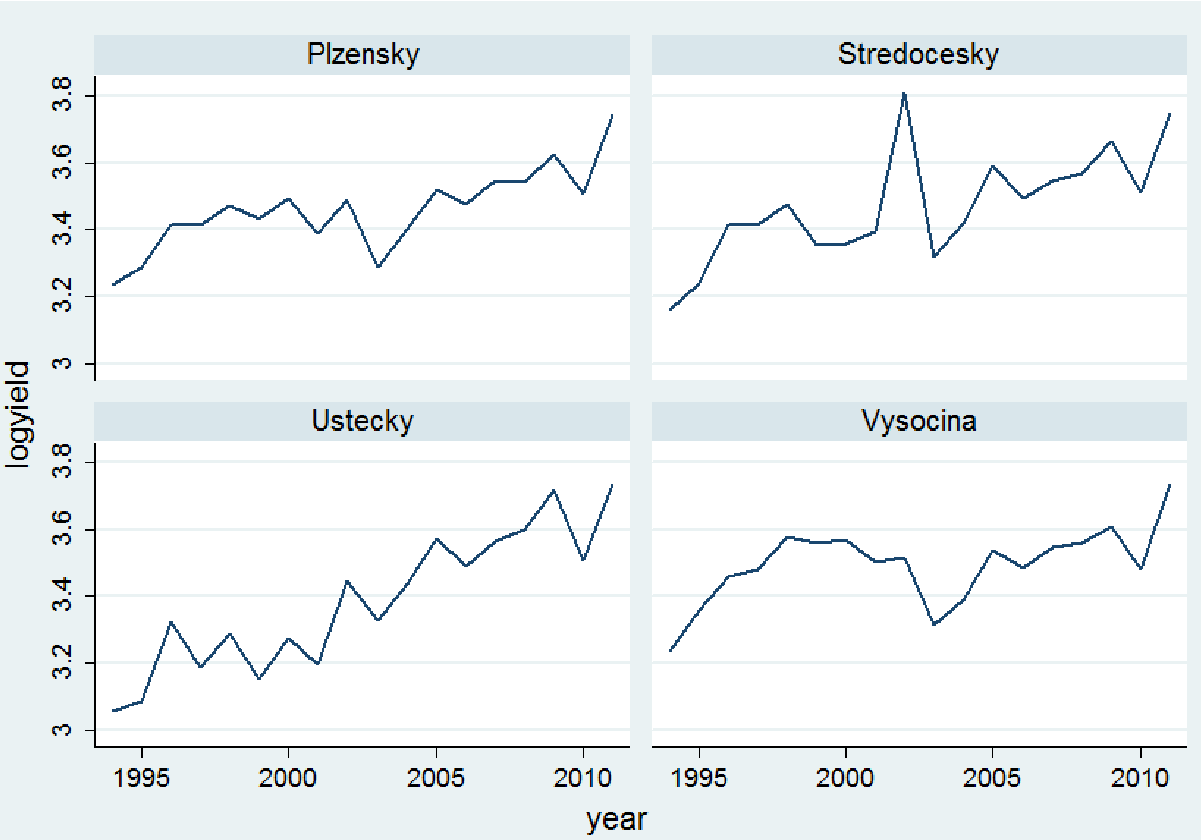
Our paper also brings a new original contribution to the Czech and Slovak biofuels related economic literature. The emphasize of Czech and Slovak academic economists interested in the biofuels [Ciaian and Kancs (2011), Chrz et al. (2014), Kristoufek et al. (2012, 2013, 2014), Pokrivcak and Rajcaniova (2011), Rajcaniova and Pokrivcak (2011), Rajcaniova et al. (2013), Vacha et al. (2013)] was so far oriented primarily on the pricing of ethanol and bioediesel or on the welfare analysis of biofuels policies (Drabik, 2012), and it was conducted only in the framework of commercially well developed first-generation biofuels.

2. Data

To answer our question, we used the data on the overall yield of corn for silage, share of GM corn sown area, average temperature, and average rainfall in the Czech Republic for the years 1994 through 2011 for each of the 14 regions in the Czech Republic. There are no observations missing, therefore we have balanced panel data. The data set is available on request.

Data on corn for silage were obtained through personal communication with the Czech Statistical Office. They involve data on sown area in hectares (ha) and crop in tons (t). Yield was calculated for each year and region by dividing crop by sown area and therefore it is measured in t/ha. For statistical purposes, corn for silage is weighted right after harvesting without letting the crop dry (Czech Statistical Office, 2012). The whole plant is used for silage and therefore the whole plants are being weighted. Yield therefore measures how many tons of corn biomass has grown on 1 hectare of sown area. The highest yield in our dataset is 45.2 t/ha, the lowest one is 18.9 t/ha. Mean value of corn yield in our data is 33 t/ha.

Figure 1. Logarithm of corn yield in specific regions through the years 1994 - 2011

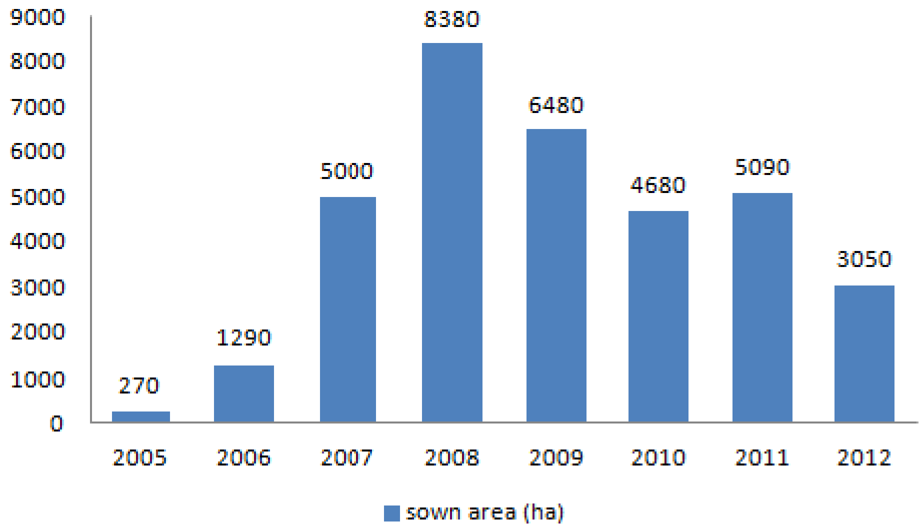


Source: Data from the Czech Statistical Office.

As we can see in Figure 1, logarithm of yield shows clear upward trend. The trend is visible in all 14 regions of Czech Republic. For illustration, we decided to include figures of Stredocesky, Plzensky, and Vysocina regions because of the clear trend and large sown area of corn. Ustecky region is included because of the large share of GM corn.

Data on the sown area of GM corn measured in ha were obtained through the communication with The Ministry of the Environment of the Czech Republic, which is legally obliged to collect information on all GM crops grown in the Czech Republic. Original data were arranged according to individual farms and listed by the date of notification. These data had to be rearranged to the form suitable for our analysis – according to year and region. Sown area of GM corn was divided by total sown area of corn to get the share of land dedicated to GM corn. The maximum share was achieved in Ustecky region in 2009 where GM corn accounted for 21% of corn sown area. The median is slightly under 2%. GM corn has been grown in the Czech Republic since 2005, until then the share of GM corn sown area is 0.

Figure 2. Sown area of GM corn in CZ through the years 2005 - 2012



Source: Data from Ministry of the Environment of the Czech Republic.

The low adoption rate of GM corn in Czech Republic is caused by legislative obstacles and regulations as well as general resentment to GM technology. In Figure 2, we can see that the adoption of GM corn in CZ has increased sharply since 2005 to its peak of $8,380$ ha in 2008. During the next years the sown area has steadily declined to $3,035$ ha in 2012. Both sharp rise and steady decline are not caused by legislation only. There has been a sudden increase in European corn borer occurrence in the period 2003-2006 when its occurrence in the Czech Republic was high, while in 2007 and 2008 it was medium to low (Kristkova, 2010).

As the regular pesticides used against corn borer lose their efficiency over time and the modification of their content is needed (also known as secondary pests issues), there was an incentive for the farmers to increase the GM sown area or to newly adopt the GM technology. Study done by Sexton and Zilberman (2011) concludes that the yield gains associated with the adoption of the GM technology are also effected by pest pressure and the availability of pesticides. Kocourek and Stara (2012) confirm in their study on the effectiveness of control measurements on the corn borer that there has been a great abundance of the corn borer in the Central Europe during the first decade of the 21st century. Until 2008, farmers had time to acquire required technology for the use of conventional methods of protection and new conventional techniques emerged. After pesticides with adjusted content were produced and the use of GM technology stopped the overgrowth of corn borer farmers could return to the use of conventional methods of protection as they do not require such a bureaucratic hassle.

An example of administrative restrictions is the EU regulation that requires farmers to keep minimal distance of GM crops from the non-GM crops. Groeneveld et al. (2013) say that this law can seriously limit the area of GM crop. However another study done on the GM corn by Skevas et al. (2010) in Portugal shows that such restriction does not necessarily limit the area dedicated to GM crops severely.

The survey of Czech GM corn producers (both active ones and the ones who dropped out of GM corn production) presented by Kristkova (2010) clearly shows that extensive administration is the most important disadvantage of Bt corn cultivation for Czech participants at GM corn market. Another important perceived disadvantage of GM corn was insufficient demand from prospective buyers of GM corn. This low demand was generally a result of anti-GM sentiment and regulations on EU markets. The results of this survey presented by Kristkova (2010) are based on responses up to 2008. There was no survey of Czech GM corn market conducted after 2009. However occasional brief statements from Czech Ministry of Agriculture, from farmers' organizations or other involved stakeholders presented all over the period 2009-2013 generally show excessive administration and insufficient demand as the two main reasons why the Czech GM corn market is steadily declining since 2009.

For the growth of corn, two weather factors are crucial: temperature and rainfall. In our analysis, both temperature and rainfall are used in monthly manner. On average, corn in the Czech Republic is sown in May and harvested in August (Vrzal et al, 1995). Therefore, average regional temperature and rainfall for the months of May, June, July, and August were taken. Temperature is measured in $^{\circ}C$, rainfall in millimeters ($1mm = 1l/m^2$). Data on both temperature and rainfall were downloaded from the web site of the Czech

Hydrometeorological Institute.

The yield of corn is influenced by many other factors besides temperature and rainfall. Two main factors important for corn yield that are not included in our analysis due to data availability are altitude and amount of fertilizers used (Vrzal et al, 1995). Omitting these two factors should not invalidate our analysis. Potential bias resulting from possible correlation of fertilizers use and GM seeds use is analyzed in Section 6. Altitude can be considered as an individual heterogeneity which is controlled for in the panel data estimators. As an approximation of the technology development, the time trend is included in our model.

3. Model

Based on available data and reviewed literature, following model was used to investigate the effect of share of overall corn sown area dedicated to GM corn on corn yields. Variables used in the model are following: logarithm of corn yield ($logyield$), share of GM corn on overall corn sown area multiplied by 100 ($GMshare100$) for interpretation purposes, average rainfall in the months of May, June, July, and August ($rmay$, $rjune$, $rjuly$, and $raug$, respectively), average temperature in the corresponding months ($tmay$, $tjune$, $tjuly$, and $taug$, respectively), and time trend ($year$). Combining the time trend with the logarithmic corn yield implicitly assumes an exponential technological development (as the first-order approximation). Time periods are denoted with subscript t and regions with subscript i. We have data available for the years 1994 - 2011, therefore $t = 1, 2, ..., 18$. The Czech Republic consists of 14 regions so that $i = 1, 2, ...14$. The whole is then written as

$$\begin{aligned} logyield_{it} = \beta_0 + \beta_1 GMshare100_{it} + \beta_2 rmay_{it} + \beta_3 rjune_{it} + \beta_4 rjuly_{it} + \\ + \beta_5 raug_{it} + \beta_6 tmay_{it} + \beta_7 tjune_{it} + \beta_8 tjuly_{it} + \\ + \beta_9 taug_{it} + \beta_{10} year_{it} + u_{it} \end{aligned} \tag{1}$$

For the error term u_{it}, it holds that $u_{it} = \mu_i + \nu_{it}$ where μ_i denotes the cross-section specific components (also called time-invariant) and ν_{it} is remainder effect. The time-invariant error includes regional specifics that do not change over time. Such regional specifics include land fertility, altitude, and other. The model has been estimated by Pooled OLS, FE, and RE procedures which are described in the following section.

Before turning to the methodology, we shortly discuss the expectations of the model.

The crucial expectation is a positive effect of GM corn on corn yields which leads us to positive β_1. Significance of this effect is difficult to forecast. The share of GM corn in the Czech Republic is small.

Technology plays an important role in agriculture. Each year new fertilizers, chemical treatments, and improved techniques like irrigation systems are developed. As mentioned above, technological progress can be expressed in the time trend and we anticipate β_{10} being positive and significant. Both rainfall and temperature will be jointly significant over included months. Significance in each month is difficult to forecast but in general, these two factors are important for corn, especially in May and June (Vrzal et al, 1995).

Further expectation about our model is present heterogeneity. The fertility rate in each region is different as well as altitude and other climatic conditions.

4. Methodology

The model was estimated by standard panel data procedures – Pooled OLS, FE, and RE using software Stata/IC 12.0. In this section, the details of all three econometrical methods are described. The description of Haussman test and Breusch-Pagan test for heterogenity is also present. Description of methodology is based on Baltagi (2008) and Woolridge (2009).

4.1 Pooled Ordinary least squares

The main benefit of pooled OLS is increased sample size thanks to adding time dimension. To obtain Pooled OLS, we need to have a random sample at two or more points in time. Advantage of Pooled OLS is that we have bigger data set and can estimate the change in relationships among variables over time. Unfortunately, we have no use for this advantage when exploring the influence of GM corn share on overall corn yield. Pooled OLS estimators are unable to control for individual heterogeneity. Not controlling for individual heterogeneity results in biased estimators. Following FE and RE procedures, we are able to control for individual heterogeneity.

4.2 Fixed effect

Fixed effect model treats time-invariant μ_i as fixed parameter and estimates it. Consider following model where k is the number of independent variables, $i = 1, 2, \ldots N$, $t = 1, 2, \ldots, T$, μ_i is the time-invariant and ν_{it} is the remainder effect:

$$y_{it} = \beta_0 + \beta_1 x_{it1} + ... + \beta_k x_{itk} + \mu_i + \nu_{it} \quad (2)$$

Fixed effect procedure involves time demeaning, which averages Eq. 2 and subtracts it from the original equation:

$$y_{it} - \overline{y}_{it} = \beta_1 (x_{it1} - \overline{x}_{i1}) + ... + \beta_k (x_{itk} - \overline{x}_{ik}) + \mu_i - \overline{\mu}_i + \nu_{it} - \overline{\nu}_i \quad (3)$$

The time-invariant μ_i is constant over time and therefore it is swept away from the equation. The same holds for the constant term β_0. The model can be written using the demeaned variables as

$$\ddot{y}_{it} = \beta_1 \ddot{x}_{it1} + ... + \beta_k \ddot{x}_{itk} + \ddot{\nu}_{it}. \quad (4)$$

FE estimation accounts for individual heterogeneity but cannot estimate the effect of such time-invariant variables. This does not interfere with our goal as we are not trying to estimate these effects. Using FE estimation provides us with consistent estimates under standard assumptions.

4.3 Random effect

If we think of μ_i in our model as random, we cannot use FE any longer as it turns into an inefficient estimator. The simple OLS procedure could be used while we believe μ_i to be uncorrelated with explanatory variables but OLS ignores serial correlation in the error term. If we assume μ_i to be uncorrelated with each explanatory variable in all time periods and also uncorrelated with all ν_{it}, we can use RE model. The RE model is specified as

$$y_{it} = \beta_0 + \beta_1 x_{it1} + ... + \beta_k x_{itk} + u_{it}, \quad (5)$$

where $u_{it} = \mu_{it} + \nu_{it}$ is called a composite error term.

RE model is estimated using the quasi-demeaned data. We obtain the quasi-demeaned data in a following way. Firstly, we assume that

$$Corr(u_{it}, u_{is}) = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\nu^2} \quad (6)$$

for all $t \neq s$ where $\sigma_\mu^2 = Var(\mu_i)$ and $\sigma_\nu^2 = Var(\nu_{it})$. Secondly, we subtract the averaged equation multiplied by λ from the original model where

$$\lambda = 1 - \left(\frac{\sigma_\nu^2}{\sigma_\nu^2 + T\sigma_\mu^2} \right)^{1/2}. \tag{7}$$

This leads us to the following equation using the quasi-demeaned data:

$$y_{it} - \lambda \overline{y}_{it} = \beta_0(1-\lambda) + \beta_1(x_{it1} - \lambda \overline{x}_{i1}) + \ldots + \beta_k(x_{itk} - \lambda \overline{x}_{ik}) + \\ +(u_{it} - \lambda \overline{u}_i) \tag{8}$$

By putting our data through the GLS procedure, we obtain uncorrelated errors. In practice, we need to obtain an estimate of λ as it is composed of theoretical variances. Such estimate of λ is obtained according to Eq. 7 using Pooled OLS procedure. Thus the RE model is estimated using the FGLS procedure.

RE estimator is consistent and approximately normally distributed with valid standard statistical inference under standard assumptions. Estimating the model through RE allows for variables constant over time. Crucial assumption for the consistency of RE is μ_i being uncorrelated with explanatory variables. Under such assumptions, the RE estimator is more efficient than the FE estimator.

4.4 Tests

To decide between our three models, we need to perform statistical tests. To decide whether or not we can use Pooled OLS, we use the Breusch-Pagan test (B-P). The Hausman test is used to decide between FE and RE models.

After estimating the model by RE, we can run the Lagrange multiplier test developed by Breusch and Pagan (1980) to test for heterogenity. B-P test is specified by

$$H_0 : Var(\mu_i) = 0, \tag{9}$$

$$H_1 : Var(\mu_i) \neq 0. \tag{10}$$

Under H_0, the Pooled OLS model is preferred as variation in μ_i is zero and we therefore find no evidence for heterogenity. Under H_1, we assume heterogeneity is present. RE procedure gives better estimates of true coefficients because it accounts for individual heterogeneity.

The Haussman test is based on exploring the relationship between μ_i and explanatory variables x_{it}. The hypotheses are as follows:

$$H_0 : cov(\mu_i, x_{it}) = 0 \tag{11}$$

$$H_1 : cov(\mu_i, x_{it}) \neq 0 \tag{12}$$

Under H_0, there is no correlation between μ_i and x_{it} so that both FE and RE are consistent. Using the RE procedure gives us asymptotically more efficient estimates. Under H_1, RE estimates are no longer consistent due to violationof the model assumptions. In conclusion, the RE estimates are preferred under H_0 and the FE estimates are preferred under H_1.

5. Empirical results

The estimated models described in the previous section are summarized in Appendix A.

5.1 Model estimates

As we look at the results of all three models, we can see that they have many common features. Both the OLS and FE models have high R^2 – 0.49 and 0.57, respectively. The RE model gives χ^2 statistic, testing the joint significance of the included parameters, equal to 287.35 with the p-value very close to 0. These numbers show that the dependent variable is well explained by our model. If we look further on similarities in our three models, we can see that the signs of all coefficients across the three models are the same. Difference between our models is in the significance level of coefficients.

Share of the GM crops has a positive sign in all three models – ranging from 0.004 in the OLS model to 0.006 in both FE and RE models. The signs of $GMshare100$ coefficients do not differ but their significance levels do. In the OLS estimation, the coefficient of $GMshare100$ is not significant at even 10% significance level. In fact the exact p-value is 0.18 (t-statistic$=1.36$). In both FE and RE models, the coefficient is significant at 5% level (t-statistics are 2.0 and 1.97, respectively). The quantitative interpretation of our FE and RE models is that if we dedicate 1 more percentage point of corn sown area to the GM corn, we increase the overall corn yield by 0.6% t/ha.

Technological progress contained in our regression in the time trend has also positive effect on the corn yields. The estimated coefficient is 0.015 with significance level 1% in all three models. This shows us the importance of technological improvements in agriculture.

The key interest in our analysis lies on the coefficient of $GMshare100$ while both rainfall and temperature are control variables. However, to fully describe the results of our three models, we include also description of estimated rainfall and temperature coefficients.

Average rainfalls are jointly significant in all three models with p-value very close to 0. Such strong significance confirms the importance of positive influence of rainfalls to the corn yields. All three models tell us that rainfall is important especially in the months of June and July. The estimated coefficients by the months of May and August are zero to the third decimal point and their significance is also negligible.

The strong influence of temperature on the corn yield is confirmed by a strong joint significance of the average monthly temperatures. The p-value of joint significance test in all three models is close to 0 (F-statistics are 4.8 with 241 df in the OLS model, 10.9 with 228 df in the FE model, and $\chi_4^2 = 34.5$ in the RE model). The average temperature in May has a positive sign and it is significant at 1% level in all three models (t-statistics are around 3.5). Temperature in June has a negative sign but it is the least significant temperature term in all three models. Temperatures in July and August have also negative sign and are significant at 1% level (t-statistics range from 3.4 to 4.6) in the FE and RE models.

Results concerning the rainfall and temperature are in line with the agronomic literature. May is important as the corn germinates and growth sets off. Corn needs both moisture and warm temperature. Rainfall is not significant in May as the corn uses especially moisture from defrosted soil. The intensive growth takes place in the months of June and July. Both the rainfall and temperature are crucial at this stage. Corn needs sufficient amount of rainfall and suitable temperature to create biomass. Corn is very demanding on rainfall. Interestingly, too high temperature has a negative effect. The optimum temperature for vegetative growth is around 20 $^\circ$C. Higher temperatures slow down the creation of biomass and therefore lead to lower yields of corn for silage. The temperature is important during the whole growth of corn. In the Czech Republic, harvesting of corn for silage proceeds on average during August. Rainfall is no longer crucial for corn because the biomass has already been created (Vrzal et al, 1995).

5.2 Testing the models

We have three models with comparable results. It is still necessary to decide which model suits our data best. It is possible to compare our three models based on tests described in Section 4.

After running the RE procedure, we can exploit the B-P test for heterogeneity. If we look at the results of the B-P test, we can see that the $H_0 : Var(\mu_i) = 0$ is strongly rejected with p-value very close to 0 (χ^2 equal to 72.44). There is a strong sign of heterogeneity in our model which is in line with our expectations. This tells us that the RE model is preferred to Pooled OLS. To compare the FE and RE models we used the Hausman specification test. The result of the test yields sign of correlation in the error term. We reject H_0 at 3% significance level (test statistic 19.94). In this case Haussman test tells us to prefer FE model over RE model.

All of our three models have given us similar estimates but based on the B-P test for heterogeneity and Hausman specification test, we can point out the most relevant model. The B-P test tells us that heterogeneity is present in our data. This rules out Pooled OLS model and leaves us with FE and RE models that are able to cope with heterogeneity. Both these models give us almost the same estimates. If we still want to find the most relevant model, we look at the Hausman test for specification which tells us to prefer FE model over RE. Therefore, we prefer the FE model.

6. Discussion

In this section, we compare our expectations with relationships among variables as estimated by the FE model which showed up to suit our data best. The table with results and significance of each estimate can be found in Appendix A and the description of results is given in Section 1. For an easier comparison of our expectations with relationships found in the model, we include the estimated equation:

$$\begin{aligned} logyield_{it} &= -26.809 + 0.006 GMshare100_{it} + 0.001 rjune_{it} + \\ &+ 0.001 rjuly_{it} + 0.023 tmay_{it} - 0.011 tjune_{it} - \\ &- 0.021 tjuly_{it} + 0.031 taug_{it} + 0.015 year_{it} + u_{it} \end{aligned} \tag{13}$$

Variables *rmay* and *raug* do not appear in the equation because their estimated coefficients were 0 to third decimal place. Our first and crucial expectation regarding our data was that heterogeneity is present there. After testing the models and choosing the FE model as best fitting our data, we can say that our expectation was confirmed. Important implication is that there are regional specifics influencing the yield.

Our expectation regarding the question whether or not the GM corn increases the corn yields was affirmed by our model. The estimated coefficient is not only positive but also significant at 5% level. To recall the interpretation from Section 1, we remind that this estimate tells us that if we dedicate 1 more percentage point of corn sown area to GM corn, we increase the overall corn yield by $0.6\%\ t/ha$. Consequent paragraphs show us that this is a considerably high effect.

As mentioned in Section 2 describing our data, we have no data available on the amount of fertilizers used. Because the use of fertilizers and the use of GM seeds might be correlated, we have to consult the potential bias. There are three options:

$$corr(fertilizers, GM) > 0 \tag{14}$$

$$corr(fertilizers, GM) < 0 \tag{15}$$

$$corr(fertilizers, GM) = 0 \tag{16}$$

The equations (14, 15, 16) show positive correlation, negative correlation, and no correlation between use of fertilizers and use of GM seeds, respectively.

If the first option is true and farmers tend to use more fertilizers when they adopt GM seeds, our estimates would be biased upward. Negative correlation between use of fertilizers and use of GM seeds represents the situation when farmers use less fertilizers after they adopt GM seeds. Such relationship would result in downward bias of our estimates. Based on the findings of Zilberman et al. (2004), GM seeds do not influence the yield directly and therefore the same amount of fertilizers should be used whether the conventional or GM seeds are used. There are many reasons for correlation that stem from the cause of adopting GM seeds. We can speculate that if the farmer purchases more expensive GM seeds then he is less likely to buy costly fertilizers. Other speculation could be that if the use of GM seeds reduces the use of herbicides and pesticides, the application of fertilizers is more likely. Nevertheless, we believe that zero correlation between use of fertilizers and use of GM seeds is most likely and therefore our estimates are unbiased.

The largest share of the GM corn was achieved in 2009 in Ustecky region where the GM corn accounted for 21% of corn sown area. For various reasons, the GM corn cannot be adopted on 100% scale. Let's consider the 21% as a boundary for the GM corn adoption in the Czech Republic. The average share of corn sown area dedicated to the GM corn in 2011 is 2.6%. By the FE model, we estimate that if 18.4 more percentage points of corn sown area were dedicated to the GM corn, an increase of 10.6% would be achieved in the crop yield. The 95% confidence interval for our estimate is $(0.2, 21.2)$. Such broad confidence interval can be explained by heterogeneity of the regions. Nevertheless, the important information contained in this prediction is the positive sign of the effect. The average yield in 2011 was

42 t/ha. Using the 10.6% as the best prediction, the adoption of the GM corn to 21% of corn sown area would increase the yield to 46.5 t/ha. Such yield overcomes the maximum yield of our data set by more than 1 t/ha. When interpreting these results we should keep in mind that our linear regression provides us with coefficients for marginal changes. Therefore if we consider more sizeable changes in the values of variables, these marginal changes implied by regression coefficients obviously do not have to hold exactly true. Similarly, the linearity of our model does not imply that the true underlying share on GM corn on the overall corn yield has to be linear too. The linearity of our model is just a modeling simplification.

The true maximum achievable share of GM corn is much higher than 21%. In 2009, the share of the GM corn in the USA was 85% (GMO Compass, 2010). After consulting the maximum share of the GM corn in Czech Republic with the company Pioneer, which sells genetically modified seeds in the Czech Republic, we came to the conclusion that 85% is a reachable share. After including 85% to our computations, we gain an increase of nearly 50% with 95% confidence interval equal to $(7.6, 9\ 48)$. The confidence interval is again very broad due to regional heterogenity. Using 50% as the best estimate, we reach the yield of 63 t/ha.

To evaluate our expectations toward temperature and rainfall, we have to take two steps. Firstly, we have to look at the joint significance over included months. Both temperature and rainfall are strongly significant which is in line with our expectations. Secondly, we have to look at individual months. When it comes to rainfall, only June and July are left in our equation. This does not confirm our expectation about the first two months being crucial for the corn growth. On the other hand, temperature is significant in all four months (at 1% in May, July and August, at 10% in June).

The model confirmed majority of our expectations and all of our important expectations (heterogeneity, effect of the GM corn on corn yields and time trend). It even gave us more significant results on the effect of the GM corn on overall corn yields than we expected.

When compared with other papers (Sexton and Zilberman (2011, 2012), Wesseler et al. (2011), Kuosmanen et al. (2006) or Kocourek and Stara (2012)) our study came to very similar conclusions supporting the overall positive economic impact of GM corn.

Sexton and Zilberman (2011) investigate the effect of GM crops on the food supply. They determine the yield effect accountable to GM crops. Among others they are examining the case of corn with HT modification. In their analysis Sexton and Zilberman (2011) distinguish between two effect of the GM technology - the one that directly effects the output and the one that stems from decreasing the damage. The yield gains for HT corn are estimated to be 45.6%. Yield gains are higher in the areas with high pest pressure. Sexton and Zilberman (2012) exploit spatial and temporal variation in the adoption of agricultural biotechnology across countries in order to estimate the impact of adoption on food supply. They show that genetically engineered crops significantly increase yields on adopting farms.

The study conducted by Kuosmanen et al.(2006) focuses on the Bt cotton in China. Because of the rich dataset, they were able to control for many factors such as concentration of the Bt toxin in the leaves and inputs like labor. The most interesting finding of that study is that Bt modification of cotton works best at low pest pressure - more clearly the effectiveness of protection decreases with the pest pressure increase. Nevertheless the results are still in agreement with our findings. The high concentration of Bt toxin yields slightly negative results but the authors suggest that it might be because of the decrease in effectiveness in currently used technology (conventional methods are used along with GM modifications).

7. Conclusions

In this work, we wanted to shed some light on the possibilities arising from genetic engineering with respect to biofuel industry. The production of biofuels is plentiful all over the world and genetic engineering could significantly increase its potential. The commercially available technique to produce biofuels at present time is conventional food crop based production. Two previous studies conducted by Nolan and Santos (2012) and Xu et al. (2010) in the USA confirmed the positive effect of genetic engineering on corn for grain yields.

Advanced techniques of biofuel production are not yet commercially available but quick improvements are expected in the field of cellulose based biofuels. Such biofuels can be made from any cellulose biomass. The EU sees the future of biofuel industry in advanced production techniques, therefore we focused on the potentials of the GM crops with respect to cellulose based biofuels production.

In the Czech Republic, the GM corn is grown predominantly as corn for silage. In our analysis, we focused on the question whether the use of the GM corn statistically significantly increases the yield of corn for silage in the environmental conditions of the Czech Republic. We built upon previously mentioned studies examining corn for grain yields. We used weather conditions – monthly temperature and monthly rainfall – as control variables and we included the time trend to account for technological development.

We estimated our model by Pooled OLS, FE and RE. Results obtained from all these three specifications were qualitatively quite similar, which shows good robustness of our results. Results estimated by all three models were in line with our expectations of positive effect of the GM modifications on corn for silage yields. The FE model showed up as best-fitting our data while it helps to treat regional heterogeneity that is present in our dataset. Estimates from the FE model suggest that if the GM corn was adopted on 21% (which is the maximum adoption rate in the Czech Republic achieved in Ustecky region) of corn sown area the yield would increase by 10.6% which gives us average yield of 46.5 t/ha. Our model is limited by large uncertainty which is reflected by broad confidence interval of $(0.2\%, 21.2\%)$.

If we extend the adoption rate on 85% of corn sown area, the uncertainty increases. The confidence interval widens to $(7.6\%, 94.8\%)$ with the best prediction being nearly 50%. Such increase gives us average yield of 63 t/ha. These results are in agreement with both studies from the USA, although they cannot be directly compared as those studies examine corn for grain yields.

The contribution of this work stems not only from unique dataset but also from an innovative connection of two topics: biofuel industry and genetic engineering. Biofuel production is supported and plentiful all over the world but genetic engineering faces legislative obstacles. Our work supports the idea of softened legislation toward the GM crops. As genetic engineering can positively influence the yield of crops used for biofuel production, it can also significantly lower the cost of biofuel production.

While our model is quite simple and limited because of severely limited data availability, it is nevertheless the first attempt to test and quantify the potential for the role, which the genetically modified crops may play in future development of advanced cellulosic biofuels in Central and Eastern Europe. Further analysis should focus on the extension of the dataset to reduce the uncertainty of the results. We suggest inclusion of the field trials and data on fertilizers use into the dataset. The work should be also extended on additional crops that can be used for cellulose based biofuels production as soon as the needed data on these crops in Central and Eastern Europe is available. It would be very valuable to investigate the potential of genetic modifications for other plants used for cellulose based biofuels (Miscantus, switchgrass, rye, temperate climate bamboo, etc.). These cellulose based biofuels were already examined by Khanna, Dhungana, and Clifton-Brown (2008) who model the cost of production of ethanol from miscanthus and switchgrass in Illinois.

Appendix A. Tables of results

Table 1: OLS estimation results

Variable	Coefficient	(Std. Err.)
GMshare100	0.004	(0.003)
rmay	0.000	(0.000)
rjune	0.001***	(0.000)
rjuly	0.001***	(0.000)
raug	0.000	(0.000)
tmay	0.029***	(0.008)
tjune	-0.002	(0.007)
tjuly	-0.008	(0.005)
taug	-0.022***	(0.008)
year	0.015***	(0.002)
Intercept	-26.336***	(3.372)
N	252	
R^2	0.492	
$F_{(10,241)}$	23.35	

Significance levels : * : 10%   ** : 5%   *** : 1%

Table 2: FE estimation results

Variable	Coefficient	(Std. Err.)
GMshare100	0.006**	(0.003)
rmay	0.000*	(0.000)
rjune	0.001**	(0.000)
rjuly	0.001***	(0.000)
raug	0.000*	(0.000)
tmay	0.023***	(0.007)
tjune	-0.011*	(0.007)
tjuly	-0.021***	(0.005)
taug	-0.031***	(0.007)
year	0.015***	(0.002)
Intercept	-26.809***	(2.999)
N	252	
R^2	0.570	
$F_{(23,228)}$	30.242	

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Table 3: RE estimation results

Variable	Coefficient	(Std. Err.)
GMshare100	0.006**	(0.003)
rmay	0.000	(0.000)
rjune	0.001***	(0.000)
rjuly	0.001***	(0.000)
raug	0.000	(0.000)
tmay	0.025***	(0.007)
tjune	-0.008	(0.007)
tjuly	-0.017***	(0.005)
taug	-0.028***	(0.007)
year	0.015***	(0.002)
Intercept	-26.471***	(3.042)
N	252	
Log-likelihood	.	
$\chi^2_{(10)}$	287.353	

Significance levels : $*$: 10% $**$: 5% $***$: 1%

References

Badi H. Baltagi. Econometrics. Springer-Verlag Berlin Heidelberg, 4rd edition, 2008. ISBN: 978-3-540-76515-8.

Andrea Bastianin, Marzio Galeotti, and Matteo Manera. Causality and Predictability in Distribution: The Ethanol-Food Price Relation Revisited. Energy Economics, forthcoming in 2014.

Andrea Bastianin, Marzio Galeotti, and Matteo Manera. Food versus Fuel: Causality and Predictability in Distribution. Working Papers 241, University of Milano-Bicocca, Department of Economics, March 2013.

Andrea Bastianin, Marzio Galeotti, and Matteo Manera. Biofuels and food prices: Searching for the causal link. Working Paper 239, University of Milano-Bicocca, Department of Economics, March 2013.

Andrea Bastianin, Matteo Manera, M. Nicolini and I. Vignati. 2012. Speculation, Returns, Volume and Volatility in Commodities Futures Markets. Review of Environment, Energy and Economics - Re3, Fondazione Eni Enrico Mattei, http://dx.doi.org/10.7711/feemre3.2012.01.002

Andrea Bastianin, Matteo Manera, A. Markandya and E. Scarpa 2011. Oil Price Forecast Evaluation with Flexible Loss Functions. Working Papers 2011.91, Fondazione Eni Enrico Mattei.

Andrea Bastianin. 2009. Modelling Asymmetric Dependence Using Copula Functions: An application to Value-at-Risk in the Energy Sector. Working Papers 2009.24, Fondazione Eni Enrico Mattei.

Jayson Beckman, Thomas Hertel, and Wallace Tyner. Validating energy-oriented CGE models. Energy Economics, 33(5):799–806, September 2011.

Volker Beckmann, Claudio Soregaroli, and Justus Wesseler. Coexistence rules and regulations in the European Union. American Journal of Agricultural Economics, 88(5):1193–1199, 2006.

Colin A. Carter, Gordon C. Rausser, and Aaron Smith. The effect of U.S. ethanol mandate on corn prices. Presentation at Fifth Berkeley Bioeconomy Conference, March 2012.

Ujjayant Chakravorty, Marie-Helene Hubert, Michel Moreaux, and Linda Nostbakken. Will biofuel mandates raise food prices? Working Paper 2011-01, University of Alberta, May 2011.

Stepan Chrz, Karel Janda, and Ladislav Kristoufek. Modelovani provazanosti trhu potravin, biopaliv a fosilnich paliv. Politicka Ekonomie, Forthcoming 2014.

Pavel Ciaian and D'Artis Kancs. Food, energy and environment: Is bioenergy the missing link? Food Policy, 36(5):571–580, October 2011.

Czech Statistical Office. Rocni vykaz o sklizni zemedelskych plodin: Zem 6-01. Downloaded: 25.4.2013, 5 2012.

Harry de Gorter, Dusan Drabik, and David R. Just. How biofuels policies affect the level of grains and oilseed prices: Theory, models, and evidence. Global Food Security, 2(2):82–88, 2013.

Dusan Drabik. The theory of biofuel policy and food grain prices. Working Paper 2011-20, Cornell University, March 2012.

GMO Compass. Genetically modified plants: Global cultivation area. Downloaded: 15.2. 2013, 03 2010.

Rolf A. Groeneveld, Justus Wesseler, and Paul Berentsen. Dominos in the dairy: An analysis of transgenic maize in Dutch dairy farming. Ecological Economics, 86:107–116, 2013.

Karel Janda, Ladislav Kristoufek, and David Zilberman. Biofuels: Policies and impacts. Agricultural Economics - Czech, 58(8):367–371, August 2012.

Madhu Khanna, Basanta Dhungana, and John Clifton-Brown. Costs of producing miscanthus and switchgrass for bioenergy in Illinois. Biomass and Bioenergy, 32(6):482–493, June 2008.

Frantisek Kocourek and Jitka Stara. Efficacy of Bt maize against European Corn Borer in Central Europe. Plant Protection Science, 48:S25–S35, 2012.

Marie Kristkova. Experience with Bt Maize Cultivation in the Czech Republic 2005–2009. Ministry of Agriculture of the Czech Republic, April 2010.

Ladislav Kristoufek, Karel Janda, and David Zilberman. Correlations between biofuels and related commodities before and during the food crisis: A taxonomy perspective. Energy Economics, 34(5):1380–1391, September 2012.

Ladislav Kristoufek, Karel Janda, and David Zilberman. Regime-dependent topological properties of biofuels networks. European Physical Journal B, 86(2):Article 40, February 2013.

Ladislav Kristoufek, Karel Janda, and David Zilberman. Price transmission between biofuels, fuels, and food commodities. Biofuels, Bioproducts and Biorefining, Forthcoming 2014.

Timo Kuosmanen, Diemuth Pemsl, and Justus Wesseler. Specification and estimation of production functions involving damage control inputs: A two-stage, semiparametric approach. American Journal of Agricultural Economics, 88(2):499–511, 2006.

Saban Nazlioglu and Ugur Soytas. World oil prices and agricultural commodity prices:

Evidence from an emerging market. Energy Economics, 33(3):488–496, May 2011.

Elizabeth Nolan and Paulo Santos. The Contribution of Genetic Modification to Changes in Corn Yield in the United States. American Journal of Agricultural Economics, 94(5):1171–1188, 2012.

Jan Pokrivcak and Miroslava Rajcaniova. Crude oil price variability and its impact on ethanol prices. Agricultural Economics – Czech, 57(8):394–403, August 2011.

Deepak Rajagopal and David Zilberman. Review of environmental, economic and policy aspects of biofuels. Policy Research Working Paper 4341, The World Bank, September 2007.

Miroslava Rajcaniova, Dusan Drabik, and Pavel Ciaian. How policies affect international biofuel price linkages. Energy Policy, 59(C):857–865, August 2013.

Miroslava Rajcaniova and Jan Pokrivcak. The impact of biofuel policies on food prices in the European Union. Journal of Economics (Ekonomicky casopis), 59(5):459–471, 2011.

Teresa Serra and David Zilberman. Biofuel-related price transmission literature: A review. Energy Economics, 37:141–151, May 2013.

Teresa Serra, David Zilberman, and Jose M. Gil. Price volatility in ethanol markets. European Review of Agricultural Economics, 38(2):259–280, 2011.

Teresa Serra, David Zilberman, Jose M.Gil, and Barry K. Goodwin. Nonlinearities in the U.S. corn-ethanol-oil-gasoline price system. Agricultural Economics, 42(1):35–45, January 2011.

Steven Sexton and David Zilberman. How agricultural biotechnology boosts food supply and accomodates biofuels. Technical report, National Bureau of Economic Research, 2011. NBER Working Paper No. 16699.

Steven Sexton and David Zilberman. Land for food and fuel production: The role of agricultural biotechnology. In Joshua S. Graff-Zivin and Jeffrey M. Perloff, editors, The Intended and Unintended Effects of U.S. Agricultural and Biotechnology Policies, NBER book, chapter 8. University of Chicago Press, 2012.

Theodoros Skevas, Pedro Fevereiro, and Justus Wesseler. Coexistence regulations and agriculture production: A case study of five Bt maize producers in Portugal. Ecological Economics, 69(12):2402–2408, 2010.

Lukas Vacha, Karel Janda, Ladislav Kristoufek, and David Zilberman. Time-frequency dynamics of biofuel-fuel-food system. Energy Economics, 40:233–241, November 2013.

Jaroslav Vrzal and Daniel Novak. Zaklady pestovani kukurice a jednoletych picnin. Agrodat, 1995. ISBN: 80-7105-097-0.

Justus Wesseler. The economics of coexistence. Presentation at Fifth Bioeconomy

Conference: Renewable Resources, Berkley, 2012.

Justus Wesseler, Sara Scatasta, and El Hadji Fall. The environmental benefits and costs of genetically modified (GM) crops. In Colin A. Carter, GianCarlo Moschini, and Ian Sheldon, editors, Genetically Modified Foods and Global Welfare, number 10 in Frontiers of Economics and Globalization, chapter 7, pages 173–199. Emerald Group Publishing, 2011.

Jeffrey M. Wooldridge. Introductory econometrics: a modern approach, volume 4. South-Western Pub, 2009.

Zheng Xu, David A. Hennessy, and GianCarlo Moschini. Have biotech seeds increased maize yields? In Annual Meeting, July 25-27, 2010, Denver, Colorado, number 61303. Agricultural and Applied Economics Association, 2010.

Zibin Zhang, Luanne Lohr, Cesar Escalante, and Michael Wetzstein. Mitigating volatile U.S. gasoline prices and internalizing external costs: A win-win fuel portfolio. American Journal of Agricultural Economics, 90(5):1218–1225, December 2008.

Zibin Zhang, Luanne Lohr, Cesar Escalante, and Michael Wetzstein. Ethanol, corn, and soybean price relations in a volatile vehicle-fuels market. Energies, 2(2):320–339, 2009.

Zibin Zhang, Luanne Lohr, Cesar Escalante, and Michael Wetzstein. Food versus fuel: What do prices tell us. Energy Policy, 38(1):445–451, January 2010.

David Zilberman, Holly Ameden, Gregory Graff, and Matin Qaim. Agricultural biotechnology: productivity, biodiversity, and intellectual property rights. Journal of Agricultural & Food Industrial Organization, 2(2):3, 2004.

David Zilberman, Gal Hochman, Deepak Rajagopal, Steve Sexton, and Govinda Timilsina. The impact of biofuels on commodity food prices: Assessment of findings. American Journal of Agricultural Economics, 95(2):275–281, 2013.

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