

The perspectives for genetically modified cellulosic biofuels in the Central European conditions

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Abstract: This paper connects the biofuels literature with the genetic modifications literature by considering the potential of genetic modifications for increasing the efficiency of the cellulosic biofuels production. This is done for one particular case through analyzing the effect of genetically modified corn adoption on the overall yields of corn for silage. Our econometric model confirms that the use of genetically modified corn with the 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.

Key words: cellulosic biofuels, genetic modifications

The main objective of this paper is to connect the biofuels literature, for a recent representative review see Janda et al. (2012), with the 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 the GM corn adoption on the 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 the Central Europe. The GM technology is also associated with lower costs of planting and could result in the lower cost of biofuels production.

The analytical part of this work deals with the question whether the use of genetically modified corn with the 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 the 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 the yield of the GM corn is 1.4–1.5 times higher than the yield of the regular corn. Another important outcome of their analysis is that the Bt corn is associated with an increase in corn yields but the HT corn seems to be yield neutral. The Bt corn is an insect resistant crop which contains a gene of the soil bacterium called the *Bacillus thuringiensis* (hence Bt crops), while HT stands for the herbicide-tolerant GM technology. This result of Nolan and Santos (2012) has an important implication for our analysis since the only the GM corn hybrids grown in the Czech Republic have inserted the MON810 gene resulting in the Bt modification. In our analysis, we would like to confirm the assumption of the positive effect of the Bt corn on the 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 the influence of GM on grain yield, we are interested in the overall biomass yield. While the results of Nolan and Santos (2012) are, therefore, directly relevant for the

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first generation conventional biofuels produced from corn grain, our results are directly relevant for the second generation advanced biofuels production.

The potential of GM crops in the EU is decreased by the conservative legislation (Beckmann et al. 2006 and Groeneveld et al. 2013) which results in too little effort put into the GM research. Therefore in Europe, we do not have any 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 the GM corn for grain in USA by Xu et al. (2010) analyzed the effect of the 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 the weather conditions as well.

Both above mentioned studies investigate the effect of the 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 the GM product are rigorous and result in the 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 the GM corn on corn for grain yields in the 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 the cellulose based ethanol are already available in Crescentino (Italy) on the commercial scale and in a number of pilot plans in the USA and Europe, like for example the 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 the ethanol production would be smaller.

While the references mentioned in the previous paragraphs were concerned primarily with the GM crops, there is also a very sizable literature dealing with the use of corn as feedstock for biofuels. In this

literature, many economic modelling techniques are used to model the impact of the corn based ethanol from different points of view. The basic distinction may be made between the structural and reduced form models. Structural models are based on the economic theory complemented with some technological assumptions. Reduced form models are usually concerned only with the statistical properties of the 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 et al. (2011) in the context of the CGE modelling, or by de Gorter et al. (2013) in the partial equilibrium models. A detailed taxonomy of structural models and their results with respect to the economics of corn ethanol biofuels is provided by Rajagopal and Zilberman (2007) and their comparison with the reduced form models is given by Zilberman et al. (2012).

The reduced form models of corn ethanol usually focus on relationships among the prices of the 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 et al. 2011a) and Brazilian (Serra et al. 2011b) ethanol markets, where the Brazilian case is dealing with the 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 the related commodities. Recently, Bastianin et al. (2009, 2011, 2012, 2013a,b, 2014) in a series of papers starting already in 2009 or Carter et al. (2012) investigated the relations among the prices of corn and other biofuel related commodities using the US data. Nazlioglu and Soytaş (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 the 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 emphasis of Czech and Slovak academic economists interested in the biofuels (Ciaian and Kancs 2011; Pokrivcak and Rajcaniova 2011; Rajcaniova and Pokrivcak 2011; Kristoufek et al. 2012, 2013, 2014; Rajcaniova et al. 2013; Vacha et al. 2013; Chrzącz et al. 2014) was so far oriented primarily on the pricing of ethanol and biodiesel or on the welfare analysis of biofuels policies (Drabik 2012), and it was

conducted only in the framework of the commercially well developed first-generation biofuels.

DATA

To answer our question, we used the data on the overall yield of corn for silage, the share of the GM corn sown area, the average temperature, and the 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 the personal communication with the Czech Statistical Office. They involve data on the sown area in hectares (ha) and crop in tons (t). The yield was calculated for each year and region by dividing the crop by the 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. The yield therefore measures how many tons of corn biomass has grown on 1 hectare

of the sown area. The highest yield in our dataset is 45.2 t/ha, the lowest one is 18.9 t/ha. The mean value of corn yield in our data is 33 t/ha.

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

Data on the sown area of the 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. The original data were arranged according to the individual farms and listed by the date of notification. These data had to be rearranged to the form suitable for our analysis – according to the year and region. The sown area of the GM corn was divided by the total sown area of corn to get the share of land dedicated to the GM corn. The maximum share was achieved in the Ústecký region in 2009, where the GM corn accounted for 21% of the corn sown area. The median is slightly under 2%. The GM corn has been grown in

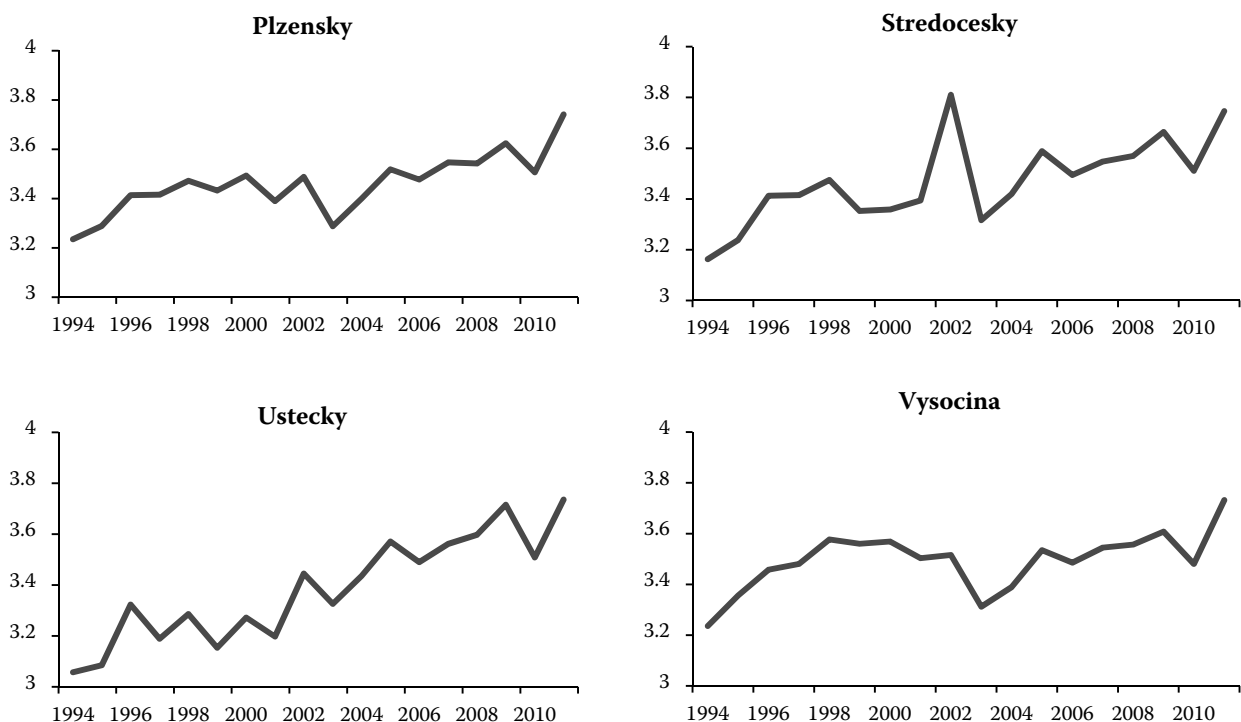


Figure 1. The logarithm of corn yield in the specific regions through the years 1994–2011

Source: Data from the Czech Statistical Office

the Czech Republic since 2005, until then the share of the GM corn sown area is 0.

The low adoption rate of the GM corn in the Czech Republic is caused by legislative obstacles and regulations as well as the general resentment to the GM technology. In Figure 2, we can see that the adoption of the GM corn in the CR has increased sharply since 2005 to its peak of 8380 ha in 2008. During the next years, the sown area has steadily declined to 3035 ha in 2012. Both the sharp rise and the steady decline are not caused by the legislation only. There has been a sudden increase in the 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 the 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. The study done by Sexton and Zilberman (2011) concludes that the yield gains associated with the adoption of the GM technology are also affected by the 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 the required technology for the use of the conventional methods of protection and new conventional techniques emerged. After pesticides with the adjusted content were produced and the use of the GM technology stopped the overgrowth of corn borer, the 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 a minimal distance of the GM crops from the non-GM crops. Groeneveld et al. (2013) say that this law can seriously limit the area of the 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 the GM crops severely.

The survey of the Czech GM corn producers (both active ones and the ones who dropped out of the GM corn production) presented by Kristkova (2010) clearly shows that the extensive administration is the most important disadvantage of the Bt corn cultivation for Czech participants in the GM corn market. Another important perceived disadvantage of the GM corn was the insufficient demand from the prospective buyers of the GM corn. This low demand was generally a result of the anti-GM sentiment and the regulations on the EU markets. The results of this survey presented by Kristkova (2010) are based on responses up to 2008. There was no survey of the Czech GM corn market conducted after 2009. However, occasional brief statements from the Czech Ministry of Agriculture, from the farmers' organizations or other involved stakeholders presented all over the period 2009–2013 generally show an 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 the monthly manner. In average, corn in the Czech Republic is sown in May and harvested in August (Vrzal and Novak 1995). Therefore, the average regional temperature and rainfall for the months of May, June, July, and August were taken. Temperature is measured in °C, rainfall in millimetres (1 mm = 1 l/m²). Data on both temperature and rainfall were downloaded from the web site of the Czech Hydro-meteorological 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 the data availability are altitude and the amount of fertilizers used (Vrzal and Novak 1995). Omitting these two factors should not invalidate our analysis. The potential bias resulting from the possible correlation of the fertilizers use and the GM seeds use is analyzed in Discussion. Altitude can

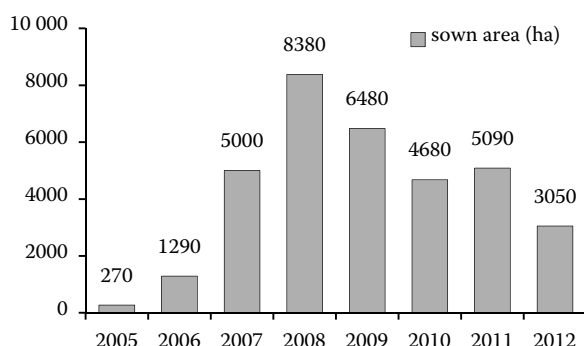


Figure 2. Sown area of the GM corn in the CR through the years 2005–2012

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

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.

MODEL

Based on the available data and the reviewed literature, the following model was used to investigate the effect of the share of the overall corn sown area dedicated to the GM corn in corn yields. Variables used in the model are the following: the logarithm of corn yield (*logyield*), the share of the GM corn in the overall corn sown area multiplied by 100 (*GMshare100*) for interpretation purposes, the average rainfall in the months of May, June, July, and August (*rmay*, *rjune*, *rjuly*, and *raug*, respectively), the 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 the subscript *t* and regions with the subscript *i*. We have data available for the years 1994–2011, therefore $t = 1, 2, \dots, 18$. The Czech Republic consists of 14 regions, so that $i = 1, 2, \dots, 14$. The whole is then written as

$$\begin{aligned} \text{logyield}_{it} = & \beta_0 + \beta_1 \text{GMshare100}_{it} + \beta_2 \text{rmay}_{it} + \\ & + \beta_3 \text{rjune}_{it} + \beta_4 \text{rjuly}_{it} + \beta_5 \text{raug}_{it} + \beta_6 \text{tmay}_{it} + \\ & + \beta_7 \text{tjune}_{it} + \beta_8 \text{tjuly}_{it} + \beta_9 \text{taug}_{it} + \beta_{10} \text{year}_{it} + u_{it} \quad (1) \end{aligned}$$

For the error term u_{it} , it holds that $u_{it} = \mu_i + v_{it}$ where μ_i denotes the cross-section specific components (also called time-invariant) and v_{it} is the 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 the GM corn on the 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, the technological

progress can be expressed in the time trend and we anticipate β_{10} being positive and significant. Both the rainfall and temperature will be jointly significant over the 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 and Novak 1995).

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

METHODOLOGY

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

Pooled Ordinary least squares

The main benefit of the Pooled OLS is the increased sample size thanks to adding the time dimension. To obtain the Pooled OLS, we need to have a random sample at two or more points in time. The advantage of the Pooled OLS is that we have a 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 the GM corn share on the overall corn yield. The Pooled OLS estimators are unable to control for the individual heterogeneity. Not controlling for the individual heterogeneity results in biased estimators. Following the FE and RE procedures, we are able to control for the individual heterogeneity.

Fixed effect

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

$$y_{it} = \beta_0 + \beta_1 x_{it} + \dots + \beta_k x_{itk} + \mu_i + v_{it} \quad (2)$$

The fixed effect procedure involves time demeaning, which averages the Equation 2 and subtracts it from the original equation:

$$y_{it} - \bar{y}_{it} = \beta_1(x_{it1} - \bar{x}_{i1}) + \dots + \beta_k(x_{itk} - \bar{x}_{ik}) + \mu_i + \bar{\mu}_i + v_{it} - \bar{v}_i \quad (3)$$

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

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

The FE estimation accounts for the individual heterogeneity but it 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 the FE estimation provides us with consistent estimates under standard assumptions.

Random effect

If we think of μ_i in our model as random, we cannot use the 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 the OLS ignores the 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 v_{it} , we can use the RE model. The RE model is specified as

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

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

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

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

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

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

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

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

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 the Equation 7 using the Pooled OLS procedure. Thus the RE model is estimated using the FGLS procedure.

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

Tests

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

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

$$H_0: \text{Var}(\mu_1) = 0 \quad (9)$$

$$H_1: \text{Var}(\mu_1) \neq 0 \quad (10)$$

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

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

$$H_0: \text{cov}(\mu_1, x_{it}) = 0 \quad (11)$$

$$H_1: \text{cov}(\mu_1, x_{it}) \neq 0 \quad (12)$$

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 , the RE estimates are no longer consistent due to the violation of the model assumptions. In conclusion, the RE estimates are preferred under H_0 and the FE estimates are preferred under H_1 .

EMPIRICAL RESULTS

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

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. The difference between our models is in the significance level of coefficients.

The 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 the *GMshare100* coefficients do not differ but their significance levels do. In the OLS estimation, the coefficient of the *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 the corn sown area to the GM corn, we increase the overall corn yield by 0.6% t/ha.

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

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

The average rainfalls are jointly significant in all three models with p -value very close to 0. Such strong significance confirms the importance of the positive influence of rainfalls to the corn yields. All three models tell us that the 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 the 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 $\chi^2_4 = 34.5$ 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). The 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 a 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 the 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 a sufficient amount of rainfall and a suitable temperature to create biomass. Corn is very demanding on the rainfall. Interestingly, a too high temperature has a negative effect. The optimum temperature for the vegetative growth is around 20 °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 in average during August. Rainfall is no longer crucial for corn because the biomass has already been created (Vrzal and Novak 1995).

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 the section Methodology.

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 $H_0: \text{Var}(\mu_i) = 0$ 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 the Pooled OLS. To compare the FE and RE models, we used the Hausmann 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 the Hausmann test tells us to prefer the FE model over the RE model.

All of our three models have given us similar estimates, but based on the B-P test for heterogeneity and Hausmann 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 the Pooled OLS model and leaves us with the 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 Hausmann test for specification which tells us to prefer the FE model over the RE. Therefore, we prefer the FE model.

DISCUSSION

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

$$\begin{aligned} \text{logyield}_{it} = & -26.809 + 0.006\text{GMshare100}_{it} + \\ & + 0.001\text{rjune}_{it} + 0.001\text{rjuly}_{it} + 0.023\text{tmay}_{it} - \\ & - 0.011\text{tjune}_{it} - 0.021\text{tjuly}_{it} + 0.031\text{taug}_{it} + \\ & + 0.015\text{year}_{it} + u_{it} \end{aligned} \quad (13)$$

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 the 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. An 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 the Introduction, we remind that this estimate tells us that if we dedicate 1 more percentage point of the corn sown area to the 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 the section Data describing our data, we have no data available on the amount of the fertilizers used. Because the use of fertilizers and the use of the GM seeds might be correlated, we have to consult the potential bias. There are three options:

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

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

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

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

If the first option is true and farmers tend to use more fertilizers when they adopt the GM seeds, our estimates would be biased upward. The negative correlation between the use of fertilizers and the use of GM seeds represents the situation when farmers use less fertilizers after they adopt the GM seeds. Such relationship would result in the downward bias of our estimates. Based on the findings of Zilberman et al. (2004), the GM seeds do not influence the yield directly and therefore the same amount of fertilizers should be used whether the conventional or the GM seeds are used. There are many reasons for the correlation that stem from the cause of adopting the GM seeds. We can speculate that if the farmer purchases more expensive GM seeds then he/she is less likely to buy costly fertilizers. Other speculation could be that if the use of the GM seeds reduces the use of herbicides and pesticides, the application of fertilizers is more likely. Nevertheless, we believe that zero correlation between the use of fertilizers and the 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 the Ustecký region where the GM corn accounted for 21% of the corn sown area. For various reasons, the GM corn cannot be adopted on 100% scale. Let us consider the 21% as a boundary for the GM corn adoption in the Czech Republic. The aver-

age share of the 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 the 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 the 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 the 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 the regression coefficients obviously do not have to hold exactly true. Similarly, the linearity of our model does not imply that the true underlying share of the GM corn in the overall corn yield has to be linear too. The linearity of our model is just a modelling simplification.

The true maximum achievable share of the 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 the 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, 94.8). The confidence interval is again very broad due to the regional heterogeneity. Using 50% as the best estimate, we reach the yield of 63 t/ha.

To evaluate our expectations toward the temperature and rainfall, we have to take two steps. Firstly, we have to look at the joint significance over included months. Both the temperature and rainfall are strongly significant which is in line with our expectations. Secondly, we have to look at the individual months. When it comes to the 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, the temperature is significant in all four months (at 1% in May, July and August, at 10% in June).

The model confirmed the majority of our expectations and all of our important expectations (heteroge-

neity, 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 the 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 the GM corn.

Sexton and Zilberman (2011) investigate the effect of GM crops on the food supply. They determine the yield effect accountable to the GM crops. Among others, they are examining the case of corn with the HT modification. In their analysis, Sexton and Zilberman (2011) distinguish between two effect of the GM technology – the one that directly affects the output and the one that stems from decreasing the damage. The yield gains for the HT corn are estimated to be 45.6%. Yield gains are higher in the areas with a high pest pressure. Sexton and Zilberman (2012) exploit the spatial and temporal variation in the adoption of agricultural biotechnology across countries in order to estimate the impact of the adoption on the food supply. They show that genetically engineered crops significantly increase the yields on the 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 many factors such as the concentration of the Bt toxin in the leaves and the inputs like labour. The most interesting finding of that study is that the Bt modification of cotton works best at the low pest pressure – more clearly the effectiveness of the protection decreases with the pest pressure increase. Nevertheless, the results are still in agreement with our findings. The high concentration of the Bt toxin yields slightly negative results but the authors suggest that it might be because of the decrease in effectiveness in the currently used technology (conventional methods are used along with the GM modifications).

CONCLUSIONS

In this work, we wanted to shed some light on the possibilities arising from genetic engineering with respect to the 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 the 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 the 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 the cellulose based biofuels production.

In the Czech Republic, the GM corn is grown predominantly as the 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 the previously mentioned studies examining corn for grain yields. We used weather conditions – the monthly temperature and the monthly rainfall – as control variables and we included the time trend to account for the technological development.

We estimated our model by the Pooled OLS, FE and RE. Results obtained from all these three specifications were qualitatively quite similar, which shows a good robustness of our results. Results estimated by all three models were in line with our expectations of the 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 the 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 the Ustecky region) of the corn sown area the yield would increase by 10.6% which gives us the average yield of 46.5 t/ha. Our model is limited by a large uncertainty which is reflected by the 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 the 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 the corn for grain yields.

The contribution of this work stems not only from unique dataset but also from an innovative connection of two topics: the biofuel industry and genetic engineering. The biofuel production is supported and

plentiful all over the world but genetic engineering faces legislative obstacles. Our work supports the idea of the softened legislation toward the GM crops. As genetic engineering can positively influence the yield of crops used for the biofuel production, it can also significantly lower the cost of the biofuel production.

While our model is quite simple and limited because of the 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 the future development of the advanced cellulosic biofuels in the Central and Eastern Europe. A further analysis should focus on the extension of the dataset to reduce the uncertainty of the results. We suggest the inclusion of the field trials and the data on fertilizers use into the dataset. The work should be also extended on the additional crops that can be used for the cellulose based biofuels production as soon as the needed data on these crops in the Central and Eastern Europe is available. It would be very valuable to investigate the potential of genetic modifications for other plants used for the cellulose based biofuels (Miscanthus, switchgrass, rye, temperate climate bamboo, etc.). These cellulose based biofuels were already examined by Khanna et al. (2008), who model the cost of the production of ethanol from the miscanthus and switchgrass in Illinois.

Appendix A. Tables of results

Table 1. OLS estimation results

Variable	Coefficient	Std. Err.
<i>GMshare100</i>	0.004	(−0.003)
<i>r_{may}</i>	0.000	(0.000)
<i>r_{june}</i>	0.001***	(0.000)
<i>r_{july}</i>	0.001***	(0.000)
<i>raug</i>	0.000	(0.000)
<i>t_{may}</i>	0.029***	(−0.008)
<i>t_{june}</i>	−0.002	(−0.007)
<i>t_{july}</i>	−0.008	(−0.005)
<i>taug</i>	−0.022***	(−0.008)
<i>year</i>	0.015***	(−0.002)
<i>Intercept</i>	−26.336***	(−3.372)
<i>N</i>		252
<i>R</i> ²		0.495
<i>F</i> _(10; 241)		23.35

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

Table 2. FE estimation results

Variable	Coefficient	(Std. Err.)
<i>GMshare100</i>	0.006**	(−0.003)
<i>r_{may}</i>	0.000*	(0.000)
<i>r_{june}</i>	0.001**	(0.000)
<i>r_{july}</i>	0.001***	(0.000)
<i>raug</i>	0.000*	(0.000)
<i>t_{may}</i>	0.023***	(−0.007)
<i>t_{june}</i>	−0.011*	(−0.007)
<i>t_{july}</i>	−0.021***	(−0.005)
<i>taug</i>	−0.031***	(−0.007)
<i>year</i>	0.015***	(−0.002)
<i>Intercept</i>	−26.809***	(−2.999)
<i>N</i>	252	
<i>R</i> ²	0.57	
<i>F</i> _(23; 228)	30.242	

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

Table 3. RE estimation results

Variable	Coefficient	(Std. Err.)
<i>GMshare100</i>	0.006**	(0.003)
<i>r_{may}</i>	0.000	(0.000)
<i>r_{june}</i>	0.001***	(0.000)
<i>r_{july}</i>	0.001***	(0.000)
<i>raug</i>	0.000	(0.000)
<i>t_{may}</i>	0.025***	(0.007)
<i>t_{june}</i>	−0.008	(0.007)
<i>t_{july}</i>	−0.017***	(0.005)
<i>taug</i>	−0.028***	(0.007)
<i>year</i>	0.015***	(0.002)
<i>Intercept</i>	−26.471***	(3.042)
<i>N</i>	252	
Log-likelihood	.	
$\chi^2_{(10)}$	287.353	

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

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