The Effects of Prices on Acreages and Yields of Biofuel Feedstock in the European Union

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Abstract

A theoretical model is built and estimated to analyze the effects of crop prices on the yields and acreages of biofuel feedstock in the European Union. We find no effects of crop prices on crop yield for the aggregated European Union in the period 2000 – 2015. However, we do find a negative price effect of rapeseed and sugar beet prices on rapeseed and sugar beet yields, respectively, for Central and Eastern European Countries. We also find a positive relationship between sugar beet prices and sugar beet yield in the period 2010 – 2015. For wheat acreage we find that wheat prices and available arable land have a positive influence. For rapeseed acreage we find a counterintuitive positive effect of wheat prices, a negative effect of sugar beet prices, and an, also counterintuitive, negative effect of available arable land.

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1. Introduction

In the 21st century the world has seen two large food crises. Around 2008 and 2011 food prices increased by as much as 50 percent (USDA 2011). These events have raised several questions, for example, on the effect of rising food prices on political unrest (e.g., Bellemare 2015) or their potential impact on the world's developing countries (e.g., Headey 2016). In this thesis, we take a step back and look at the direct effects of food price changes on the yields and acreages of selected crops in the European Union in the period 2000 – 2015. First, however, it is relevant to understand why food prices increased so much in price. This issue has sparked a lot of debate. Both the different factors as well as their magnitudes are debated in the literature.

Abbott et al. (2009) attribute the rising food prices to a variety of reasons, including demand and supply curves shifts, weather issues and exchange rate variability. Headey and Fan (2010) add that many possible causes can be identified and that the price changes are the result of interacting factors, rather than a single factor. Gilbert (2010), on the other hand, focusses on macroeconomic developments and the economic growth in Asia (mainly China). Whereas these examples focus on several factors, de Gorter et al. (2015, p. 45) seem to have found one culprit: ethanol production, or more specifically, its production process, which "has great importance in explaining the recent [2008 and 2011] rise in food commodity prices". Abbot et al. (2009) agree that biofuel policies played a role, but this effect should not be overstated. Headey et al. (2010) find that the oil-biofuel nexus was one of the main drivers behind the prices surges, but that other factors, such as export restrictions and panic purchases exacerbated the situation. A complete analysis of the rising food prices can be found in Headey and Fan 2010 and de Gorter et al. 2015.

Biofuels and biofuel policies were not only blamed for the food price spikes, Searchinger et al. (2008) also found that greenhouse gas emission reductions of biofuels were overstated, as (indirect) land use change (e.g., converting forests into crop land) was not taken into account, thereby attacking the presumed environmental benefits of biofuels. Later research (e.g., Dumortier et al. 2011, Miao et al. 2015), however, pointed out that the results of Searchinger et al. (2008) themselves were overstated as price-induced yield responses were not taken into account.

To answer questions about how public policy (e.g., biofuel policies) or climate change may affect yields and acreages, we first have to look at how these factors respond to price changes. When answering questions of how public policy or climate change will affect agricultural output, some research (e.g. Dhuyvetter et al. 2008) focus on how output can be increased (e.g., through yield increases). We argue that a farmer maximizes his profits, which depend on input and output prices. So, even when a production increase may be desirable following, for example, a certain policy or climate change, price changes play an important role in determining whether and how it will happen. To understand this decision-making process, it is important to know what the effect of crop prices on crop yields and acreages are. We focus on the effects of crop prices changes on yield and acreage allocations, but leave out the question what has caused these price changes in the first place.

A solid body of literature on the (environmental) effects of land use and yield change due to public policy and price changes exists already (e.g., Searchinger et al. 2008, Dumortier et al. 2011, Gardebroek et al. 2017). However, some papers only focus on land-use changes, others do include yield increases, but do so by estimating the elasticity of yield with respect to crop prices. Keeney and Hertel (2009) write that the use of complex assumptions of interacting markets in computational models may have clouded the effect of output to price in recent economic literature.

In our thesis both yield and acreage changes are analyzed. We separate the effect of prices on output into yield and acreage effects. This separation both simplifies our model and allows us to identify separate effects. We take a further step back by only looking at the price effects and the subsequent acreage and yield responses, recognizing that price changes can happen for a variety of reasons. We leave out any potential environmental effects of changing crop acreages and yields. One should, however, keep in mind that environmental concerns are one of the main drivers behind the question of the effect of public policies and prices on acreage and yield.

We develop a novel microeconomic framework in which profits are maximized by choosing optimal acreage and yield, which in turn depend on specific, convex cost-functions. This way the effect of feedstock prices on acreages and yield can be disentangled and estimated. We will both develop a microeconomic model and estimate it econometrically. Adding an econometric analysis to our theoretical insights is useful, as empirical evidence is used to test our theoretical findings (Gilbert 2010).

Our research adds to the growing body of literature on the food price spikes of 2008 and 2011. We look at the effects of these rising food prices on acreages and yield of three crops that also served as biofuel feedstock in the period 2000 – 2015. Biofuels and biofuels policies saw a rise in importance in this period and are often included as one of the (main) causes for the aforementioned food price increases, therefore we choose to focus on crops that also serve as biofuel feedstock. The European Commission (2017) has stated that 80 percent[1] of the crop output increase of biofuel feedstock will be accounted for through productivity gains. This point is made in relationship with the increased demand for food and feed for a growing and more affluent

[1] It should be noted that the European Commission here refers to the 2016-2025 OECD-FAO agricultural outlook (2016), which has a focus on sub-Saharan Africa. It could be argued that this figure might not be applicable to the European Union.

population (mostly in developing countries), implying that yield increases might mitigate the possible negative consequences of biofuel policies on food prices (EC 2017). We look at the period 2000 – 2015 to find what the effects of crop prices on crop yields are, as this relationship is relevant when combined with projected yield increases.

We will not explicitly investigate the link between biofuel policies and prices empirically, for two reasons. First of all, it is not entirely within the scope of this thesis. Secondly, data on biofuels prices, especially from countries in the east of the European Union, is limited, which makes it hard to analyze the true effects. Our prime interest lies in the effect of crop prices on yields and acreages. We acknowledge that there may be a link between biofuel (policies) and crop prices, but do not explicitly assume this, nor do we draw any conclusions based on this.

We focus on three food crops: wheat, rapeseed and sugar beet, which are also important (in terms of their share) biofuel feedstock in the European Union. In our model we look at the effect of the price developments on the yields and acreages of these crops. We have chosen these crops as they may not only be affected by price changes of the 21st century, but that also serve as biofuel feedstock.

We find some significant relationships between crop prices and crop yields, but not when we look at the European Union as a whole for the period 2000 – 2015. We find that rapeseed and sugar beet prices negatively impact rapeseed and sugar beet yields, respectively, for a subset of countries in Central and Eastern Europe. We find a positive relation between wheat acreage and wheat prices and the availability of arable land. Furthermore, we find that rapeseed acreage decreases as the price of sugar beet increases. Counterintuitively, rapeseed acreage increases when wheat prices increase, and decreases when the availability of arable land increases.

2. Theoretical considerations of the effects of food prices on acreage and yield

2.1 The effect of crop prices on yields

The effect of a crop price increase on yield is ambiguous. On the one hand, a price increase could incentivize better input use or more productive management practices, which have a positive effect on yield (Feng and Babcock 2010). On the other hand, a price increase, leading to an acreage increase (see discussion below), may result in acreage expansion into land or soil of lower quality with a lower yield per hectare, which could drive down the average yield (Angelsen 2010). Note that the first effect could set off a cycle by making it worthwhile to start using even more marginal land.

Furthermore, if a price increase were to affect the crop rotation decisions of a farmer (i.e., continuous monoculture of the more expensive crop) this may also have a negative effect on crop yields (Hennessy 2006). Miao et al. (2015) find that corn prices have a significant positive impact on corn yield, but soybean prices do not significantly impact soybean yield. The latter may be explained by the intensive (i.e., yield increase) and extensive (i.e., acreage increase) margin offsetting each other.

Keeney and Hertel (2008) summarize several studies on yield responses to price changes. There is limited empirical work and most literature in this area focusses on US agriculture. Keeney and Hertel (2008) cite several papers (e.g., Choi & Helmberger 1993, Lyons & Thompson 1981) that find a positive, significant relationship between corn prices and corn yields. However, they also note that there are examples where crop prices do not have a significant effect on yield. They point out that variety selection and crop rotation are key determinants of (wheat) yields.

Just like an increase in the output of a farm can be split into intensive and extensive productivity gains, the changes in yield can be split into reversible yield increases, for example due to fertilizer use, and irreversible yield improvements, due to increased technological developments and plant breeding (Edwards et al. 2010). Both of these effects could occur as a consequence of crop price increase. It could also be argued that the European Union creates a safety net for irreversible yield improvements by adopting policies that act as an insurance of a minimum price. A major difference between these two changes in yield is the rate of return; whereas increased fertilizer use may increase output in the same year, increased spending in plant breeding development may only yield results years later. In our research we focus on crops that also serve as biofuel feedstock. Edwards et al. (2010) write that there is a significant correlation between long term yield increases and policy and public and private expenditure. This effect, however, may not yet be visible for biofuel policy induced research spending in the European Union, because of the longer rate of return.

Specific subsidies for research and development (R&D) may also boost yield per hectare directly. Since firms do not reap the full benefit of their own R&D investments, as knowledge spillovers occur (Parson and Phillips 2007), it may make sense for governments to subsidize R&D investments to try and obtain a more socially optimal investment level. The International Institute for Sustainable Development (IISD 2013) writes that no studies quantifying the social rate of return for biofuel-induced R&D spending exist yet. EU biofuel policies are dominated by market price support mechanisms (e.g., the mandate), so these direct effects play little or no role on yield developments of the crops we discuss and will not be analyzed further in our research.

2.2 The effect of crop prices on acreage

Whereas the effect of crop price increases on crop yield is ambiguous, the effect on acreage seems more clear-cut in most research. For example, Huang and Khanna (2010), Miao et al. (2015) and Gardebroek et al. (2017) find a positive relation between own crop prices and crop acreages and a negative relationship between cross-prices and crop acreage. From this we expect that, for example, the price of rapeseed has a positive influence on rapeseed acreage and a negative influence on wheat acreages. Note that crop prices influence acreage allocation for one crop when they are relatively more extreme than price changes of other crops (Gardebroek et al. 2017). The effect of prices can be a cross-border relation. For example, the demand driven price increase of soybean in recent years in China, has been met by an acreage expansion in Latin America (Abbott et al. 2011). Since we focus only on the European Union in this thesis, we do not incorporate this in our model.

Huang and Khanna (2010) summarize several studies in which the elasticity of biofuel feedstock acreage (mostly corn, wheat, and soybean) with respect to their own price is calculated. In all cases a positive elasticity is found, meaning that the acreage of a crop increases as its price increases. Huang and Khanna (2010) also find negative cross-price effects. Intuitively this makes sense, as a price increase of one crop would lead to an acreage increase of that crop, which can come at the expense of the acreage of another crop, unless the total land acreage available has increased. All this indicates acreage allocation decisions are the result of several crop output price changes.

Wright and Wimberly (2013) find that increased prices of biofuel feedstock (corn and soy) in the United States have led to the conversion of grassland into arable land. This explicitly shows that acreage expansion can also occur without coming at the expense of the acreage of other crops.

The EPA (2010) reports that acreage expansion in the European Union in the period 2001 – 2007 has mainly come at the cost of pasture and grasslands.

2.3 Interaction effects between yields and acreage

The previous section showed that own prices can influence the yield per hectare (for which the effect is ambiguous) and the acreage devoted to a crop (where a price increase results in more land devoted to that crop). Furthermore, there may also be cross-price effects, where the price of soybeans affects the acreage allocated to corn (Huang and Khanna 2010). Note, however, that there is little, if any, literature on the cross-price elasticity of yield (i.e., the effect of a price change of soybean (for example) on the yield per hectare of corn).

Another interaction effect can be found between expected yield and acreage (Weersink et al. 2010). In such a case the "own-yield" effect (e.g., the elasticity of acreage supply of corn with respect to the expected yield of corn) is usually qualitatively different from the "cross-yield" effect (e.g., the elasticity of acreage supply of corn with respect to the expected yield of soybeans). Weersink et al. (2010) find that an increase in expected yield of corn has a positive effect on corn acreage, whereas an increase of expected soybean or winter wheat yield has a negative effect on corn acreage. Overall, the elasticity with respect to expected yield is slightly higher (except for wheat) than the elasticity with respect to expected prices.

Some authors (e.g., Dhuyvetter et al. 2008) calculate the needed increase in the supply of certain feedstock to meet the rising, policy-driven, biofuel feedstock demand. They show that such an increase can be obtained both through an increase of acreage as well as yield, noting that a more optimistic yield trend would result in a lower "need" for feedstock acreages. Even though this is technically correct, we argue that the prime motive for an individual farmer (in our model) is to maximize his profits, not maximize the output of a certain crop. As discussed earlier, in the case of a crop price increase (which could occur following an increased biofuel demand), we expect acreage allocated to that crop will increase, whereas the effect on yield is ambiguous.

3. The EU biofuel feedstock market

3.1 EU biofuel and feedstock markets

In 2015 bioethanol accounted for almost 2 percent of the volume of all fuel use (excluding jet fuel) and biodiesel accounted for roughly 4 percent in the European Union (USDA 2017). Germany was the largest consumer of ethanol in the period 2011-2015, consuming around 30 percent of the total EU volume. Other large consumers were the United Kingdom and France, both taking roughly a 15 percent share. Production follows a similar pattern as consumption, with Germany, France and the United Kingdom producing most of the fuel, all taking a 17-20 percent share. For biodiesel, production takes mostly place in Germany and France, which account for about 50 percent of biodiesel produced in the European Union in the period 2011-2015. Germany and France are also the largest consumers (around 35 percent), with no other country consuming over ten percent of the total biodiesel consumption (Eurostat 2017a).

The feedstock most used for ethanol are sugar beet, corn and wheat. In the period 2006 – 2015 these feedstock accounted for roughly 80 percent of the total bioethanol production. The feedstock portfolio is less diverse for biodiesel; in the period 2006 – 2015, rapeseed accounted for 64 percent of total feedstock use. Its share is declining over the years, with used cooking oil (UCO) and palm oil taking larger shares. This means that a lower share of feedstock is produced within the European Union, as palm oil is imported and UCO is a non-agricultural product. Together these feedstock accounted for 37% of feedstock used in 2015, while rapeseed accounted for 49 percent (USDA 2017). Note that biofuel production uses a higher percentage of total rapeseed production, than sugar beet and wheat, as those crops are mainly used for alternative purposes. For example, in 2004 EU biodiesel production used 27 percent of rapeseed production, whereas EU bioethanol production used only 0.42 percent and 0.81 percent of total wheat and sugar beet production, respectively (Schnepf 2006).

3.2 EU policy regarding biofuel and feedstock yield and acreage

In 2009 the European Commission issued an important piece of biofuel legislation; the 2009/28 directive specified that 10 percent of the transport fuel of EU member states should come from renewable sources by 2020. In the second EC progress report – which is published once every two years to track the progress of Member States – the first mention is made of possible food price increases due to the policy. The report states that it is important to assess whether EU biofuel consumption contributed in any way to these price increase, but conclusive evidence is not given (EC 2013).

Through time, the European Commission requires stricter laws for (indirect) land use change, because of its possible environmental consequences (see, for example, the progress reports of 2013 and 2015). This indicates that concerns of acreage reallocations due to biofuel policies were taken seriously by the European Commission. Note, however, that the focus in the reports is on land use change outside the European Union. In 2017 the European Commission also mentions crop yield improvements for biofuel feedstock, as mentioned in the introduction.

The supply of feedstock is an important cost component of the biofuel production process, making it crucial to the success of the EU biofuel goals (Schnepf 2006). This also highlights the importance of EU policy affecting important feedstock crops. In the period 2000 – 2015 EU support mechanisms have been simplified with the advent of the Direct Payment System, as payments are mostly decoupled and production subsidies have disappeared (Baldwin and Wyplosz 2015).

Rapeseed production has been influenced by set-aside arrangements, agreed upon in the Blair House Agreements. The set-aside arrangement made it possible to cultivate energy crops on land that was meant to be set-aside, but was abolished in the context of the CAP 2008 health check (EC 2011). Technically any non-food crop could be grown on the set-aside land, in practice, however, it was mostly devoted to rapeseed cultivation (EC 2006). In 2006, the EU sugar beet sector was reformed. Internal price support schemes were slashed, and the intervention purchase system was eliminated. Both measures reduce incentives for farmers to grow sugar beet. However, from this moment sugar beet could be used as an energy crop (like rapeseed), with sugar being produced for the purpose of biofuel production being excluded from the sugar quotas (Schnepf 2006). Note that the sugar quota system in the European Union was abolished in 2017 (EC 2016), but since we consider the period 2000 – 2015 this does not affect our analysis.

3.3 One European Union, multiple settings

The period 2000 – 2015 also saw the accession of several new member states, most notably in 2004 when 10 countries, mostly from Central and Eastern Europe joined the union. Latruffe et al. (2012) write that these countries, from here on referred to as Central and Eastern European Countries (CEECs) trail the other member states in terms of agricultural production. They write that technical efficiency is usually lower (because of market and institutional failures) and that there are substantial potential improvement possibilities. The data we use also shows that yield per hectare are lower in these countries, although the differences do not seem to be significant (Eurostat 2017c). In our analysis we will have a closer look if there are any differences in yield and acreage allocation decisions between CEECs and other countries.

In terms of biofuel policy the biggest change occurred in 2009, when Directive 2009/28 replaced previous legislation. The 2009/28 included the 10 percent mandate. This mandate was compulsory, contrary to the previous (2005) mandate of 2 percent (Banse et al. 2011). The European Commission does not provide a uniform measure to implement their biofuel policies;

instead it provides a framework which allows member states to use various instruments to obtain their targets (see Sorda et al. (2010) for a more elaborate discussion on EU biofuel policies and their implementation). Since implementation on national level can occur at different times, we can only analyze the possible effect of this directive by looking at differences between the periods 2000 – 2009 and 2010 – 2015.

To capture these multiple settings, we estimate three different models. In Model I we look at all selected countries in the period 2000 – 2015. In Model II, we divide the countries into two groups: the CEECs and the “Old Member-States” (OMS). In Model III we analyze the differences between the period 2000 – 2009 and 2010 – 2015. We use the year 2009 as the cut-off point, as we assume that policy-induced changes take some time to occur. In chapter 4 the exact specifications of the different models is discussed.

4. Theoretical model, estimation and data

4.1 A microeconomic model

Consider a representative farmer who chooses optimal acreage and yields of three crops: wheat, rapeseed and sugar beet, to maximize his profits. The prices of the crops, as well as of land are exogenous to the farmer. Increases in yields and acreage result in higher costs, which we model using convex cost functions. Combining revenues and costs, we can derive the profit function. Profits are, in part, determined by output prices, as these determine optimal supply according to duality theory (Jehle and Reny 2011). This means that output prices will have an indirect effect on yield in the model. The profit function can be written as

$$\pi = p_1 y_1 L_1 + p_2 y_2 L_2 + p_3 y_3 (\bar{L} - L_1 - L_2) - C_1(y_1) L_1 - C_2(y_2) L_2 - C_3(y_3)(\bar{L} - L_1 - L_2) -$$
$$\varphi_1(L_1) - \varphi_2(L_2) - \varphi_3(\bar{L} - L_1 - L_2) - w\bar{L}, \qquad i = 1, 2, 3 \qquad (1)$$

where p_i refers to the crop prices, y_i refers to crop yields and L_i refers to crop acreages. $C_i(y_i)$ and $\varphi_i(L_i)$ denote the cost functions for crop yields and acreages, respectively. The subscript refers to the three different crops. Production equals the product of yield, y_i, and acreage, L_i, devoted to a crop

$$Y_i = y_i L_i, \qquad (2)$$

while revenues depend on the production at the output price, p_i

$$R_i = p_i \, y_i \, L_i. \qquad (3)$$

We split the costs into three cost functions. First, a yield-specific cost function

$$C_i(y_i) = A_i y_i^{\varepsilon_i}, \qquad (4)$$

where A_i is a positive constant and ε_i is the elasticity of costs with respect to yield. In most literature (e.g., Sobolevsky et al. 2005, Miao et al. 2015) elasticity of yield with respect to the crops' own price is used. We use a different elasticity, as we want a farmer in this model to have the possibility to increase his yield (at a certain cost) to reach the point where yield and acreage maximize profits. Equation (4) represents the yield-specific costs and has to be multiplied by L_i to find the total costs of yield for a crop. Note that all different costs involved in increasing yield (e.g., increased fertilizer use or increased R&D spending) are included in $C_i(y_i)$. The acreage-cost function has a similar structure:

$$\varphi_i(L_i) = B_i L_i^{\alpha_i}, \tag{5}$$

where B_i is a positive constant and α_i is the elasticity of costs with respect to land used.[2] This function specifies that there are costs involved when land use is increased (e.g., labor or capital costs). Lastly, rental costs of the total land area, $\bar{L}$, are captured by the rental rate, w. Land used for L_3 is calculated as the total land area, $\bar{L}$, minus acreage allocated to the first two crops (L_1 and L_2). $\varphi_i(L_i)$ captures all costs that can occur when acreage is expanded. We do not specify how a farmer can increase his yield or acreage (acknowledging that this can happen in many different ways), as this reduces the complexity of the model and makes it more intuitively comprehensible. To solve our profit maximization problem, we use the following yield-specific costs function

$$C_i(y_i) = \frac{1}{2} A_i y_i^2 . \tag{6}$$

This form makes the model solution analytically simpler and helps with intuition. Note that this specific relationship between crop yields and costs (i.e., a yield increase of one-percent is

[2] Note that the value of α_i has to be larger than one for this curve to be convex. If this is not the case, from some point onwards farmers will be able to keep increasing their acreage without a (substantial) cost increase. Note that the same line of reasoning can be applied to ε_i.

accommodated by a cost increase of two percent) may not hold. We expect that A_i is positive, as a negative value for A_i would indicate negative costs, since yields cannot be negative. Land-specific costs have a similar structure

$$\varphi_i(L_i) = \frac{1}{2} B_i L_i^2. \tag{7}$$

We use these specific cost functions in maximizing total profits. Therefore, we take partial derivatives of the profit function with respect to y_i and L_i. These first-order conditions are derived from equation (1)

$$\frac{\partial \pi}{\partial y_1} = p_1 L_1 - C_1'(y_1) L_1 = 0 \tag{8}$$

$$\frac{\partial \pi}{\partial y_2} = p_2 L_2 - C_2'(y_2) L_2 = 0 \tag{9}$$

$$\frac{\partial \pi}{\partial y_3} = p_3(\bar{L} - L_1 - L_2) - C_3'(y_3)(\bar{L} - L_1 - L_2) = 0 \tag{10}$$

$$\frac{\partial \pi}{\partial L_1} = p_1 y_1 - p_3 y_3 - C_1(y_1) + C_3(y_3) - \varphi_1'(L_1) + \varphi_3'(\bar{L} - L_1 - L_2) = 0 \tag{11}$$

$$\frac{\partial \pi}{\partial L_2} = p_2 y_2 - p_3 y_3 - C_2(y_2) + C_3(y_3) - \varphi_2'(L_2) + \varphi_3'(\bar{L} - L_1 - L_2) = 0 \tag{12}$$

Note that $C_i'(y_i)$ in equations (8) – (10) collapses to $A_i y_i$ and $\varphi_i'(L_i)$ in equations (11) and (12) collapses to $B_i L_i$, because of the specific form of our cost functions. Rewriting these first-order-conditions, the following solutions can be obtained from equations (8) – (10):

$$y_1 = \frac{1}{A_1} p_1 \tag{13}$$

$$y_2 = \frac{1}{A_2} p_2 \tag{14}$$

$$y_3 = \frac{1}{A_3} p_3 \tag{15}$$

From equations (13) – (15) we find that crop yield in our model only depends on the own-price of the crop. Note that we expect this effect to be positive, as we expect A_i to be positive.

Solving equations (11) and (12) for L_1 and L_2 we obtain (see appendix)

$$L_1 = \frac{B_2 + B_3}{2A_1(B_1B_2 + B_1B_3 + B_2B_3)}P_1^2 - \frac{B_3}{2A_2(B_1B_2 + B_1B_3 + B_2B_3)}P_2^2 - \frac{B_2}{2A_3(B_1B_2 + B_1B_3 + B_2B_3)}P_3^2 + \frac{B_2B_3}{(B_1B_2 + B_1B_3 + B_2B_3)}\bar{L} \quad (16)$$

$$L_2 = -\frac{B_3}{2A_1(B_1B_2 + B_1B_3 + B_2B_3)}P_1^2 + \frac{B_1 + B_3}{2A_2(B_1B_2 + B_1B_3 + B_2B_3)}P_2^2 - \frac{B_1}{2A_3(B_1B_2 + B_1B_3 + B_2B_3)}P_3^2 + \frac{B_1B_3}{(B_1B_2 + B_1B_3 + B_2B_3)}\bar{L} \quad (17)$$

From equations (16) and (17) it can be seen that the land devoted to a crop depends positively on its own price, but negatively on both other prices in our model. Since we focus on the effects of crop prices on acreage and yield, we disregard any interaction effects between acreage and yield of different crops, as found by, for example, Weersink et al. (2010).

We estimate five equations: (13) – (17). We estimate the equations (13) – (15) as

$$Yield_i = \alpha_i + \beta_i P_i + \sum_{t=1}^{16} \delta_t T_t + \varepsilon_i \qquad i = 1,2,3, \quad t = 1,2,3,\ldots,15,16 \quad (18)$$

where $i = 1$ corresponds to wheat, $i = 2$ to rapeseed and $i = 3$ to sugar beet and ε_i is the error term. β_i corresponds to $\frac{1}{A_i}$ in equations (13) – (15). Year specific dummy variables, T_t, are added, as yield may depend on year effects (e.g., weather). The year 2000 is used as the base year. α_i is the intercept. Equations (13) – (17) do not include a constant term. We included the intercept for estimation purposes. Excluding the intercept would force the regression through the origin. Note that the intercept has no intrinsic meaning, since our independent variables (prices and arable land) are never equal to zero. We estimate equations (16) and (17) as

$$Acreage_j = \alpha_j + \beta_{ji}P_1^2 + \beta_{ji}P_2^2 + \beta_{ji}P_3^2 + \gamma_{ji}L + u_j \qquad j = 1,2 \qquad i = 1,2,3, \tag{19}$$

where i again refers to the crops, j refers to the acreage equation, where $j = 1$ for wheat and $j = 2$ for rapeseed. For example, the coefficient β_{13} refers to influence of the price of sugar beet on the acreage of wheat and β_{23} refers to the influence of the price of sugar beet on the acreage or rapeseed. α_j is the intercept, γ_{ij} is the parameter for arable land, and u_{ij} is the error term.

β_{11} (the effect of wheat prices on the optimal acreage of wheat) in equations (19) refers to the component $\frac{B_2+B_3}{2A_1(B_1B_2+B_1B_3+B_2B_3)}$ in equation (16) and β_{12} (the effect of rapeseed price on the optimal acreage of wheat) refers to the component $\frac{B_3}{2A_2(B_1B_2+B_1B_3+B_2B_3)}$ of equation (16). Note that in this case we do not explicitly calculate specific values for A_i and B_i, but for the coefficients β_{ji}. There is no reason to assume that for our values of the different β_{ji}'s there exist some values A_i and B_i, which would solve our equations (16) and (17). In chapter 4.2 we explain why we deviate from our microeconomic model here.

4.2 Estimation approach

We estimate three models in total, following our discussion in chapter 3.3. In the first model, all countries for the complete period are considered. In the second model we compare the OMS with the CEECs. The OMS refer to Austria, Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Spain, Sweden and the United Kingdom. The CEECs are Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, and Slovenia. Model III distinguishes between the periods 2000 – 2009 and 2010 – 2015. We estimate equations (18) and (19) for all three models. We have 10 estimates in total: two estimates (yield and acreage) for all selected countries in 2000 – 2015 and the same two estimates for every different case (OMS, CEECs, before 2009 and after 2009) of the other models.

To estimate the equations (18) and (19) we use Zellner's (1962) method of seemingly unrelated regressions (SUR). Using a system estimator has the advantage of increased efficiency in estimation, as the information on different equations is combined (Moon and Perron 2006). The explanatory variables differ for each crop-specific estimate of equation (20). For example, in the wheat yield equation, wheat price is an explanatory variable, whereas in the rapeseed yield equation, rapeseed price is an explanatory variable. We use a system estimator, as we assume that the error terms are correlated across the equations.

Since our explanatory variables are the same for each crop-specific estimate of equation (21) (e.g., estimating the optimal amount of acreage of wheat depends on the same explanatory variables for estimating the optimal amount of acreage of rapeseed), using a system estimator, like SUR, will give us the same estimates as using an individual Ordinary Least Squares (OLS) method for each equation (Verbeek 2008). However, we choose to use also SUR instead of OLS for the estimation of the acreage equation as we assume that the error terms are related for the equations, which will not affect the coefficients, but will give us more appropriate standard errors.

We use the Breusch-Pagan test to test whether the equations of different yields and acreages are independent. If the equations are independent (i.e., there is no significant correlation of the residuals across the acreage equations), no efficiency can be gained by using the SUR. We run this test for all different scenarios in all three models. In all of our yield equations of every model we find a significant correlation of the residuals. This means that we can gain efficiency for the estimation of the yield equations by using SUR.

For the case of acreage equations, we find a significant correlation between the error terms of the wheat acreage equation and the rapeseed acreage equation for Model I, where all selected countries are included for the period 2000 – 2015. For Model II, where we compare the OMS and the CEECs, we do not find any reason to reject the null-hypothesis of independent acreage equations for either group considered. This means that the error terms of the wheat and acreage equations are not correlated. This is the case for the both OMS and for the CEECs. For Model III we find that the equations are not independent in the period 2000 – 2009, but they are independent in the period 2010 – 2015. So, we can gain efficiency by using SUR when estimating the period 2000 – 2009, but not when estimating the period 2010 – 2015. These results indicate that we do not gain efficiency in either scenario of Model II, or the period 2010 – 2015 of Model III when using SUR. However, the differences in estimates between an OLS and a SUR estimate in these cases are also minor. We have chosen to use SUR in all three models, as this helps with the presentation of the findings and there are no immediate drawbacks. The full test results can be seen in chapter 2 of the appendix.

Equation (21) is non-linear in crop prices and should therefore be estimated using Non-Linear Seemingly Unrelated Regressions (NLSUR). Using *Stata*, however, it was not possible to solve our system of equations. The solutions given by *Stata* were not stable, which could be the result of collinearity. Correlation between two explanatory variables is not necessarily a problem, but if it is too high it may lead to unreliable estimates (Verbeek 2008). Another reason may be the complexity of the equations in combination with the low number of observations. Because of this infeasibility, we decided to estimate a simple linear version where the structural parameters are summarized by aggregate parameters.

Since farmers can only respond to price changes after these have occurred, using current-year prices may bias the results. We follow Gardebroek et al. (2017) in using one-year lagged prices, as Miao et al. (2015) point out that there is no proxy for expected prices (e.g., current-year futures prices or one-year lagged prices) which outperforms lagged prices in describing farmers' expectations. We use lagged prices for both the yield (18) and acreage (19) equations. In our model $\bar{L}$ is the sum of L_1, L_2 and L_3. For estimation purposes, however, we use the total of arable land from Eurostat (2017c). This is done because using the sum of the three acreages would imply that the acreage of one of our three crops can only increase if the acreage devoted to one of the other crops decreases. Acreage expansion, however, can also come at the costs of land used for other purposes.

Since our units of observations are observed multiple times, we are dealing with a panel data set. The main approaches to the fitting of panel data models are fixed effect regressions and random effects regressions. Our observations cannot be described as a random sample from a given population, so the use of fixed effects is advised by Dougherty (2011). Especially yields, but also acreages, may vary across countries due to factors such as weather changes and soil types (Gardebroek et al. 2017). This could lead to biased estimates, due to unobserved heterogeneity (Verbeek 2008). We use within-transformation, to deal with this problem. We do this by calculating individual means for every country and subtracting the observed values from the calculated individual mean. We then use these calculated values in the regression. The within-transformation takes away the average differences between countries (both observable and unobservable effects). As the average differences between countries (e.g., rainfall) no longer play a role in our analysis, we can focus on the effect of the crop prices.

We estimate yields and acreages for countries that join borders, so spatial autocorrelation may be a problem, as unobserved effects in the error terms can be similar between nearby countries due to geographical reasons. This could lead to incorrect standard errors. Several test for cross-sectional dependence (Frees 1995, Friedman 1937 and Pesaran 2004) can be done using a *Stata* routine developed by De Hoyos and Sarafidis (2006), but our sample does not have enough common observations to perform these tests. So we are unable perform a formal test to detect the presence of spatial autocorrelation. A test developed by Wooldridge (2002), implemented in *Stata* by Drukker (2005) was used to detect the presence of serial correlation.

For the yield equation we only find serial correlation for the rapeseed yield in Model I (at the 5-percent significance level). In all other yield equations, serial correlation is not found. For the acreage equations we find a high F-value for the test for autocorrelation for the acreage equation of rapeseed in Model I (significant at the 1-percent level). The full test results can be seen in chapter 2 of the appendix. Using robust standard errors may solve the problems of autocorrelation. However, robust standard errors cannot be used in case of SUR estimations, as *Stata* does not allow for this option. One way to deal with this is to use Generalized Method of Moments instead of SUR, which does allow for the use of robust standard-errors. Our limited data set, however, seemed not compatible with GMM, as *Stata* was unable to solve the system of acreage equations. Since we have no formal test to back up our suspicion of spatial-autocorrelation and limited evidence of serial correlation, we will resort to the use of SUR without robust standard errors. We deal with serial correlation later in the discussion of the results.

4.3 Data

Data on crop yields and acreages on national level were collected from Eurostat (2017b). A number of countries is missing in the analysis. We have excluded some countries because of their size and lack of observations (Luxembourg, Malta, Cyprus, Croatia, Estonia, Latvia and Lithuania). We exclude Greece, Portugal and Ireland as they were not big producers of the three crops and had large amounts of missing observations. In total 18 countries were in the set for a period of 16 years, resulting in 288 observations.

In cases where yield statistics are unavailable (e.g., for sugar beet in almost all years and countries), the yields are calculated by dividing the production (in 1000 tonnes) by the acreage (in 1000 hectares) of the crop. For prices, indices are used with the year 2000 as the base year (Eurostat 2017c). The reason for this is that Eurostat offers more data on price indices than on absolute prices. Price indices post-2008 are only available with base years 2005 or 2010. This data has been manually transformed to fit the other data (i.e., have the same base-year). During this process, it became clear that the Eurostat data is sometimes internally inconsistent.

After grouping the data by country, we obtain an unbalanced data set, as some observations are missing for certain countries. The data set could be made balanced by manually deleting the years and countries for which no data is available. This could lead to a bias, as the resulting data set may not be representative of our sample (Dougherty 2011). However, one should keep in mind that the unbalanced data set may also give biased estimates if the reasons the missing observations are endogenous to our model (Verbeek 2008). In some cases our data has observations that seem to be missing at random (e.g., one data point in a series is missing for one country). In other cases a complete series (i.e., all sixteen observations for a certain country) may be missing. *Stata* allows unbalanced data sets when using SUR.

Table 1

Descriptive statistics of dependent and independent variables for the sixteen selected countries (2000 – 2015)

	Observations	Mean	Standard Deviation	Minimum	Maximum
Crop Acreage (1000 hectares)					
Wheat	287	3034.15	2843.64	94.76	9645.80
Rapeseed	288	296.51	428.00	0.10	1615.90
Sugar beet	262	108.72	124.81	0.01	459.40
Crop yield (1000 tonnes per hectare)					
Wheat	286	2.72	0.85	0.90	4.39
Rapeseed	288	2.68	0.89	0.47	4.69
Sugar beet	262	56.71	17.29	10.50	96.94
Crop price indices (base year 2000)					
Wheat	284	102.96	24.56	53.90	197.56
Rapeseed	213	133.10	36.07	69.09	246.03
Sugar beet	272	82.62	22.88	35.19	169.80

Source: Eurostat (2017b,c)

Table 1 shows the number of observations for all variables. The price indices for rapeseed lack more observations than others, as some, mainly Southern, countries, do not have data on rapeseed prices. Note that they do report acreage and production figures (from which yield is calculated). The standard deviations for the crop acreages are high, relative to their means. The reason for this are the large differences between the acreages of different countries (e.g., the average wheat acreage of France in the period 2000 – 2015 is more than 9 million hectares, whereas for the Netherlands that figure hovers are 0.2 million hectares).

From the data we can see that the acreage of sugar beet has been decreasing steadily since 2000, whereas the acreages of rapeseed and wheat have been increasing. We can see two large drops in wheat acreage, in 2003 and 2006. The absolute yield (in 1000 tonnes per hectare) of all three crops yields has increased in the period 2000-2015. Both wheat and rapeseed yield (per 1000 hectare) show the same pattern, with high yields in 2004 and 2008, and lower yields in 2003, 2007 and 2012. The yield fluctuations for sugar beet are lower.

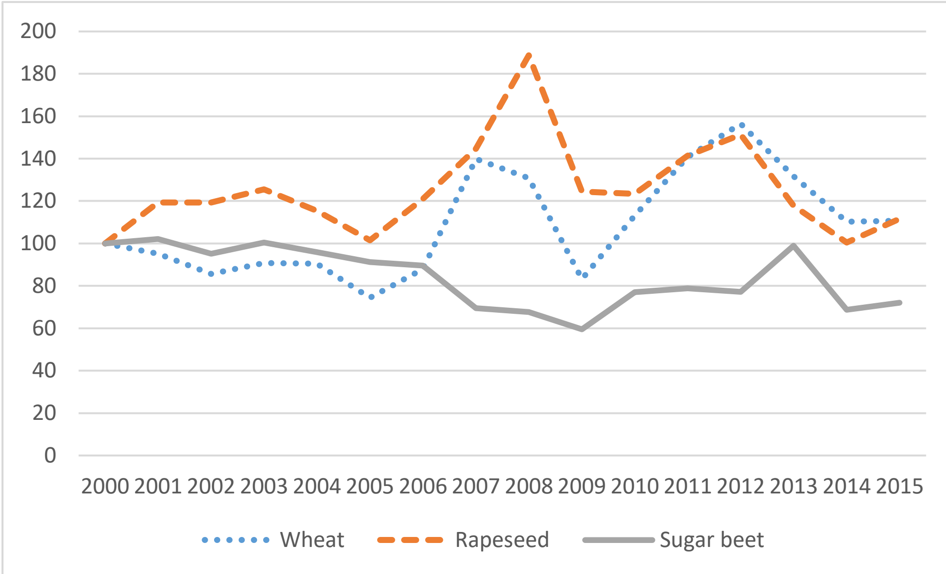

Figure 1: Development of average crop price indices for all countries for 2000 – 2015 (Eurostat 2017b).

Figure 1 shows the price developments of wheat, rapeseed and sugar beet for the period 2000 – 2015. Note that we have used an average of the price-indices here over the various countries here. This graph only shows the development of the price with the 2000 price as a base year. This means that two countries could both have a rapeseed index price of 120 in 2003, but that this does not mean that there is no price difference in the actual rapeseed prices between those countries. The price developments of the crops show both price shocks of the 2008 and 2011 food crises for wheat and rapeseed, but sugar beet prices are not affected by these developments. The price of sugar beet decreases for most of the period. The prices of wheat and rapeseed show an upward trend at some times, but are only 10-percent higher in 2015 compared to 2000 (on average).

5. Estimation results and discussion

Table 2 shows the estimation results of the yield equations of wheat, rapeseed, and sugar beet in the period 2000 – 2015. Model I shows the result for all 18 countries in this period. In Model II the countries have been divided into two groups, the OMS and the CEECs. In Model III, we have divided the time period into two separate periods: 2000 – 2009 and 2010 – 2015.

5.1 Estimation results of the yield equations

In our microeconomic model there is a positive relationship between crop prices and crop yields as can be seen from equations (13) – (15). Although we noted earlier that the effects of prices on yield is ambiguous from a more theoretical viewpoint. All yield equations in all models are estimated using SUR. The full *Stata* output can be found in the chapter 2.1 – 2.3 in the appendix.

In none of the yield regressions of Model I does the own lagged price of the crop have a significant impact on the yield. Miao et al. (2015) also find a non-significant price effect for soybean yields in the United States, but do find a significant price effect for corn yields. In our case we can conclude that lagged prices do not affect optimal yields. The price effects, however, are significant if the OLS regression is run without year dummies. The year dummies, on the other hand, are almost all significantly different from zero. This indicates that year specific circumstances (e.g., weather) do influence yield, whereas we conclude that prices do not. Joint F-tests on these dummies were significant at the 5-percent level, indicating that, taken together, the dummies had a significant influence on yield. In the same line, the F-tests for joint significance for all explanatory variables (i.e., lagged prices and year dummies) are also significant.

We can compare the results of CEECs in the period 2000 – 2015 with the OMS and with the combined estimation, where all countries were included. We find that rapeseed and sugar beet prices negatively impact rapeseed and sugar beet yields, respectively. The effect of rapeseed prices is significant at the 1-percent significance level, whereas the effect of sugar beet prices is significant at the 5-percent level. This does not follow our microeconomic model, where the relationship is positive, but we have seen that there are several theoretical considerations which explain why crop prices can negatively influence crop yields. For illustration, the value of -0.006 we find for the influence of rapeseed prices on rapeseed yields, should be interpreted as follows: a unit increase in the lagged price index for rapeseed results in a decrease of 6 tons per 1000 hectares.

We do not find the same effect for the OMS, where the coefficients remain insignificant. So crop prices do affect crop yields (in two cases) for the CEECs, but do not do so for the OMS. This would indicate that prices are more important for yield decisions in the CEECs than in the OMS. It could be the case that price have affected crop rotation decisions or have worked as an incentive to use more marginal land of lower soil quality in the CEECs, which could explain the negative relationship. One should also keep in mind that there is a yield gap between the OMS and the CEECs and that yield increases may be harder to realize in the OMS.

In Model III we find similar results. For the period 2000 – 2009 we find no significant relationships between crop prices and crop yields. For the period 2010 – 2015 we only find an effect of sugar beet prices on sugar beet yield. We find a positive, significant (at the 5-percent significance level), effect of 0.066 in this case. This means that a unit increase in the lagged price index for sugar beet results in an increase of 66 tons per 1000 hectares. Since we do not find any significant coefficients for the period 2000 – 2009, and only one significant coefficient for the period 2010 – 2015, it is difficult to compare the two periods. In either case we can say that there seems to be no difference between the two periods. We find no impact of the 2009 biofuel directive (or the 2008 CAP health check).

The R^2 values range between 0.50 and 0.66 for Model I, between 0.46 and 0.81 for Model II, and between 0.45 and 0.59 for Model III. In Model II the R^2 values are higher in all cases for the CEECs than for the OMS. This means more of the variation in yields in CEECs can be attributed to crop prices and the year dummies than is the case for the OMS, which implies that the explanatory variables are relatively more important in explaining yields in CEECs than in the OMS. This is to be expected as we found two significant relationships in the case of the CEECs, but none for the OMS. In Model III there is no clear difference between the R^2 values of the periods before and after 2009. The intercepts are significant in all but one case across all models, but do not have any intrinsic meaning. The baseline for the dummy variable is 2000 in the "before 2009" estimation of model III and 2010 in the "after 2009" estimation.

Table 2
Parameter estimates of the yield equations.

Model I†

	Wheat	*Rapeseed*	*Sugar beet*
Own price effect	-0.000 (0.001)	-0.000 (0.001)	0.008 (0.017)
Intercept	-0.180 (0.092)*	-0.328 (0.106)***	-7.187 (1.580)***
R^2	0.50	0.57	0.66
X^2-test joint significance	182.79***	242.95***	353.56***
X^2-test year dummies	148.64***	213.86***	306.76***
Countries	18	18	18
Observations	185	185	185

Model II††

		OMS			CEECs	
	Wheat	*Rapeseed*	*Sugar beet*	*Wheat*	*Rapeseed*	*Sugar beet*
Own price effect	0.001 (0.001)	0.000 (0.001)	0.025 (0.033)	0.002 (0.002)	-0.006 (0.002)***	-0.043 (0.025)**
Intercept	0.086 (0.094)	-0.362 (0.130)***	-5.168 (1.979)***	-0.653 (0.105)***	-0.293 (0.148)***	-13.034 (1.910)***
R^2	0.46	0.49	0.66	0.71	0.81	0.73
X^2-test joint significance	95.68***	106.65***	214.20***	187.49***	328.44***	187.49***
X^2-test year dummies	67.19***	86.19***	148.89***	156.07***	320.06***	195.80***
Countries	11	11	11	7	7	7
Observations	111	111	111	74	74	74

Model III†††

		Before 2009			After 2009	
	Wheat	*Rapeseed*	*Sugar beet*	*Wheat*	*Rapeseed*	*Sugar beet*
Own price effect	0.001 (0.001)	-0.000 (0.001)	-0.019 (0.020)	-0.001 (0.001)	0.001 (0.001)	0.066 (0.029)**
Intercept	-0.177(0.097)*	-0.327 (0.109)***	-7.660 (1.587)***	-0.198 (0.072)*	0.012 (0.088)	1.240 (1.307)
R^2	0.45	0.50	0.45	0.50	0.49	0.59
X^2-test joint significance	101.38***	126.47***	102.60***	60.99***	60.82***	88.06***
X^2-test year dummies	74.35***	117.83***	96.61***	58.88***	60.29***	81.66***
Countries	18	18	18	18	18	18
Observations	124	124	124	61	61	61

Source: own calculations. *Notes:* The own price effect refers to the price parameter in each equation. For every crop only the lagged price of itself is used in the estimation. *, ** and *** indicates statistical significance in a two-tailed test at the 10%, 5% and 1% levels, respectively. For more detailed output, consult appendix 2. † refers to the OLS estimations using all selected countries, †† and ††† refer to the estimations where the observations have been split into different groups. For discussion, see chapter 3.3.

Table 3
Parameter estimates of the acreage equations.

Model I†			Model II††			
			OMS		CEECs	
	Wheat	*Rapeseed*	*Wheat*	*Rapeseed*	*Wheat*	*Rapeseed*
Wheat price	0.011 (0.004)***	0.003 (0.002)*	0.007 (0.004)*	0.006 (0.002)***	0.020 (0.007)***	-0.002 (0.003)
Rapeseed price	-0.004 (0.002)	0.000 (0.001)	-0.002 (0.003)	-0.001 (0.001)	-0.002 (0.003)	0.001 (0.001)
Sugar beet price	0.007 (0.004)	-0.006 (0.002)***	0.004 (0.007)	-0.007 (0.004)**	0.007 (0.005)	-0.005 (0.001)***
Arable land	0.126 (0.026)***	-0.032 (0.013)**	0.009 (0.027)	0.024 (0.014)*	0.431 (0.042)***	-0.175 (0.017)***
Intercept	8.422 (13.574)	-2.662 (6.533)	2.586 (13.398)	1.329 (8.313)	23.799 (17.958)	-9.866 (6.981)
R^2	0.15	0.16	0.03	0.18	0.58	0.63
X^2-test joint significance	33.14***	37.25***	3.76	24.77***	115.32***	141.28***
Countries	18	18	11	11	7	7
Observations	194	194	111	111	83	83

Model III†††				
	Before 2009		After 2009	
	Wheat	*Rapeseed*	*Wheat*	*Rapeseed*
Wheat price	0.016 (0.004)***	0.004 (0.003)	0.004 (0.007)	0.002 (0.002)
Rapeseed price	-0.001 (0.002)	-0.001 (0.002)	0.002 (0.003)	-0.000 (0.001)
Sugar beet price	0.002 (0.004)	-0.003 (0.003)	-0.024 (0.018)	0.006 (0.005)
Arable land	0.053 (0.025)**	0.004 (0.014)	0.321 (0.068)***	-0.149 (0.021)***
Intercept	71.233 (16.837)***	-30.905 (9.447)***	-118.9 (52.3)**	48.7 (16.2)***
R^2	0.15	0.04	0.29	0.47
X^2-test joint significance	23.23***	5.34	26.10***	57.36***
Countries	18	18	18	18
Observations	130	130	64	64

Source: own calculations
Notes: All prices are lagged and squared in the model. *, ** and *** indicates statistical significance in a two-tailed test at the 10%, 5% and 1% levels, respectively. For more detailed output, consult appendix 2.
† refers to the OLS estimations using all selected countries, †† and ††† refer to the estimations where the observations have been split into different groups. For discussion, see chapter 3.3.

5.2 Estimation results of the acreage equations

Table 3 shows the parameter estimates for the acreage equations of wheat and rapeseed for all selected countries in the period 2000 – 2015. The three different models are the same as in the case of the yield estimations. Following our microeconomic model, we expect own price effects (i.e., the effect of wheat prices on the acreage of wheat and the effect of rapeseed prices on the acreage of rapeseed) to be positive. Cross-price effects (e.g., the effect of rapeseed prices on wheat acreage) are expected to be negative. The expected effect of the arable land variable is positive, with more land available leading to an increase in crop acreages.

We use lagged, squared crop prices as independent variables. The dependent variables, acreages, are in 1000 hectares. The following example from Model I shows how the coefficients are interpreted from a statistical point of view: for every unit increase in the lagged, squared price of wheat, a 0.011 unit increase in wheat acreage is expected. A 0.011 unit increase would translate into an acreage expansion of 11 hectares of wheat, *ceteris paribus.* However, equations (16) and (17) allow us to look at the marginal effects of prices by taking partial derivatives of the acreage equations with respect to said prices. These derivatives can be evaluated at certain points (e.g., average price in the OMS or a certain year) to see their marginal effects on the acreage. Note that the qualitative effect is the same (i.e., a positive influence of wheat prices on wheat acreage is also positive at the margin).

In Model I, we see that our expectations hold for some variables, but not for all. The sugar beet price effect in the estimate of wheat acreage is positive, whereas our theory indicates that it should be negative. Note, however, that this parameter is not significantly different from zero. In the estimate for rapeseed acreage, the parameters for wheat, and arable land do not have the sign we expect and are both significant at the 10 and 5 percent level, respectively. Also note that rapeseed prices do not have a significant influence on either wheat or rapeseed acreage.

The picture is similar for the OMS in the second model. All coefficients have the same sign in the equation of wheat acreage, although only wheat is significant at the 10-percent significance level. In Model I, both wheat and arable land are significant at the 1-percent significance level. If we compare our finding for the rapeseed acreage equation of OMS with the Model I we find that the sign of arable land has flipped. It is significant at the 5-percent level in Model I and at the 10-percent level at Model II for the OMS. So, an increase of available arable land leads to a decrease of rapeseed acreage when all countries are included in the model, but it leads to an increase of rapeseed acreage when only the OMS are considered, *ceteris paribus*. The effect of rapeseed prices on rapeseed acreages has also flipped, but is not significant in either case.

When we look at the estimations for the CEECs, we find that the coefficients in case of the wheat equations are almost identical to our findings in Model I. In both cases, only the lagged, squared price of wheat and arable land are significant (in all cases at the 1-percent level). The effects, however, are stronger in the CEECs (e.g., whereas a unit increase in the lagged, squared price of wheat results in a wheat acreage expansion of 11 hectares when all countries are considered, it leads to a wheat acreage expansion of 20 hectares when only the CEECs are included in the model. For the equations of rapeseed acreage the same story holds, with one exception. The effect of lagged, squared wheat prices on rapeseed acreage is positive (and significant at the 10-percent level) in Model I, but negative (and not significant) for the CEECs in Model II. For the other coefficients we find that the same are significant in the case of both acreage equations (albeit at different significance levels).

We find some minor differences when we compare the OMS with the CEECs in Model II. In the equations of wheat acreage of the OMS, only the own-price has a significant effect, whereas both wheat price and arable land have a significant effect in the case of CEECs. The lagged, squared wheat price has a counterintuitive, positive (and significant at the 1-percent level) effect on the rapeseed acreage of the OMS. This would imply that rapeseed acreages increases, as wheat prices increase, *ceteris paribus.* For the CEECs the effect is negative, as expected, but not significant. Arable land also has a negative (and significant at the 1-percent) influence on rapeseed acreage for CEECs, whereas its influence is positive (and significant at the 10-percent) for the OMS. The latter sign is what we expect from theory, as the former dictates that the acreage of rapeseed decreases as total arable land increases, *ceteris paribus*.

For the period 2010 – 2015 in Model III not a single crop price coefficient is statistically different from zero, indicating that crop prices had no effect on crop acreage allocation after 2009. One should keep in mind, however, that in only one case, crop prices had a significant influence on crop acreage in the period 2000 – 2009. In that period, only the coefficient of the wheat price of the wheat acreage equation is significant (at the 1-percent level). Its sign and magnitude are the same as in Model I. The availability of arable land on wheat acreages before 2009 and on wheat and rapeseed acreages after 2009 also has the same impact as in Model I. The other coefficients are not significantly different from zero in Model III, making a meaningful comparison with Model I difficult.

The R^2 values are 0.15 and 0.16 for Model I, and range between 0.03 and 0.63 for Model II, and range between 0.04 and 0.47 for Model III. The equations of the CEECs have the highest values at 0.58 and 0.63, whereas the equations of the OMS yield R^2 values of just 0.03 and 0.18.

This means more of the variation in acreages in CEECs can be attributed to crop prices than is the case for the OMS.

For the rapeseed acreage equations in Model III the R^2 is 0.04 in the first period and 0.47 in the second period. For wheat a similar, albeit smaller, difference is found as the R^2 takes the value of 0.15 (2000 – 2009) and 0.29 (2010 – 2015). So, more of the variation in the acreages in the period 2010 – 2015 can be attributed to crop prices than in the period 2000 – 2009. For rapeseed this may be due to the abolishment of the set-aside agreement. As the preferential treatment of rapeseed vis-à-vis other crops disappeared (set aside land could no longer be used to grow arable crops), rapeseed may have had to “compete” more with other crops. This would explain an increase in the importance of rapeseed prices in rapeseed acreage decisions.

We use chi-squared-tests on the specific equations within the SUR estimation. So we test the joint significance of the explanatory variables for each equations (e.g., wheat acreage) separately. In all cases, except for the OMS estimates (Model II) and the 2000 – 2009 estimates (Model III), we find a highly significant chi-squared value and firmly reject the null hypothesis of no joint significance. We assume that at least one of the coefficients is not equal to zero. The only equation where the chi-squared-test for joint significance is not significant is the wheat acreage equations of the OMS. Here we cannot reject the hypothesis that all explanatory variables are equal to zero. In this case, an estimate with only the intercept would not do statistically worse (Verbeek 2008).

For the CEECs (Model II) we find that rapeseed and sugar beet prices negatively influence rapeseed yields and sugar beet yields, respectively. Furthermore, we find that rapeseed prices have no significant influence on either wheat or rapeseed acreages, whereas the price of sugar beet has a negative (and significant at the 1-percent level) influence on rapeseed acreage, but no significant influence on wheat acreages. So, when sugar beet prices increase, both the sugar beet yield and rapeseed acreage are expected to decrease. Note that sugar beet production may increase if sugar beet acreage increases (following the decrease of rapeseed acreage), even though yield decreases.

As we find almost no other significant relationships between crop yields and crop prices (see table 2), we are not able to draw any meaningful statements regarding the interaction effects of crop yields and acreage. For example, if we look at rapeseed acreages and yields in the period 2010 – 2015 (Model III), we find that a price increase is met with both a decrease of yield and acreage, which would mean a double blow to rapeseed output. However, neither coefficient is significantly different from zero, so we should be very cautious when drawing conclusions.

In all three SUR models for acreage, we find instances of autocorrelation in at least one equation (see appendix chapter 2.4 – 2.6 for the tests). Since we cannot use robust standard errors, we will use a different method to check whether the effects of serial correlation have an impact on our estimation. We use our SUR estimate from Model I and create lagged residuals variables for both the wheat and rapeseed acreage in *Stata.* We then proceed to estimate the same model, with the created lagged residuals as an additional explanatory variable. Serial correlation implies that two or more of our consecutive error terms are correlated. By including the lagged residuals in our estimation, we can confirm the presence of autocorrelation, if they are significantly different from zero. Furthermore, including these lagged residuals captures their effect on acreages. This can then not be captured by our other explanatory variables (i.e., crop prices and arable land), which may have been the case in our SUR without lagged residuals.

We find that the lagged residuals have t-test statistics of 5.39 and 15.13, respectively, and reject the hypothesis that they are equal to zero. The effect of wheat prices, sugar beet prices and arable land on the acreage of wheat is the same as in the SUR in Model I, although arable land is now only significant at the 5-percent level, instead of the 1-percent level. The effect of rapeseed prices, however, is now negative and significantly different from zero, while it used to be only negative. For the rapeseed acreage equation, the effect of wheat prices, rapeseed prices and arable land has changed. Wheat prices used to have a counter-intuitive, positive (and significant at the 10-percent level) influence on rapeseed acreage, the effect is now negative and not significantly different from zero. Rapeseed prices, which have a positive effect, are now significant at the 5-percent level, while they were not significant before. Arable land had a counter-intuitive negative (and significant at the 5-percent level) impact on rapeseed acreages, but is now not significantly different from zero. The R^2 and chi-squared values have increased for the rapeseed acreage equation.

So including the lagged residuals has only a minor effect on the wheat acreage equation. The effects on the rapeseed acreage equation, however, are larger, especially for the arable land coefficient. This follows from the fact that the Wooldridge test for serial correlation indicates that there is no autocorrelation in the wheat acreage equation, but that it is present in our rapeseed acreage equation. The above results confirm this. The results also indicate that our SUR estimate in Model I may be inefficient and that the standard errors are calculated in a wrong way. The estimate itself, however, remains unbiased (Verbeek 2008). The output from this SUR can be found in chapter 2.7 of the appendix.

6. Conclusions and discussion

6.1 Conclusions

This thesis has analyzed the effects of crop price changes on crop yields and acreages in the European Union in the period 2000 – 2015. Our results shows that there is little evidence for a link between wheat, rapeseed, and sugar beet prices and wheat, rapeseed and sugar beet yields, respectively in the European Union in the period 2000 – 2015. Year effects (e.g., weather) seem more important in determining crop yields. We do find a difference between CEECs and countries in the rest of Europe (in the paper we defined these countries as OMS, since all them joined the European Union in the 20th century), as crop prices seem more important in yield decision in the CEECs than in the OMS. For the CEECs we find a negative relationship between rapeseed prices and rapeseed yield, and between sugar beet prices and sugar beet yield. We find no difference between the time periods 2000 – 2009 and 2010 – 2015. We do, however, find that sugar beet prices positively influenced sugar beet yields in the period 2010 – 2015.

Wheat acreages are positively influenced by wheat prices and the available arable land. For rapeseed we find a counterintuitive, positive relationship between rapeseed acreage and wheat prices. We also find the counterintuitive, negative relationship between rapeseed acreage and the available arable land. The relationship between sugar beet prices and rapeseed acreage is negative, as we expect from theory. There are only minor differences between the wheat and rapeseed acreages estimations of the OMS and the CEECs and between our findings for the periods 2000 – 2009 and 2010 – 2015. This indicates that acreage allocation with respect to crop prices does not differ between the OMS and the CEECs. We also do not find an effect of the EU biofuel policy (or the 2008 CAP health check), as there seem to be no structural difference between the two time periods in Model III.

Wheat prices have a positive influence on both wheat and rapeseed acreages (except for rapeseed acreages of CEECs) with varying significance levels. The positive relationship between wheat prices and wheat acreages is consistent with our theory, whereas the positive relationship between wheat prices and rapeseed is not. For sugar beet prices we always find a counterintuitive, positive influence on wheat acreages, and a negative influence on rapeseed acreages in all cases, except for the period 2010 – 2015, but the significance level differs between the equations. Note that we do not find a single case where rapeseed prices significantly influence either wheat or rapeseed acreages. For available arable land we find positive relationships in the case of both wheat and rapeseed acreages. The significance level of this effect varies for the wheat equations. For rapeseed we only find significant influence of arable land when the relationship is negative. We find some instances of a positive relationship between available arable land and rapeseed acreages, but none of these are significant.

This thesis has only touched upon the effects of crop prices on crop yields and acreages for a small number of crops. This research could be extended by looking at the possible effects of public policies (e.g., biofuel policies) on crop prices and their subsequent effect on crop yield and acreage. Furthermore, the interaction between prices, yields and acreages also has consequences for environmental analysis. When researching the possible environmental effects of price changes or public policy, one should keep in mind how yield and acreage respond to prices in the first place. The microeconomic model used in this paper could also be enhanced, for example, inputs could be explicitly modelled to show the effects of input prices as well as output prices. These questions show that there are still many opportunities for further research in this topic.

6.2 Assumptions and caveats

In our microeconomic model, certain assumptions are made with respect to the cost functions. We suppose that the elasticity of costs with respect to yield (acreage) is 2. This implies that a 1-percent increase of yield (acreage) comes at the expense of a two-percent increase of the total costs of yield (acreage). We mainly assume this elasticity for mathematical convenience. As stated before, most literature focusses on the crop price elasticities of yield (acreage) and the elasticities in this form have not been computed to our knowledge.

Furthermore, our estimated model differs from our microeconomic model in three aspects. In our microeconomics model some terms (A_i and B_i) are identified which help build our yield and acreage equations. In this process several relationships between these parameters are found. In theory, we could estimate the model, finding six values for A_i and B_i (note that $i = 1,2,3$), which would then be used to calculate the β_i's and β_{ij}'s in our equations estimations. *Stata*, however, could not find a solution to this non-linear model. The estimates obtained using SUR in no way guarantee that the relationships between A_i, B_i, β_i and β_{ij}, as identified in our microeconomic model, hold in our estimation. Secondly, whereas our microeconomic model uses $\bar{L}$ (which is the sum of L_1, L_2, and L_3), our estimation uses L for arable land, acknowledging that the three crops we use do not account for total use of arable land. Lastly, we include intercepts in our estimations, as we do not want to force the regressions through the origin. In our microeconomic model, however, intercepts are not included.

In this research we have used price indices as explanatory variables for the yields and acreage of three selected crops. We do not explicitly take the volatility of these prices into account. Haile et al. (2014) argue that crop price volatility introduces risks that affect a farmers' decision making. They include volatility into their estimation and find that it has a significant, negative influence on crop acreages of corn, wheat, soybean and rice. Chavas and Hold (1990) provide more evidence of farmers' risk aversion and how this influences acreage decisions. We do not include price volatility and risk aversion in our model, but it could be argued that price volatility (especially following the recent price shocks) may have influenced farmers' decision making and should be taken into account.

Furthermore, several other factors that play a role in the literature on crop prices and yield and acreage allocation decisions are not included in our model. Keeney and Hertel (2009) look at the interaction between yield, acreage and bilateral trade responses. They highlight the importance of trade patterns in international commodity markets. In our model, we assume a farmer chooses the optimal acreage and yield for a certain crop. Several papers (e.g., Hertel and Tsigas 1988, Hertel et al. 2008, Palatnik et al. 2011), however, show limitations of and costs associated with land use change. We do not explicitly take these into account in our model. There are more factors which influence the relationship between crop prices and crop yields and acreages that we do not include in our model or discuss in this paper. We argue that what our models lacks in complexity, it gains in its clarity. By simplifying our cost curves and focusing primarily on the effects of prices changes we are able to present a streamlined model that is intuitively clear.

Appendices

Appendix 1 – Derivation steps and results

Using equations (11) and (12) the optimal input demand functions can be found for land. We rewrite

$$\frac{\partial \pi}{\partial L_1} = p_1 y_1 - p_3 y_3 - C_1(y_1) + C_3(y_3) - \varphi_1'(L_1) + \varphi_3'(\bar{L} - L_1 - L_2) = 0$$

to

$$p_1 y_1 - C_1(y_1) - \varphi_1'(L_1) = p_3 y_3 - C_3(y_3) - +\varphi_3'(\bar{L} - L_1 - L_2),$$

where $\varphi_1'(L_1) = B_1 L_1$ and $\varphi_3'(\bar{L} - L_1 - L_2) = B_3(\bar{L} - L_1 - L_2)$. Then we substitute $y_1 = \frac{p_1}{A_1}$ and $y_3 = \frac{p_3}{A_3}$, to get

$$p_1 \frac{p_1}{A_1} - \frac{1}{2} A_1 * \left(\frac{p_1}{A_1}\right)^2 - B_1 L_1 = p_3 \frac{p_3}{A_3} - \frac{1}{2} A_3 * \left(\frac{p_3}{A_3}\right)^2 - B_3(\bar{L} - L_1 - L_2)\,.$$

Since $p_1 \frac{p_1}{A_1}$ is equal to $\frac{{p_1}^2}{A_1}$ and $A_1 * \left(\frac{p_1}{A_1}\right)^2$ is equal to $\frac{{p_1}^2}{A_1}$, the left part collapses to $\left(1 - \frac{1}{2}\right)\frac{{p_1}^2}{A_1} - B_1 L_1$, which is the same as $\frac{{p_1}^2}{2A_1} - B_1 L_1$. The same steps can be applied to the right hand side to obtain:

$$\frac{p_1^2}{2A_1} - B_1 L_1 = \frac{p_3^2}{2A_3} - B_3(\bar{L} - L_1 - L_2).$$

Moving $B_3 L_1$ to the left hand side, $\frac{p_1^2}{2A_1}$ to the right hand side and multiplying by -1, we obtain

$$(B_1 + B_3)L_1 = \frac{1}{2A_1} P_1^2 - \frac{1}{2A_3} P_3^2 + B_3(\bar{L} - L_2),$$

from which L_1 can be derived:

$$L_1 = \frac{\frac{1}{2A_1} P_1^2 - \frac{1}{2A_3} P_3^2 + B_3(\bar{L} - L_2)}{B_1 + B_3}.$$

The same steps can be used to find L_2 from equation (12):

$$L_2 = \frac{\frac{1}{2A_1} P_2^2 - \frac{1}{2A_3} P_3^2 + B_3(\bar{L} - L_1)}{B_2 + B_3}.$$

Plugging in the value found for L_1 into equation (17), we find:

$$\frac{p_2^2}{2A_2} - B_2 L_2 = \frac{p_3^2}{2A_3} - B_3 \bar{L} + B_3 \frac{\frac{1}{2A_1} P_1^2 - \frac{1}{2A_3} P_3^2 + B_3(\bar{L} - L_2)}{B_1 + B_3} + B_3 L_2.$$

We can rewrite this to find L_2. First, $B_3 L_2$ is moved to the left hand side, $\frac{p_2^2}{2A_2}$ is moved to the right hand side and the whole equation is multiplied by -1 to obtain

$$B_2L_2 + B_3L_2 = -\frac{p_3^2}{2A_3} + \frac{p_2^2}{2A_2} + B_3\bar{L} - B_3\frac{\frac{1}{2A_1}P_1^2 - \frac{1}{2A_3}P_3^2 + B_3(\bar{L} - L_2)}{B_1 + B_3}$$

We then multiply by the whole equation by $(B_1 + B_3)$,

$$(B_1 + B_3)(B_2L_2 + B_3L_2) = -\frac{(B_1 + B_3)p_3^2}{2A_3} + \frac{(B_1 + B_3)p_2^2}{2A_2} + (B_1B_3 + B_3^2)\bar{L} - \frac{B_3}{2A_1}P_1^2 + \frac{B_3}{2A_3}P_3^2 - B_3^2(\bar{L} - L_2)$$

This can be rewritten to

$$(B_1B_2 + B_1B_3 + B_2B_3 + B_3^2)L_2 = -\frac{(B_1 + B_3)p_3^2}{2A_3} + \frac{(B_1 + B_3)p_2^2}{2A_2} + (B_1B_3 + B_3^2)\bar{L} - \frac{B_3}{2A_1}P_1^2 + \frac{B_3}{2A_3}P_3^2 - B_3^2\bar{L} + B_3^2L_2.$$

$B_3^2L_2$ moves to the left hand side, and the B_3^2 terms cancel out. The same can be seen for B_3^2 terms on the right hand side:

$$(B_1B_2 + B_1B_3 + B_2B_3)L_2 = -\frac{(B_1 + B_3)p_3^2}{2A_3} + \frac{(B_1 + B_3)p_2^2}{2A_2} + (B_1B_3)\bar{L} - \frac{B_3}{2A_1}P_1^2 + \frac{B_3}{2A_3}P_3^2$$

Rewriting and ordering the equation gives us

$$(B_1B_2 + B_1B_3 + B_2B_3)L_2 = -\frac{B_3}{2A_1}P_1^2 + \frac{B_1 + B_3}{2A_2}p_2^2 - \frac{B_1 + B_3}{2A_3}p_3^2 + \frac{B_3}{2A_3}P_3^2 + (B_1B_3)\bar{L},$$

which can be simplified to

$$(B_1B_2 + B_1B_3 + B_2B_3)L_2 = -\frac{B_3}{2A_1}P_1^2 + \frac{B_1 + B_3}{2A_2}p_2^2 - \frac{B_1}{2A_3}p_3^2 + (B_1B_3)\bar{L}$$

since $-\frac{(B_1+B_3)}{2A_3}p_3^2 + \frac{B_3}{2A_3}P_3^2$ equals $-\frac{B_1}{2A_3}p_3^2$. To find L_2, both sides are divided by $(B_1B_2 + B_1B_3 + B_2B_3)$,

which gives:

$$L_2 = -\frac{B_3}{2A_1(B_1B_2 + B_1B_3 + B_2B_3)}P_1^2 + \frac{B_1 + B_3}{2A_2(B_1B_2 + B_1B_3 + B_2B_3)}P_2^2 - \frac{B_1}{2A_3(B_1B_2 + B_1B_3 + B_2B_3)}P_3^2 + \frac{B_1B_3}{(B_1B_2 + B_1B_3 + B_2B_3)}\bar{L}$$

This same process can be applied to L_2 in combination with equation (16), to find the optimal value for L_1.

Appendix 2 – Stata output

2.1 Stata output of yield equations – Model I

```
. xtserial wd_yieldWheat wd_lagrpWheat

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      17) =      2.379
           Prob > F =      0.1413

. xtserial wd_yieldRape wd_lagrpRape

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      13) =      4.956
           Prob > F =      0.0443

. xtserial wd_yieldSugarbeet wd_lagrpSugarbeet

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      17) =      0.174
           Prob > F =      0.6817
```

Figure 2: Wooldridge test for autocorrelation for yield equations of wheat, rapeseed and sugar beet, from top to bottom, respectively, for all selected countries (2000 – 2015).

Seemingly unrelated regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
wd_yieldWh~t	185	16	.2615491	0.4971	182.79	0.0000
wd_yieldRape	185	16	.3005348	0.5675	242.95	0.0000
wd_yieldSu~t	185	16	4.394957	0.6564	353.56	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
wd_yieldWheat						
wd_lagrpWheat	-.0002839	.0009805	-0.29	0.772	-.0022057	.0016378
YD2	.0693925	.1132427	0.61	0.540	-.1525591	.2913442
YD3	.0869889	.1159322	0.75	0.453	-.1402341	.3142119
YD4	-.304808	.1166798	-2.61	0.009	-.5334962	-.0761197
YD5	.4393939	.1161395	3.78	0.000	.2117647	.667023
YD6	.2230639	.11989	1.86	0.063	-.0119162	.4580441
YD7	-.1066465	.1205597	-0.88	0.376	-.3429391	.1296461
YD8	-.1489657	.1207553	-1.23	0.217	-.3856418	.0877104
YD9	.5216231	.1240196	4.21	0.000	.2785492	.764697
YD10	.2877603	.1263674	2.28	0.023	.0400847	.535436
YD11	-.0095894	.1225702	-0.08	0.938	-.2498225	.2306437
YD12	.2456649	.1242085	1.98	0.048	.0022208	.489109
YD13	.1620905	.1281307	1.27	0.206	-.089041	.413222
YD14	.2579476	.129519	1.99	0.046	.004095	.5118001
YD15	.6898089	.1274926	5.41	0.000	.4399281	.9396898
YD16	.5217138	.1243899	4.19	0.000	.2779142	.7655134
_cons	-.1802361	.0924917	-1.95	0.051	-.3615165	.0010442
wd_yieldRape						
wd_lagrpRape	-9.84e-06	.0008491	-0.01	0.991	-.001674	.0016543
YD2	-.0131889	.1334288	-0.10	0.921	-.2747045	.2483267
YD3	-.1544814	.1344527	-1.15	0.251	-.418004	.1090411
YD4	-.3962306	.1340914	-2.95	0.003	-.659045	-.1334162
YD5	.5718694	.1336287	4.28	0.000	.309962	.8337767
YD6	.3053731	.1385135	2.20	0.027	.0338917	.5768546
YD7	.2671049	.1386114	1.93	0.054	-.0045685	.5387782
YD8	.2264347	.1384855	1.64	0.102	-.044992	.4978614
YD9	.4575215	.1396468	3.28	0.001	.1838188	.7312242
YD10	.5916596	.144962	4.08	0.000	.3075393	.8757799
YD11	.2595035	.1402079	1.85	0.064	-.0152989	.5343058
YD12	.2901509	.1427777	2.03	0.042	.0103117	.5699902
YD13	.3102595	.1479161	2.10	0.036	.0203494	.6001697
YD14	.5092455	.1493327	3.41	0.001	.2165587	.8019323
YD15	1.025354	.1436415	7.14	0.000	.7438214	1.306886
YD16	.7538866	.1425036	5.29	0.000	.4745846	1.033189
_cons	-.3281006	.1062219	-3.09	0.002	-.5362917	-.1199094
wd_yieldSugarbeet						
wd_lagrpSugarbeet	.0079076	.0168638	0.47	0.639	-.0251449	.04096
YD2	-1.994271	1.989283	-1.00	0.316	-5.893195	1.904652
YD3	3.461277	2.031106	1.70	0.088	-.5196163	7.442171
YD4	-1.09668	2.01793	-0.54	0.587	-5.051751	2.858391
YD5	4.92054	2.016822	2.44	0.015	.9676411	8.873439
YD6	6.597958	2.147918	3.07	0.002	2.388116	10.8078
YD7	3.788882	2.092833	1.81	0.070	-.312995	7.890759
YD8	4.074193	2.0411	2.00	0.046	.0737104	8.074676
YD9	9.475678	2.050024	4.62	0.000	5.457704	13.49365
YD10	11.0407	2.085022	5.30	0.000	6.954132	15.12727
YD11	7.761721	2.042985	3.80	0.000	3.757543	11.7659
YD12	17.85578	2.083377	8.57	0.000	13.77243	21.93912
YD13	9.613494	2.084128	4.61	0.000	5.528678	13.69831
YD14	11.01357	2.083725	5.29	0.000	6.929548	15.0976
YD15	21.51011	2.087092	10.31	0.000	17.41948	25.60073
YD16	11.06374	2.08341	5.31	0.000	6.980327	15.14714
_cons	-7.186997	1.579758	-4.55	0.000	-10.28327	-4.090728

Figure 3: SUR regression for yield of wheat for all selected countries (2000 – 2015).

```
Correlation matrix of residuals:

                     wd_yieldWheat     wd_yieldRape  wd_yieldSugarbeet
    wd_yieldWheat           1.0000
     wd_yieldRape           0.4000           1.0000
wd_yieldSugarbeet           0.4018           0.1614             1.0000

Breusch-Pagan test of independence: chi2(3) =    64.288, Pr = 0.0000
```

Figure X: Breusch-Pagan test of independence of yield equations for all selected countries (2000 – 2015).

```
 ( 1)  [wd_yieldWheat]YD2 = 0
 ( 2)  [wd_yieldWheat]YD3 = 0
 ( 3)  [wd_yieldWheat]YD4 = 0
 ( 4)  [wd_yieldWheat]YD5 = 0
 ( 5)  [wd_yieldWheat]YD6 = 0
 ( 6)  [wd_yieldWheat]YD7 = 0
 ( 7)  [wd_yieldWheat]YD8 = 0
 ( 8)  [wd_yieldWheat]YD9 = 0
 ( 9)  [wd_yieldWheat]YD10 = 0
 (10)  [wd_yieldWheat]YD11 = 0
 (11)  [wd_yieldWheat]YD12 = 0
 (12)  [wd_yieldWheat]YD13 = 0
 (13)  [wd_yieldWheat]YD14 = 0
 (14)  [wd_yieldWheat]YD15 = 0
 (15)  [wd_yieldWheat]YD16 = 0

           chi2( 15) =  148.64
         Prob > chi2 =    0.0000
```

```
 ( 1)  [wd_yieldRape]YD2 = 0
 ( 2)  [wd_yieldRape]YD3 = 0
 ( 3)  [wd_yieldRape]YD4 = 0
 ( 4)  [wd_yieldRape]YD5 = 0
 ( 5)  [wd_yieldRape]YD6 = 0
 ( 6)  [wd_yieldRape]YD7 = 0
 ( 7)  [wd_yieldRape]YD8 = 0
 ( 8)  [wd_yieldRape]YD9 = 0
 ( 9)  [wd_yieldRape]YD10 = 0
 (10)  [wd_yieldRape]YD11 = 0
 (11)  [wd_yieldRape]YD12 = 0
 (12)  [wd_yieldRape]YD13 = 0
 (13)  [wd_yieldRape]YD14 = 0
 (14)  [wd_yieldRape]YD15 = 0
 (15)  [wd_yieldRape]YD16 = 0

           chi2( 15) =  213.86
         Prob > chi2 =    0.0000
```

```
 ( 1)  [wd_yieldSugarbeet]YD2 = 0
 ( 2)  [wd_yieldSugarbeet]YD3 = 0
 ( 3)  [wd_yieldSugarbeet]YD4 = 0
 ( 4)  [wd_yieldSugarbeet]YD5 = 0
 ( 5)  [wd_yieldSugarbeet]YD6 = 0
 ( 6)  [wd_yieldSugarbeet]YD7 = 0
 ( 7)  [wd_yieldSugarbeet]YD8 = 0
 ( 8)  [wd_yieldSugarbeet]YD9 = 0
 ( 9)  [wd_yieldSugarbeet]YD10 = 0
 (10)  [wd_yieldSugarbeet]YD11 = 0
 (11)  [wd_yieldSugarbeet]YD12 = 0
 (12)  [wd_yieldSugarbeet]YD13 = 0
 (13)  [wd_yieldSugarbeet]YD14 = 0
 (14)  [wd_yieldSugarbeet]YD15 = 0
 (15)  [wd_yieldSugarbeet]YD16 = 0

           chi2( 15) =  306.76
         Prob > chi2 =    0.0000
```

Figure 4: Chi-squared test for year dummy variables for yield of wheat, rapeseed and sugar beet, from left to right, respectively, for all selected countries (2000 – 2015).

2.2 Stata output of yield equations – Model II

```
. xtserial wd_yieldWheat wd_lagrpWheat

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      10) =      0.802
           Prob > F =      0.3917

. xtserial wd_yieldRape wd_lagrpRape

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,       6) =     11.531
           Prob > F =      0.0146

. xtserial wd_yieldSugarbeet wd_lagrpSugarbeet

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      10) =      1.494
           Prob > F =      0.2496
```

```
. xtserial wd_yieldWheat wd_lagrpWheat

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,       6) =      2.343
           Prob > F =      0.1767

. xtserial wd_yieldRape wd_lagrpRape

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,       6) =      0.431
           Prob > F =      0.5357

. xtserial wd_yieldSugarbeet wd_lagrpSugarbeet

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,       6) =      0.280
           Prob > F =      0.6159
```

Figure 5: Wooldridge test for autocorrelation for yield equations of all the OMS and the CEECs, from left to right, respectively (2000 – 2015).

Seemingly unrelated regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
wd_yieldWh~t	111	16	.2090901	0.4633	95.68	0.0000
wd_yieldRape	111	16	.2877465	0.4899	106.65	0.0000
wd_yieldSu~t	111	16	4.131487	0.6587	214.20	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
wd_yieldWheat						
wd_lagrpWheat	.0006708	.0011378	0.59	0.555	-.0015591	.0029008
YD2	-.1714447	.1167194	-1.47	0.142	-.4002106	.0573212
YD3	-.0974227	.1225688	-0.79	0.427	-.3376531	.1428078
YD4	-.3238449	.1235073	-2.62	0.009	-.5659148	-.0817751
YD5	.0356193	.1231255	0.29	0.772	-.2057023	.2769409
YD6	-.1234018	.1231612	-1.00	0.316	-.3647933	.1179897
YD7	-.3651048	.1259407	-2.90	0.004	-.6119441	-.1182654
YD8	-.3121445	.1239145	-2.52	0.012	-.5550124	-.0692767
YD9	.1547959	.1271235	1.22	0.223	-.0943615	.4039533
YD10	-.0267136	.1325342	-0.20	0.840	-.2864759	.2330486
YD11	-.2844549	.124065	-2.29	0.022	-.527618	-.0412919
YD12	-.1291421	.1231716	-1.05	0.294	-.3705541	.1122698
YD13	-.1476001	.1298008	-1.14	0.255	-.4020049	.1068048
YD14	-.112356	.1321768	-0.85	0.395	-.3714178	.1467058
YD15	.261907	.1286178	2.04	0.042	.0098208	.5139932
YD16	.2221751	.123267	1.80	0.071	-.0194238	.463774
_cons	.0863205	.0935305	0.92	0.356	-.096996	.269637
wd_yieldRape						
wd_lagrpRape	.000056	.0012512	0.04	0.964	-.0023963	.0025083
YD2	-.0753516	.1719234	-0.44	0.661	-.4123153	.261612
YD3	.016048	.1718179	0.09	0.926	-.3207089	.3528048
YD4	-.0559693	.1709647	-0.33	0.743	-.391054	.2791153
YD5	.4484944	.170178	2.64	0.008	.1149516	.7820372
YD6	.3744461	.1729119	2.17	0.030	.035545	.7133473
YD7	.3857568	.1770882	2.18	0.029	.0386702	.7328433
YD8	.2371412	.1715323	1.38	0.167	-.0990559	.5733383
YD9	.447044	.1684628	2.65	0.008	.1168629	.777225
YD10	.6829838	.1812989	3.77	0.000	.3276445	1.038323
YD11	.3844673	.1694725	2.27	0.023	.0523072	.7166274
YD12	.3724101	.1694138	2.20	0.028	.0403652	.7044549
YD13	.4004728	.1789947	2.24	0.025	.0496497	.7512959
YD14	.4344508	.182249	2.38	0.017	.0772493	.7916523
YD15	.9060717	.1709515	5.30	0.000	.5710129	1.24113
YD16	.8056138	.1685686	4.78	0.000	.4752254	1.136002
_cons	-.3624885	.130276	-2.78	0.005	-.6178248	-.1071523
wd_yieldSugarbeet						
wd_lagrpSugarbeet	.0249557	.0332677	0.75	0.453	-.0402479	.0901592
YD2	-5.627048	2.630135	-2.14	0.032	-10.78202	-.472078
YD3	.2257139	2.735853	0.08	0.934	-5.13646	5.587888
YD4	-2.686286	2.626005	-1.02	0.306	-7.833161	2.460589
YD5	.997839	2.682833	0.37	0.710	-4.260417	6.256094
YD6	2.593967	2.64524	0.98	0.327	-2.590608	7.778541
YD7	.5215676	2.612166	0.20	0.842	-4.598183	5.641318
YD8	2.728705	2.49211	1.09	0.274	-2.15574	7.613149
YD9	5.641833	2.420195	2.33	0.020	.8983387	10.38533
YD10	8.382145	2.501831	3.35	0.001	3.478647	13.28564
YD11	4.125976	2.419195	1.71	0.088	-.6155587	8.867512
YD12	15.20011	2.420368	6.28	0.000	10.45628	19.94395
YD13	6.451727	2.419209	2.67	0.008	1.710164	11.19329
YD14	7.412209	2.419393	3.06	0.002	2.670287	12.15413
YD15	17.52165	2.420157	7.24	0.000	12.77823	22.26507
YD16	8.505082	2.421067	3.51	0.000	3.759878	13.25029
_cons	-4.366132	1.972356	-2.21	0.027	-8.231878	-.5003849

Figure 6: SUR regression for yield of wheat, rapeseed, and sugar beet for the OMS (2000 – 2015).

Seemingly unrelated regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
wd_yieldWh~t	74	16	.2489631	0.7147	187.49	0.0000
wd_yieldRape	74	16	.2241032	0.8162	328.44	0.0000
wd_yieldSu~t	74	16	4.185437	0.7320	203.33	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
wd_yieldWheat						
wd_lagrpWheat	.0024228	.0023309	1.04	0.299	-.0021457	.0069912
YD2	.4642126	.1725933	2.69	0.007	.125936	.8024893
YD3	.4450982	.1717046	2.59	0.010	.1085634	.781633
YD4	-.0668193	.1728671	-0.39	0.699	-.4056326	.2719941
YD5	1.03349	.1714399	6.03	0.000	.6974737	1.369506
YD6	.8208137	.182696	4.49	0.000	.4627363	1.178891
YD7	.430358	.1862708	2.31	0.021	.065274	.795442
YD8	.2269041	.1870832	1.21	0.225	-.1397723	.5935805
YD9	1.046688	.1935024	5.41	0.000	.6674307	1.425946
YD10	.7265838	.191305	3.80	0.000	.3516328	1.101535
YD11	.5171274	.1926038	2.68	0.007	.1396308	.8946239
YD12	.9417852	.2042678	4.61	0.000	.5414277	1.342143
YD13	.5744175	.2067366	2.78	0.005	.1692213	.9796137
YD14	.7882411	.2086444	3.78	0.000	.3793057	1.197177
YD15	1.389088	.2061164	6.74	0.000	.9851078	1.793069
YD16	1.018293	.2029077	5.02	0.000	.6206015	1.415985
_cons	-.5996975	.1455843	-4.12	0.000	-.8850375	-.3143575
wd_yieldRape						
wd_lagrpRape	-.0059324	.0022873	-2.59	0.009	-.0104154	-.0014494
YD2	-.0078063	.1566897	-0.05	0.960	-.3149125	.2992999
YD3	-.3905664	.1555803	-2.51	0.012	-.6954981	-.0856346
YD4	-.7852856	.1549821	-5.07	0.000	-1.089045	-.4815263
YD5	.6854436	.1546611	4.43	0.000	.3823134	.9885738
YD6	.1547584	.164657	0.94	0.347	-.1679634	.4774801
YD7	-.0165887	.1664146	-0.10	0.921	-.3427553	.3095779
YD8	.1161764	.1671673	0.69	0.487	-.2114654	.4438183
YD9	.3908355	.1744386	2.24	0.025	.0489421	.7327288
YD10	.5674774	.177513	3.20	0.001	.2195584	.9153964
YD11	-.0619872	.1760567	-0.35	0.725	-.4070521	.2830776
YD12	.0732013	.1837511	0.40	0.690	-.2869443	.4333468
YD13	.3125969	.1982735	1.58	0.115	-.076012	.7012057
YD14	.9116926	.2007701	4.54	0.000	.5181904	1.305195
YD15	1.366253	.1837118	7.44	0.000	1.006185	1.726322
YD16	.6256389	.1833053	3.41	0.001	.2663671	.9849107
_cons	-.4019062	.138657	-2.90	0.004	-.6736689	-.1301435
wd_yieldSugarbeet						
wd_lagrpSugarbeet	-.0429152	.0249202	-1.72	0.085	-.091758	.0059275
YD2	4.245233	2.976053	1.43	0.154	-1.587725	10.07819
YD3	9.114742	2.97181	3.07	0.002	3.290103	14.93938
YD4	3.14447	2.984034	1.05	0.292	-2.70413	8.99307
YD5	11.18722	2.956986	3.78	0.000	5.391638	16.98281
YD6	15.3388	3.445894	4.45	0.000	8.584969	22.09262
YD7	10.94945	3.242961	3.38	0.001	4.593359	17.30553
YD8	7.640368	3.138588	2.43	0.015	1.488848	13.79189
YD9	17.36198	3.274335	5.30	0.000	10.9444	23.77956
YD10	16.00449	3.209279	4.99	0.000	9.714417	22.29456
YD11	14.7921	3.224322	4.59	0.000	8.472548	21.11166
YD12	23.17631	3.433398	6.75	0.000	16.44698	29.90565
YD13	16.01467	3.433949	4.66	0.000	9.284249	22.74508
YD14	18.52977	3.435347	5.39	0.000	11.79661	25.26292
YD15	30.24024	3.463679	8.73	0.000	23.45155	37.02892
YD16	16.27386	3.438084	4.73	0.000	9.535339	23.01238
_cons	-11.88081	2.433189	-4.88	0.000	-16.64977	-7.111846

Figure 7: SUR regression for yield of wheat, rapeseed, and sugar beet for the CEECs (2000 – 2015)

```
Correlation matrix of residuals:

                    wd_yieldWheat       wd_yieldRape  wd_yieldSugarbeet
    wd_yieldWheat          1.0000
     wd_yieldRape          0.4547            1.0000
wd_yieldSugarbeet          0.1395            0.0688             1.0000

Breusch-Pagan test of independence: chi2(3) =    25.634, Pr = 0.0000

Correlation matrix of residuals:

                    wd_yieldWheat       wd_yieldRape  wd_yieldSugarbeet
    wd_yieldWheat          1.0000
     wd_yieldRape          0.2541            1.0000
wd_yieldSugarbeet          0.5766            0.2862             1.0000

Breusch-Pagan test of independence: chi2(3) =    35.443, Pr = 0.0000
```

Figure 8: Breusch-Pagan test of independence of yield equations for the OMS and CEECs, from top to bottom, respectively (2000 – 2015).

```
 ( 1)  [wd_yieldWheat]YD2 = 0       ( 1)  [wd_yieldRape]YD2 = 0       ( 1)  [wd_yieldSugarbeet]YD2 = 0
 ( 2)  [wd_yieldWheat]YD3 = 0       ( 2)  [wd_yieldRape]YD3 = 0       ( 2)  [wd_yieldSugarbeet]YD3 = 0
 ( 3)  [wd_yieldWheat]YD4 = 0       ( 3)  [wd_yieldRape]YD4 = 0       ( 3)  [wd_yieldSugarbeet]YD4 = 0
 ( 4)  [wd_yieldWheat]YD5 = 0       ( 4)  [wd_yieldRape]YD5 = 0       ( 4)  [wd_yieldSugarbeet]YD5 = 0
 ( 5)  [wd_yieldWheat]YD6 = 0       ( 5)  [wd_yieldRape]YD6 = 0       ( 5)  [wd_yieldSugarbeet]YD6 = 0
 ( 6)  [wd_yieldWheat]YD7 = 0       ( 6)  [wd_yieldRape]YD7 = 0       ( 6)  [wd_yieldSugarbeet]YD7 = 0
 ( 7)  [wd_yieldWheat]YD8 = 0       ( 7)  [wd_yieldRape]YD8 = 0       ( 7)  [wd_yieldSugarbeet]YD8 = 0
 ( 8)  [wd_yieldWheat]YD9 = 0       ( 8)  [wd_yieldRape]YD9 = 0       ( 8)  [wd_yieldSugarbeet]YD9 = 0
 ( 9)  [wd_yieldWheat]YD10 = 0      ( 9)  [wd_yieldRape]YD10 = 0      ( 9)  [wd_yieldSugarbeet]YD10 = 0
 (10)  [wd_yieldWheat]YD11 = 0      (10)  [wd_yieldRape]YD11 = 0      (10)  [wd_yieldSugarbeet]YD11 = 0
 (11)  [wd_yieldWheat]YD12 = 0      (11)  [wd_yieldRape]YD12 = 0      (11)  [wd_yieldSugarbeet]YD12 = 0
 (12)  [wd_yieldWheat]YD13 = 0      (12)  [wd_yieldRape]YD13 = 0      (12)  [wd_yieldSugarbeet]YD13 = 0
 (13)  [wd_yieldWheat]YD14 = 0      (13)  [wd_yieldRape]YD14 = 0      (13)  [wd_yieldSugarbeet]YD14 = 0
 (14)  [wd_yieldWheat]YD15 = 0      (14)  [wd_yieldRape]YD15 = 0      (14)  [wd_yieldSugarbeet]YD15 = 0
 (15)  [wd_yieldWheat]YD16 = 0      (15)  [wd_yieldRape]YD16 = 0      (15)  [wd_yieldSugarbeet]YD16 = 0

          chi2( 15) =   67.19             chi2( 15) =   86.19             chi2( 15) =  148.89
        Prob > chi2 =    0.0000         Prob > chi2 =    0.0000         Prob > chi2 =    0.0000
```

Figure 9: Chi-squared test for year dummy variables for yield of wheat, rapeseed and sugar beet, from left to right, respectively, for the OMS (2000 – 2015).

```
( 1)  [wd_yieldWheat]YD2 = 0
( 2)  [wd_yieldWheat]YD3 = 0
( 3)  [wd_yieldWheat]YD4 = 0
( 4)  [wd_yieldWheat]YD5 = 0
( 5)  [wd_yieldWheat]YD6 = 0
( 6)  [wd_yieldWheat]YD7 = 0
( 7)  [wd_yieldWheat]YD8 = 0
( 8)  [wd_yieldWheat]YD9 = 0
( 9)  [wd_yieldWheat]YD10 = 0
(10)  [wd_yieldWheat]YD11 = 0
(11)  [wd_yieldWheat]YD12 = 0
(12)  [wd_yieldWheat]YD13 = 0
(13)  [wd_yieldWheat]YD14 = 0
(14)  [wd_yieldWheat]YD15 = 0
(15)  [wd_yieldWheat]YD16 = 0

          chi2( 15) =  156.07
        Prob > chi2 =    0.0000
```

```
( 1)  [wd_yieldRape]YD2 = 0
( 2)  [wd_yieldRape]YD3 = 0
( 3)  [wd_yieldRape]YD4 = 0
( 4)  [wd_yieldRape]YD5 = 0
( 5)  [wd_yieldRape]YD6 = 0
( 6)  [wd_yieldRape]YD7 = 0
( 7)  [wd_yieldRape]YD8 = 0
( 8)  [wd_yieldRape]YD9 = 0
( 9)  [wd_yieldRape]YD10 = 0
(10)  [wd_yieldRape]YD11 = 0
(11)  [wd_yieldRape]YD12 = 0
(12)  [wd_yieldRape]YD13 = 0
(13)  [wd_yieldRape]YD14 = 0
(14)  [wd_yieldRape]YD15 = 0
(15)  [wd_yieldRape]YD16 = 0

          chi2( 15) =  320.06
        Prob > chi2 =    0.0000
```

```
( 1)  [wd_yieldSugarbeet]YD2 = 0
( 2)  [wd_yieldSugarbeet]YD3 = 0
( 3)  [wd_yieldSugarbeet]YD4 = 0
( 4)  [wd_yieldSugarbeet]YD5 = 0
( 5)  [wd_yieldSugarbeet]YD6 = 0
( 6)  [wd_yieldSugarbeet]YD7 = 0
( 7)  [wd_yieldSugarbeet]YD8 = 0
( 8)  [wd_yieldSugarbeet]YD9 = 0
( 9)  [wd_yieldSugarbeet]YD10 = 0
(10)  [wd_yieldSugarbeet]YD11 = 0
(11)  [wd_yieldSugarbeet]YD12 = 0
(12)  [wd_yieldSugarbeet]YD13 = 0
(13)  [wd_yieldSugarbeet]YD14 = 0
(14)  [wd_yieldSugarbeet]YD15 = 0
(15)  [wd_yieldSugarbeet]YD16 = 0

          chi2( 15) =  195.80
        Prob > chi2 =    0.0000
```

Figure 10: Chi-squared test for year dummy variables for yield of wheat, rapeseed and sugar beet, from left to right, respectively, for the CEECs (2000 – 2015).

2.3 Stata output of yield equations – Model III

```
. xtserial wd_yieldWheat wd_lagrpWheat

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      17) =      0.039
           Prob > F =      0.8465

. xtserial wd_yieldRape wd_lagrpRape

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      13) =      3.688
           Prob > F =      0.0770

. xtserial wd_yieldSugarbeet wd_lagrpSugarbeet

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      16) =      3.705
           Prob > F =      0.0722
```

```
. xtserial wd_yieldWheat wd_lagrpWheat

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      17) =      1.620
           Prob > F =      0.2202

. xtserial wd_yieldRape wd_lagrpRape

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      12) =      0.128
           Prob > F =      0.7265

. xtserial wd_yieldSugarbeet wd_lagrpSugarbeet

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      14) =      0.415
           Prob > F =      0.5301
```

Figure 11: Wooldridge test for autocorrelation for yield equations of the period 2000 – 2009 and the period 2010 – 2015, from left to right, respectively.

Seemingly unrelated regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
wd_yieldWh~t	124	10	.2749	0.4482	101.38	0.0000
wd_yieldRape	124	10	.3088909	0.5048	126.47	0.0000
wd_yieldSu~t	124	10	4.378695	0.4515	102.60	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
wd_yieldWheat						
wd_lagrpWheat	.0011936	.0016576	0.72	0.471	-.0020553	.0044425
YD2	.069032	.1189799	0.58	0.562	-.1641644	.3022283
YD3	.0906071	.1218467	0.74	0.457	-.1482081	.3294223
YD4	-.2846098	.1238694	-2.30	0.022	-.5273894	-.0418303
YD5	.4504524	.1224094	3.68	0.000	.2105343	.6903705
YD6	.2399042	.1268302	1.89	0.059	-.0086784	.4884868
YD7	-.066091	.1315869	-0.50	0.615	-.3239966	.1918146
YD8	-.1214626	.129155	-0.94	0.347	-.3746017	.1316764
YD9	.4842841	.1343715	3.60	0.000	.2209208	.7476474
YD10	.2514663	.1365475	1.84	0.066	-.0161618	.5190944
_cons	-.176711	.0972266	-1.82	0.069	-.3672716	.0138497
wd_yieldRape						
wd_lagrpRape	-.0005286	.0014395	-0.37	0.713	-.00335	.0022928
YD2	-.0313435	.1429241	-0.22	0.826	-.3114695	.2487826
YD3	-.1659366	.1405408	-1.18	0.238	-.4413915	.1095183
YD4	-.4059775	.1395451	-2.91	0.004	-.6794809	-.1324742
YD5	.5648867	.1382633	4.09	0.000	.2938956	.8358778
YD6	.2933745	.1448644	2.03	0.043	.0094455	.5773036
YD7	.2478689	.1487103	1.67	0.096	-.043598	.5393357
YD8	.2145571	.1447876	1.48	0.138	-.0692213	.4983356
YD9	.4549816	.1436998	3.17	0.002	.1733353	.736628
YD10	.6079352	.15332	3.97	0.000	.3074335	.9084369
_cons	-.3270569	.1092459	-2.99	0.003	-.541175	-.1129388
wd_yieldSugarbeet						
wd_lagrpSugarbeet	-.0194961	.0202359	-0.96	0.335	-.0591578	.0201656
YD2	-1.045532	2.021074	-0.52	0.605	-5.006764	2.915701
YD3	4.40434	2.061558	2.14	0.033	.36376	8.444921
YD4	-.2315216	2.042843	-0.11	0.910	-4.235421	3.772378
YD5	5.778847	2.041267	2.83	0.005	1.778038	9.779657
YD6	7.851791	2.202384	3.57	0.000	3.535197	12.16838
YD7	4.921015	2.13759	2.30	0.021	.7314168	9.110614
YD8	4.699113	2.050901	2.29	0.022	.6794212	8.718804
YD9	9.793635	2.047823	4.78	0.000	5.779975	13.80729
YD10	11.18295	2.07936	5.38	0.000	7.10748	15.25842
_cons	-7.659974	1.586799	-4.83	0.000	-10.77004	-4.549904

Figure 12: SUR regression for yields of wheat, rapeseed, and sugar beet for all selected countries (2000 – 2009).

Seemingly unrelated regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
wd_yieldWh~t	61	6	.2312187	0.5007	60.99	0.0000
wd_yieldRape	61	6	.2842638	0.4912	60.82	0.0000
wd_yieldSu~t	61	6	4.200235	0.5948	88.06	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
wd_yieldWheat						
wd_lagrpWheat	-.0007176	.0011152	-0.64	0.520	-.0029033	.0014682
YD12	.2651038	.1040682	2.55	0.011	.0611339	.4690736
YD13	.1929487	.1148068	1.68	0.093	-.0320685	.4179658
YD14	.291088	.1177165	2.47	0.013	.0603678	.5218081
YD15	.7194941	.1134005	6.34	0.000	.4972332	.9417551
YD16	.5424451	.1049268	5.17	0.000	.3367925	.7480978
_cons	-.1979439	.0727159	-2.72	0.006	-.3404645	-.0554233
wd_yieldRape						
wd_lagrpRape	.0006277	.0009774	0.64	0.521	-.001288	.0025435
YD12	.0139693	.1259963	0.11	0.912	-.232979	.2609176
YD13	.0110436	.137578	0.08	0.936	-.2586042	.2806915
YD14	.2062813	.1402155	1.47	0.141	-.068536	.4810985
YD15	.7423259	.1285375	5.78	0.000	.490397	.9942548
YD16	.4857602	.124081	3.91	0.000	.2425659	.7289546
_cons	-.0599664	.0861587	-0.70	0.486	-.2288344	.1089016
wd_yieldSugarbeet						
wd_lagrpSugarbeet	.065837	.0289941	2.27	0.023	.0090096	.1226644
YD12	10.33086	1.834841	5.63	0.000	6.734636	13.92708
YD13	1.970674	1.831976	1.08	0.282	-1.619933	5.561281
YD14	3.42311	1.833015	1.87	0.062	-.1695329	7.015752
YD15	13.64418	1.831752	7.45	0.000	10.05402	17.23435
YD16	3.530985	1.834592	1.92	0.054	-.0647496	7.12672
_cons	1.240199	1.30668	0.95	0.343	-1.320847	3.801245

Figure 13: SUR regression for yields of wheat, rapeseed, and sugar beet for all selected countries (2010 – 2015).

```
Correlation matrix of residuals:

                    wd_yieldWheat       wd_yieldRape  wd_yieldSugarbeet
    wd_yieldWheat          1.0000
     wd_yieldRape          0.3618             1.0000
wd_yieldSugarbeet          0.4436             0.1616             1.0000

Breusch-Pagan test of independence: chi2(3) =    43.866, Pr = 0.0000

Correlation matrix of residuals:

                    wd_yieldWheat       wd_yieldRape  wd_yieldSugarbeet
    wd_yieldWheat          1.0000
     wd_yieldRape          0.4992             1.0000
wd_yieldSugarbeet          0.2816             0.1715             1.0000

Breusch-Pagan test of independence: chi2(3) =    21.833, Pr = 0.0001
```

Figure 14: Breusch-Pagan test of independence of yield equations the period 2000 – 2009 and the period 2010 – 2015, from top to bottom, respectively.

```
 ( 1)  [wd_yieldWheat]YD2 = 0      ( 1)  [wd_yieldRape]YD2 = 0       ( 1)  [wd_yieldSugarbeet]YD2 = 0
 ( 2)  [wd_yieldWheat]YD3 = 0      ( 2)  [wd_yieldRape]YD3 = 0       ( 2)  [wd_yieldSugarbeet]YD3 = 0
 ( 3)  [wd_yieldWheat]YD4 = 0      ( 3)  [wd_yieldRape]YD4 = 0       ( 3)  [wd_yieldSugarbeet]YD4 = 0
 ( 4)  [wd_yieldWheat]YD5 = 0      ( 4)  [wd_yieldRape]YD5 = 0       ( 4)  [wd_yieldSugarbeet]YD5 = 0
 ( 5)  [wd_yieldWheat]YD6 = 0      ( 5)  [wd_yieldRape]YD6 = 0       ( 5)  [wd_yieldSugarbeet]YD6 = 0
 ( 6)  [wd_yieldWheat]YD7 = 0      ( 6)  [wd_yieldRape]YD7 = 0       ( 6)  [wd_yieldSugarbeet]YD7 = 0
 ( 7)  [wd_yieldWheat]YD8 = 0      ( 7)  [wd_yieldRape]YD8 = 0       ( 7)  [wd_yieldSugarbeet]YD8 = 0
 ( 8)  [wd_yieldWheat]YD9 = 0      ( 8)  [wd_yieldRape]YD9 = 0       ( 8)  [wd_yieldSugarbeet]YD9 = 0
 ( 9)  [wd_yieldWheat]YD10 = 0     ( 9)  [wd_yieldRape]YD10 = 0      ( 9)  [wd_yieldSugarbeet]YD10 = 0

           chi2(  9) =   74.35            chi2(  9) =  117.83            chi2(  9) =   96.61
         Prob > chi2 =    0.0000        Prob > chi2 =    0.0000        Prob > chi2 =    0.0000
```

Figure 15: Chi-squared test for year dummy variables for yield of wheat, rapeseed and sugar beet, from left to right, respectively, for the period 2000 – 2009.

```
 ( 1)  [wd_yieldWheat]YD12 = 0     ( 1)  [wd_yieldRape]YD12 = 0      ( 1)  [wd_yieldSugarbeet]YD12 = 0
 ( 2)  [wd_yieldWheat]YD13 = 0     ( 2)  [wd_yieldRape]YD13 = 0      ( 2)  [wd_yieldSugarbeet]YD13 = 0
 ( 3)  [wd_yieldWheat]YD14 = 0     ( 3)  [wd_yieldRape]YD14 = 0      ( 3)  [wd_yieldSugarbeet]YD14 = 0
 ( 4)  [wd_yieldWheat]YD15 = 0     ( 4)  [wd_yieldRape]YD15 = 0      ( 4)  [wd_yieldSugarbeet]YD15 = 0
 ( 5)  [wd_yieldWheat]YD16 = 0     ( 5)  [wd_yieldRape]YD16 = 0      ( 5)  [wd_yieldSugarbeet]YD16 = 0

           chi2(  5) =   58.88            chi2(  5) =   60.29            chi2(  5) =   81.66
         Prob > chi2 =    0.0000        Prob > chi2 =    0.0000        Prob > chi2 =    0.0000
```

Figure 16: Chi-squared test for year dummy variables for yield of wheat, rapeseed and sugar beet, from left to right, respectively, for the period 2010 – 2015.

2.4 Stata output of acreage equations – Model I

```
Correlation matrix of residuals:

             wd_areaWheat   wd_areaRape
wd_areaWheat       1.0000
 wd_areaRape      -0.2986        1.0000

Breusch-Pagan test of independence: chi2(1) =    17.292, Pr = 0.0000
```

Figure 17: Breusch-Pagan test of independence of acreage equations for all selected countries (2000 – 2015).

```
. xtserial  wd_areaWheat wd_lagrpWheat2 wd_lagrpRape2 wd_lagrpSugarbeet2 wd_arabland

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      13) =      0.084
           Prob > F =      0.7770

. xtserial  wd_areaRape wd_lagrpWheat2 wd_lagrpRape2 wd_lagrpSugarbeet2 wd_arabland

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      13) =    264.105
           Prob > F =      0.0000
```

Figure 18: Wooldridge test for autocorrelation for acreage equations for all selected countries (2000 – 2015).

Seemingly unrelated regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
wd_areaWheat	194	4	188.573	0.1459	33.14	0.0000
wd_areaRape	194	4	90.75221	0.1611	37.25	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
wd_areaWheat						
wd_lagrpWheat2	.0105593	.0040874	2.58	0.010	.0025482	.0185704
wd_lagrpRape2	-.0035645	.0022649	-1.57	0.116	-.0080035	.0008746
wd_lagrpSugarbeet2	.0068545	.0043702	1.57	0.117	-.0017109	.0154199
wd_arabland	.1258407	.0262043	4.80	0.000	.0744812	.1772001
_cons	8.422536	13.57432	0.62	0.535	-18.18264	35.02771
wd_areaRape						
wd_lagrpWheat2	.0036276	.0019671	1.84	0.065	-.0002278	.007483
wd_lagrpRape2	.0003837	.00109	0.35	0.725	-.0017526	.00252
wd_lagrpSugarbeet2	-.0060391	.0021032	-2.87	0.004	-.0101613	-.001917
wd_arabland	-.0317887	.012611	-2.52	0.012	-.0565058	-.0070715
_cons	-2.662002	6.532745	-0.41	0.684	-15.46595	10.14194

Figure 19: SUR regression for acreage of wheat and rapeseed for all selected countries (2000 – 2015).

2.5 Stata output of acreage equations – Model II

```
Correlation matrix of residuals:

              wd_areaWheat   wd_areaRape
wd_areaWheat        1.0000
 wd_areaRape       -0.0129        1.0000

Breusch-Pagan test of independence: chi2(1) =     0.018, Pr = 0.8921
Correlation matrix of residuals:

              wd_areaWheat   wd_areaRape
wd_areaWheat        1.0000
 wd_areaRape       -0.1008        1.0000

Breusch-Pagan test of independence: chi2(1) =     0.843, Pr = 0.3584
```

Figure 20: Breusch-Pagan test of independence of acreage equations for the OMS and the CEECs, from top to bottom, respectively (2000 – 2015).

```
. xtserial wd_areaWheat wd_lagrpWheat2 wd_lagrpRape2 wd_lagrpSugarbeet2 wd_arabland

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,       6) =      0.848
           Prob > F =      0.3927

. xtserial wd_areaRape wd_lagrpWheat2 wd_lagrpRape2 wd_lagrpSugarbeet2 wd_arabland

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,       6) =    157.803
           Prob > F =      0.0000


. xtserial wd_areaWheat wd_lagrpWheat2 wd_lagrpRape2 wd_lagrpSugarbeet2 wd_arabland

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,       6) =      0.924
           Prob > F =      0.3735

. xtserial wd_areaRape wd_lagrpWheat2 wd_lagrpRape2 wd_lagrpSugarbeet2 wd_arabland

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,       6) =     73.101
           Prob > F =      0.0001
```

Figure 21: Wooldridge test for autocorrelation of acreage equations for the OMS and the CEECs, from top to bottom, respectively (2000 – 2015).

Seemingly unrelated regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
wd_areaWheat	111	4	161.8783	0.0327	3.76	0.4397
wd_areaRape	111	4	87.40434	0.1824	24.77	0.0001

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
wd_areaWheat						
wd_lagrpWheat2	.0074588	.0042162	1.77	0.077	-.0008048	.0157225
wd_lagrpRape2	-.0022065	.0025702	-0.86	0.391	-.0072441	.0028311
wd_lagrpSugarbeet2	.0044546	.0066665	0.67	0.504	-.0086114	.0175206
wd_arabland	.0091276	.0266037	0.34	0.732	-.0430147	.0612698
_cons	2.586289	15.39766	0.17	0.867	-27.59258	32.76515
wd_areaRape						
wd_lagrpWheat2	.0059983	.0022765	2.63	0.008	.0015365	.0104602
wd_lagrpRape2	-.0012319	.0013878	-0.89	0.375	-.0039519	.0014881
wd_lagrpSugarbeet2	-.0072004	.0035995	-2.00	0.045	-.0142553	-.0001456
wd_arabland	.0238185	.0143644	1.66	0.097	-.0043352	.0519721
_cons	1.328587	8.313795	0.16	0.873	-14.96615	17.62333

Figure 22: SUR regression for acreage of wheat and rapeseed for all the OMS (2000 – 2015).

Seemingly unrelated regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
wd_areaWheat	83	4	159.6601	0.5815	115.32	0.0000
wd_areaRape	83	4	62.06445	0.6299	141.28	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
wd_areaWheat						
wd_lagrpWheat2	.0200858	.0071515	2.81	0.005	.0060691	.0341024
wd_lagrpRape2	-.0023331	.0032561	-0.72	0.474	-.008715	.0040487
wd_lagrpSugarbeet2	.0067257	.0045712	1.47	0.141	-.0022338	.0156851
wd_arabland	.4307091	.0424972	10.13	0.000	.3474161	.5140021
_cons	23.79879	17.95768	1.33	0.185	-11.39763	58.9952
wd_areaRape						
wd_lagrpWheat2	-.0019201	.00278	-0.69	0.490	-.0073688	.0035286
wd_lagrpRape2	.0010242	.0012657	0.81	0.418	-.0014566	.003505
wd_lagrpSugarbeet2	-.0049438	.001777	-2.78	0.005	-.0084266	-.001461
wd_arabland	-.1747557	.0165199	-10.58	0.000	-.2071341	-.1423773
_cons	-9.866319	6.980665	-1.41	0.158	-23.54817	3.815533

Figure 23: SUR regression for acreage of wheat and rapeseed for the CEECs (2000 – 2015).

2.6 Stata output of acreage equations – Model III

```
Correlation matrix of residuals:

             wd_areaWheat   wd_areaRape
wd_areaWheat       1.0000
 wd_areaRape      -0.2478        1.0000

Breusch-Pagan test of independence: chi2(1) =     7.985, Pr = 0.0047

Correlation matrix of residuals:

             wd_areaWheat   wd_areaRape
wd_areaWheat       1.0000
 wd_areaRape       0.1792        1.0000

Breusch-Pagan test of independence: chi2(1) =     2.055, Pr = 0.1517
```

Figure 24: Breusch-Pagan test of independence of acreage equations for the period 2000 – 2009 and the period 2010 – 2015, from top to bottom, respectively.

```
. xtserial wd_areaWheat wd_lagrpWheat2 wd_lagrpRape2 wd_lagrpSugarbeet2 wd_arabland

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      13) =      0.267
           Prob > F =      0.6138

. xtserial wd_areaRape wd_lagrpWheat2 wd_lagrpRape2 wd_lagrpSugarbeet2 wd_arabland

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      13) =     53.108
           Prob > F =      0.0000
. xtserial wd_areaWheat wd_lagrpWheat2 wd_lagrpRape2 wd_lagrpSugarbeet2 wd_arabland

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      10) =      1.229
           Prob > F =      0.2935

. xtserial wd_areaRape wd_lagrpWheat2 wd_lagrpRape2 wd_lagrpSugarbeet2 wd_arabland

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      10) =     27.752
           Prob > F =      0.0004
```

Figure 25: Wooldridge test for autocorrelation of acreage equations for the period 2000 – 2009 and the period 2010 – 2015, from top to bottom, respectively.

Seemingly unrelated regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
wd_areaWheat	130	4	162.3543	0.1516	23.23	0.0001
wd_areaRape	130	4	91.09436	0.0395	5.34	0.2541

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
wd_areaWheat						
wd_lagrpWheat2	.0158894	.0044603	3.56	0.000	.0071473	.0246315
wd_lagrpRape2	-.001275	.0028491	-0.45	0.655	-.0068591	.0043091
wd_lagrpSugarbeet2	.0026387	.0044739	0.59	0.555	-.00613	.0114075
wd_arabland	.0529727	.0252571	2.10	0.036	.0034697	.1024756
_cons	71.23325	16.83667	4.23	0.000	38.23397	104.2325
wd_areaRape						
wd_lagrpWheat2	.0037309	.0025026	1.49	0.136	-.0011742	.0086359
wd_lagrpRape2	-.0007669	.0015986	-0.48	0.631	-.0039001	.0023662
wd_lagrpSugarbeet2	-.0025788	.0025102	-1.03	0.304	-.0074987	.0023412
wd_arabland	.0043752	.0141713	0.31	0.758	-.0234001	.0321505
_cons	-30.9047	9.446786	-3.27	0.001	-49.42006	-12.38934

Figure 26: SUR regression for acreage of wheat and rapeseed for all selected countries (2000 – 2009).

Seemingly unrelated regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
wd_areaWheat	64	4	180.1353	0.2896	26.10	0.0000
wd_areaRape	64	4	55.91404	0.4726	57.36	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
wd_areaWheat						
wd_lagrpWheat2	.0039656	.0067182	0.59	0.555	-.0092018	.0171331
wd_lagrpRape2	.0015509	.0034977	0.44	0.657	-.0053045	.0084064
wd_lagrpSugarbeet2	-.0239333	.0176861	-1.35	0.176	-.0585974	.0107308
wd_arabland	.321138	.0681845	4.71	0.000	.1874988	.4547772
_cons	-118.9441	52.37552	-2.27	0.023	-221.5982	-16.28993
wd_areaRape						
wd_lagrpWheat2	.0022476	.0020853	1.08	0.281	-.0018396	.0063348
wd_lagrpRape2	-.0007619	.0010857	-0.70	0.483	-.0028898	.001366
wd_lagrpSugarbeet2	.0060126	.0054898	1.10	0.273	-.0047472	.0167723
wd_arabland	-.1494995	.0211645	-7.06	0.000	-.1909812	-.1080179
_cons	48.75695	16.25737	3.00	0.003	16.89309	80.62081

Figure 27: SUR regression for acreage of wheat and rapeseed for all selected countries (2010 – 2015).

2.7 Stata output of additional tests

Seemingly unrelated regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
wd_areaWheat	174	5	177.7494	0.2299	54.76	0.0000
wd_areaRape	174	5	58.32876	0.6436	328.21	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
wd_areaWheat						
wd_lagrpWheat2	.0119647	.0041841	2.86	0.004	.0037641	.0201653
wd_lagrpRape2	-.004606	.0023071	-2.00	0.046	-.0091279	-.0000841
wd_lagrpSugarbeet2	.0065268	.0044817	1.46	0.145	-.0022572	.0153107
wd_arabland	.055831	.0275107	2.03	0.042	.001911	.1097511
lagresWheat	.4032184	.0747873	5.39	0.000	.256638	.5497988
_cons	.3708473	13.50248	0.03	0.978	-26.09353	26.83523
wd_areaRape						
wd_lagrpWheat2	-.0007517	.0013861	-0.54	0.588	-.0034684	.001965
wd_lagrpRape2	.0018152	.0007584	2.39	0.017	.0003289	.0033016
wd_lagrpSugarbeet2	-.0039128	.0014993	-2.61	0.009	-.0068514	-.0009743
wd_arabland	-.000575	.0087555	-0.07	0.948	-.0177355	.0165855
lagresRape	.7481727	.0494639	15.13	0.000	.6512252	.8451203
_cons	4.095138	4.43063	0.92	0.355	-4.588738	12.77901

Figure 28: SUR regression of the acreage of wheat and rapeseed for all selected countries, including lagged residuals (2010 – 2015).

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