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Analysis

Modelling the Effects of a Glyphosate Ban on Weed Management in Silage Maize Production

Thomas Böcker[a,*], Wolfgang Britz[a], Robert Finger[b]

[a] Institute for Food and Resource Economics, Rheinische Friedrich-Wilhelms-Universität Bonn, Germany
[b] Agricultural Economics and Policy Group, ETH Zürich, Switzerland

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ABSTRACT

A bio-economic model is developed that allows a detailed representation of optimal weed control decisions. It implements an output damage control approach for German silage maize production, considering almost eighty mechanical and herbicide based weed control options against over thirty weeds, working with detailed data on weed abundance and yields for more than three hundred municipalities in the federal state of North-Rhine-Westphalia. We apply the model to simulate economic optimal weed control over two growing periods under current environmental standards and under the scenario of a glyphosate ban as recently discussed after glyphosate was classified as probably carcinogenic to humans. Considering different levels of weed pressure, we find that adjustments in the intensity of mechanical pre-sowing strategies are an optimal response to a glyphosate ban, causing yield reductions of about 1%. In contrast, we find little evidence for a substitution towards selective herbicides post-sowing. On average, the aggregated economic impacts of a glyphosate ban are small, i.e. at about € 1–2/ha, but single farms may face higher losses at about € 10/ha.

1. Introduction

Reducing risks caused by pesticide application is a crucial component of current agri-environmental policy debates in Europe. Different measures are proposed to control pesticide use and the connected risks for the environment and human health, resulting in more sustainable agricultural systems (Lefebvre et al., 2015). The proposed measures comprise banning specific pesticides (e.g. neonicotinoids and glyphosate; Gross, 2013; Schulte and Theuvsen, 2015) or introducing pesticide taxes (Böcker and Finger, 2016; Finger et al., 2017). Especially the renewed licensing or banning of the broad-spectrum herbicide glyphosate in the EU provoked heated discussions after the International Agency for Research on Cancer classified glyphosate as "probably carcinogenic to humans" (Guyton et al., 2015). Ex-ante information on health and environmental risks reduction and on the impacts on farmer's income is needed to inform the debate on policy measures targeting pesticides (Falconer, 1998). As substitution effects with other herbicides are likely if specific products are targeted, potential changes in farm management must be depicted in detail. In the debate on banning glyphosate, however, there is a large uncertainty about those effects (Schulte and Theuvsen, 2015; see also the position paper of Steinmann et al., 2016). In this paper, we develop a tool for such detailed impact assessment of environmental standards or other policy measures affecting specific pesticides and apply it to assess a potential ban of glyphosate.

In available assessments on pesticide application behaviour of farmers, mainly econometric and optimisation modelling approaches or combinations of both are applied (see Böcker and Finger, 2017). Econometric applications are usually based on historical data, for instance of pesticide applications, and are used to explain historical developments or to make recommendations on decision making. Optimisation and simulation models presume, for example, optimal decision making based on more or less detailed production function approaches combined with an economic objective such as profit maximisation. They can hence be used for what-if-analyses even if observations are missing (Grovermann et al., 2017). Existing approaches of the latter group are, however, not detailed enough to assess measures addressing individual pesticides, such as glyphosate in our application. For example, Guan et al. (2005) work with a monetary aggregate over fungicides, herbicides and other pesticides; but, higher total costs for pesticide applications do not necessarily lead to a better weed treatment and vice versa. Babcock et al. (1992) and Kuosmanen et al. (2006) use the total amount of active substances (AS) of fungicides respectively insecticides as an indicator for pesticide use in apple production respectively cotton, neglecting any differences in risk between different AS. Karagiannis and Tzouvelekas (2012) measure insecticide

* Corresponding author at: Institut für Lebensmittel- und Ressourcenökonomik, Rheinische Friedrich-Wilhelms-Universität Bonn, Nussallee 19, 53115 Bonn, Germany.
E-mail address: t.boecker@ilr.uni-bonn.de (T. Böcker).

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application in olive orchards based on litres of insecticides, and Jacquet et al. (2011) model five different alternatives (intensive, recommended by extension services, 2 × integrated practices and organic farming practices), both ignoring the diversity of existing AS.

In this paper, we extend the literature studying policy effects on pest management by i) making use of the output damage function approach (e.g. Karagiannis and Tzouvelekas, 2012), and ii) differentiating in detail a larger set of pre-sowing and post-sowing weed control options with regard to their yield impact. Specifically, we consider for each strategy both costs and efficacy of controlling individual weeds. Moreover, we develop a framework that is site-specific and allows investigating weed management over time and space. Our empirical analysis focusses on silage maize, one of the most relevant crops in Germany, where pest management mainly relies on herbicide application (Julius Kühn-Institut, 2016). We apply the model to the Federal State of North-Rhine-Westphalia (NRW), Germany, and account for the spatial heterogeneity of weed pressure and yield potential at municipality level. The model identifies economically optimal herbicide strategies in silage maize in each municipality at given pesticide and crop prices as well as specifications and regulations of pesticide use. We apply this model to study the impact of a ban of glyphosate on herbicide use and/or mechanical weed control measures and related costs compared to the current situation. At the moment, there are no alternative chemical herbicides approved to replace glyphosate for pre-sowing application (Kehlenbeck et al., 2015[1]). Thus, mechanical weed control is the only alternative which removes all potential risks from herbicides before sowing. However, as claimed in some discussions on the topic, selective herbicides could potentially be used at higher rates after sowing, even increasing the overall health and environmental risks.

The remainder of this article is structured as follows: section 2 presents the damage control approach, the production function and its parameterisation. The data used in the model is depicted in section 3. The following section presents results, starting with some descriptive results before testing several hypotheses. Afterwards, both the model and the results are discussed and, finally, conclusions drawn.

2. Methodology

We develop a bio-economic weed control model for silage maize in m regions, i.e. 377 silage maize producing municipalities in NRW. A two-year cropping period is considered where maize is grown in each of the two years t, a standard farming practise. The expected gross margin $E(\pi)$ in year t for different pre- (index b) and post-sowing (index h) weed control strategies is defined as:

$$E(\pi_{m,t,b,h}) = [y^*_{m,t,b,h} \cdot E(P) - c(b) - c_s(b) - c(h) - c_f(y) - c_o], \tag{1}$$

where $y_{m,t,b,h}{}^*$ is the expected yield, $E(P)$ is the expected output price for maize, $c(b)$ and $c(h)$ are the pre- and post-sowing weed management (and tillage) costs for a certain strategy and $c_s(b)$ are variable costs for sowing depending on the pre-sowing strategy (the more expensive direct precision drill is needed for some types of conservation tillage). $c_f(y)$ are costs for fertiliser depending on the yield and c_o are other costs (e.g. proportionate costs for rating and liming). Harvest costs are not included because maize is sold ex field such that the buyer performs the harvest, which is also reflected in lower output prices.

2.1. The Damage Control Approach

An output damage function is used to determine the expected yield y^* (Fox and Weersink, 1995; Guan et al., 2006, 2005; Hall and Norgaard, 1973; Oude Lansink and Carpentier, 2001; Pannell, 1990; Talpaz and Borosh, 1974). It depicts first the effect of the damage control input(s) on the population of the damaging organism and from there the resulting yield reduction from surviving damaging organisms (Karagiannis and Tzouvelekas, 2012). We follow Guan et al. (2005) and distinct in the production function $y = G(x,D(h))$ between productive (x) and damage-controlling inputs (h) where $D(h)$ is the multiplicative damage controlling effect on the interval [0,1]. h is, for example, the efficacy of a herbicide against a specific weed. If $D(h)$ is equal to unity, no losses due to pests, diseases or weeds occur. Besides chemical inputs, also mechanical inputs such as hoeing or ploughing can be considered as damage-controlling, which somewhat challenges a clear distinction between h and x. Different proposals regarding the functional form of $D(h)$ have been made (see e.g. Carrasco-Tauber and Moffitt, 1992; Fox and Weersink, 1995; Kuosmanen et al., 2006; Lichtenberg and Zilberman, 1986). We follow Guan et al. (2005) and use the exponential form because it is particularly suited to represent the underlying biological processes:

$$D(h) = 1 - e^{-(\beta_0 + \beta_1 \cdot z(h))2}, \qquad \beta_0, \beta_1 \geq 0. \tag{2}$$

This functional form implies decreasing marginal damage control in input use, a reasonable assumption as, e.g., additional efforts in weed control on an almost weed free field will not lead to much higher damage control. Parameters β_0 and β_1 quantify the effects of inputs on damage control; their estimation is explained in the next sections. The decision variable in our model is $z(h)$, the chosen level of damage control.

2.2. Specification of the Damage Controlling Effect

We consider the 32 most important weeds for the case study region in our analysis (see Table 1). Each plant protection strategy is characterised by its weed specific damage control effect, i.e. a column vector h with j 1 × 32 entries ranging between 0 and 1, allowing to represent how specific herbicides and mechanical strategies differ in their impact on individual weeds. Often, an herbicide strategy comprises several herbicide products. The resulting control success is typically not additive since the comprised herbicides usually have a similar spectrum of action. More likely is the case that the maximum suppression effect of any herbicide is crucial for the success. Also, we add a multiplier a_i to each weed $w_{m,i}$ to differentiate yield depression effects by weed, depicted by the average abundance (a_i) which measures the affected area share when that weed occurs (Table 1). Finally, in order to quantify the site-specific damage controlling effect of specific herbicides, a weed-row vector w with size i 32 × 1 depicts for each municipality m the probability that a weed occurs. The three vectors – probability of weed occurrence w, affected share a, and damage control for each weed h – define jointly the control success z for each herbicide strategy j in the different municipalities m:

$$z_{m,j} = \sum_{i}^{32} w_{m,i} \cdot a_i \cdot h_{j,i}. \tag{3}$$

Eq. (3) presents the post-sowing weed controlling effects. Since we use probabilities for the determination of the damage controlling effect, the equation is dimensionless. In a similar manner, a vector $v_{m,j}$ can be constructed that accounts for pre-sowing weed management effects (denoted as $b_{j,i}$):

$$v_{m,j} = \sum_{i}^{32} w_{m,i} \cdot a_i \cdot b_{j,i}. \tag{4}$$

2.3. Choice of Functional Form and Implementing the Damage Controlling Effect

Inserting the damage control success expression from Eq. (3) in Eq. (2) yields the following specification:

[1] Note that glufosinate is no longer licensed in the EU according to the Commission Implementing Regulation (EU) No. 365/2013.