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Abstract

Despite many benefits provided by diversified cropping systems, there is a dearth of empirical evidence on the economic relevance of their effects, mainly due to lack of information on the dynamics of farmers' crop acreages. Our article contributes to fill this gap and, thereby, to shed light on a pair of apparently contradictory facts. European farmers tend to stick to specialized crop acreages despite agronomic experiments tending to show that crop diversification could reduce chemical input uses while maintaining or even enhancing arable crop yield levels

We provide estimates of the effects of previous crops and crop acreage diversity on yield and chemical input use levels based on a sample of 769 arable crop producers covering the Marne *département* in France from 2008 to 2014. Our farm level dataset combines cost accounting data, information on crop sequences as well as detailed soil and weather data. Our estimation approach relies on yield functions and input use models defined as systems of simultaneous equations. These models feature farm specific random parameters for accounting for unobserved heterogeneity across farms and farmers as well as for accommodating input use endogeneity in the considered empirical crop yield functions.

We estimate pre crop and crop acreage diversity effects for four major crops in the area. Pre crops effects on yields are estimated relatively accurately and are generally consistent with the rankings provided by crop production experts. Estimated pre crop effects on input uses are small and insignificant from a statistical viewpoint despite our large sample, suggesting that pre crops don't impact much chemical input requirements or/and that farmers tend to downplay these effects when deciding their chemical input use levels. Our results also show that crop acreage diversity positively impacts yield levels and tend to induce reductions in pesticide uses, herbicide uses in particular. Overall, our results demonstrate statistically significant though economically limited effects of pre crops and crop acreage diversity on crop gross margins. They also suggest that policy measures aimed to foster crop diversification are unlikely to significantly reduce chemical input uses on major crops if they are not supplemented by measures specifically aimed to reduce the uses of these inputs.

Keywords: crop rotation effects, crop diversification, endogeneity, random parameter, SAEM algorithm

JEL classification: Q12, C33, C63

Valeur économique des effets agronomiques de la diversification des cultures pour les agriculteurs : estimation à partir de données de comptabilité analytique des exploitations agricoles

Résumé

Malgré les nombreux bénéfices qu'apportent les systèmes de culture diversifiés, on manque aujourd'hui de preuves empiriques sur la valeur économique de leurs effets agronomiques. Ceci est principalement dû à un manque d'informations sur la dynamique des assolements des agriculteurs. Notre article contribue à combler cette lacune : nous estimons les effets de précédents culturaux et de la diversification des cultures assolées sur les rendements et les utilisations d'intrants chimiques à partir d'un échantillon de 769 producteurs de grandes cultures dans la Marne observés entre 2008 et 2014. Notre ensemble de données combine des données de comptabilité analytique des exploitations, des informations sur les séquences de cultures obtenues à partir de données administratives ainsi que des données détaillées sur la qualité des sols et sur la météo. Notre approche d'estimation repose sur des fonctions de rendement et d'utilisations d'intrants sur les cultures définis comme des systèmes d'équations simultanées. Ces modèles comportent des paramètres aléatoires spécifiques à chaque exploitation pour tenir compte de l'hétérogénéité non observée des exploitations et des agriculteurs ainsi que de l'endogénéité des intrants dans les fonctions empiriques de rendement considérées.

Nous estimons les effets précédents culturaux et diversification des assolements pour les quatre cultures principales de la région. Les effets des précédents culturaux sur les rendements sont estimés assez précisément et correspondent généralement aux classements fournis par les experts agronomes. Les effets estimés des précédents culturaux sur les utilisations d'intrants sont faibles et non significatifs d'un point de vue statistique malgré notre large échantillon, ce qui suggère que les agriculteurs ont tendance à peu en tenir compte lorsqu'ils décident de leurs niveaux d'utilisation d'intrants chimiques. Nos résultats montrent également que la diversité des cultures assolées, lorsqu'elle est décrite par un ensemble d'indicateurs approprié, a un impact positif sur les niveaux de rendement et tend à induire une réduction des utilisations de pesticides, des herbicides en particulier. Dans l'ensemble, nos résultats démontrent des effets statistiquement significatifs mais économiquement limités des précédents culturaux et de la diversification des assolements sur les marges brutes des cultures. Ils suggèrent également que les mesures politiques visant à encourager la diversification des cultures sont peu susceptibles de réduire de manière significative les utilisations d'intrants chimiques sur les principales cultures si elles ne sont pas complétées par des mesures visant spécifiquement à réduire ces utilisations d'intrants.

Mots clés : effets des rotations culturales, diversification des cultures, endogénéité, paramètres aléatoires, algorithme SAEM.

1. Introduction

The Common Agricultural Policy (CAP) recently put forward crop diversification at the farm level as a primary objective. The 2013 reform introduced a set of "crop diversification" obligations[1] as eligibility criterion for farmers to receive the green direct payments, although these obligations were not constraining for most European farms (Louhichi *et al* 2018).[2] The future CAP will include similar standards on farm crop acreages as part of its cross-compliance greening scheme. Current agri-environmental and climate schemes and future eco-schemes also aim to foster crop diversification in EU farms (*e.g.*, Guyomard *et al* 2020). According to the European Commission (EC), the greening obligations and the congruent direct payments aim at "remunerating farmers for their efforts to protect the environment and biodiversity, since market prices do not reflect the work involved" (EC 2017).[3] "Crop diversification" obligations are thus expected by the EC to incentivize farmers to produce positive externalities -and/or to reduce pollution emissions

Yet, crop diversity can also yield on-farm benefits (*e.g.*, Ikerd 1993, Lin 2011, Kremen *et al* 2012, Duru *et al* 2015, Thérond *et al* 2017). As far as agronomic effects are concerned, these benefits can arise from three main channels: pre crop effects, crop rotation effects and spatial crop diversity effects, which are defined below.

(*a*) Previous crops are expected to deliver pre crop effects to the crops that immediately follow them on the considered plot. For instance, legumes deliver nitrogen surpluses to be used by the following crops. Previous crops of a given botanic family are expected to deliver break crop effects to the following crops if these crops belong to other botanic families, by perturbing the dynamics of crop specific pest and weed populations (*e.g.*, Duru *et al* 2015, Mortensen and Smith 2020). Nitrogen surpluses and break crop effects are examples of short run effects that are delivered by previous crops to the following ones.

(*b*) Crop rotation diversification is expected, in the medium run, to modify the (periodical) equilibrium of agro-ecosystems and, thereby, to increase the delivery of ecosystem services supporting agricultural production, at the plot and farm scales (*e.g.*, Davis *et al* 2012, Duru *et al*

[1] Along with two others, the "maintenance of permanence grassland" and "ecological focus areas" obligations.

[2] Farms with more than 10 ha of arable land have to grow at least two crops, while at least three crops are required on farms with more than 30 ha of arable land. Furthermore, the main crop may not cover more than 75% of the arable land (EC 2017). Several exemptions to these rules take account of the individual situation of farmers, notably farmers with a large proportion of grassland.

[3] The environmental effects of crop diversity, especially those on natural biodiversity, are supported by the ecological and agronomic literatures (*e.g.*, Kremen and Miles 2012, Kremen *et al* 2012, Bellouin *et al* 2019 and 2021, Tamburini *et al* 2020).

2015). These effects are designated as cropping system effects thereafter.[4] These ecosystem services include both vegetation and natural enemy effects on pest and weed population regulations, pollination effects as well as improved soil structure, fertility and health (*e.g.*, Mortensen and Smith 2020). Cropping system effects, which are fully established after a few rotation cycles, are often cited as a reason for advocating crop rotation diversification (*e.g.*, Davis *et al* 2012, Duru *et al* 2015, Mortensen and Smith 2020).

(*c*) Diversified crop rotations concern crop diversity across time on a given plot and generally also imply crop acreage diversity across space at the farm level: farmers generally manage diversified crop acreages along with diversified crop rotations. Diversified crop acreages yield economic benefits that are well-known in the economics literature, including those due to risk spreading and to work peak load trimming.[5] Yet, crop diversity, as well as the presence of semi-natural habitats (*e.g*, forests, hedgerows), can also yield agro-ecological benefits whether it is implemented at the plot level, at the farm level are at a wider scale (*i.e.*, at the landscape level).[6] These agro-ecological benefits of crop diversity induce complementarities across crops at the plot or farm scales[7] and positive production externalities when they occur across farms.

Disentangling crop rotation effects and spatial crop diversity effects is difficult with farm data. Farmers simultaneously optimize crop rotation and crop acreage diversities and farm crop acreages display significant correlations across time and space. In what follows, crop acreage diversity effects will refer to both crop rotation (or cropping system) and spatial crop diversity effects. Indeed, crop acreage diversification is a key principle of agro-ecological crop production practices since suitably diversified crop production is expected to achieve relatively high yield levels while reducing chemical input requirements (*e.g.*, Kremen and Miles 2012; Kremen *et al* 2012, Duru *et al* 2015, Thérond *et al* 2017).

In this article we shed light on a pair of apparently contradictory facts. European farmers tend to stick to specialized crop acreages despite agronomic experiments tending to show that crop diversification could reduce chemical input uses while maintaining or even enhancing arable

[4] See, *e.g.*, Blanco-Canqui and Lal (2008) or Duru *et al* (2015) for presentations of the cropping system concept.

[5] See, *e.g.*, Carpentier and Letort (2014) for a recent review.

[6] Intercropping, strip cropping or mixed cropping techniques aim to take advantage of within plot crop diversity (*e.g.*, Duru *et al* 2015). Fahrig *et al* (2015), Sirami *et al* (2019), Dainese *et al* (2019) or Martin *et al* (2019) present the agro-ecological benefits of heterogeneous crop landscapes and of crop landscapes also including semi-natural habitats such as hedgerows. Landscape diversity benefits to biological pest and disease control and, thereby, can lower insecticide and fungicide uses (*e.g.*, Larsen and Noack 2017, 2021; Redlich et al 2018; Delaune et al 2021).

[7] These complementarity effects are essentially static whereas those due to crop rotations or pre crop effects are essentially dynamic.

crop yield levels (*e.g.*, Duru *et al* 2015, Thérond *et al* 2017).

Most studies considering crop acreage diversity or pre crop effects are based on agronomic experiments and focus on specific crop sequences or crop mixes[8], but little is actually known on how crop diversification actually performs in commercial farms and, more generally, on how farmers perceive and make use of pre crop and crop acreage diversity effects. Farmers may in fact be reluctant to diversify their crop acreages and rotations for many reasons. They may expect diversified cropping mixes to be less profitable than specialized ones because crops that can be introduced to diversify the acreage are less profitable than major crops or because they tend to understate the value of the agro-ecological benefits – *e.g.*, the pre crop effects and crop acreage diversity effects – induced by crop diversification (*e.g.*, Bues *et al* 2013, Preißel *et al* 2015, Zander *et al* 2016, Magrini *et al* 2016, Watson *et al* 2017, Meynard *et al* 2018). While farmers may directly benefit from agro-ecological effects induced by diversified crop rotations, for instance those improving soils or lowering pest or weed pressures against which no pesticide is available, they may downplay others. Farmers need to monitor their crops and to be willing to adjust their input uses for fully benefitting from nitrogen surpluses left by legumes or reduced pest or weed pressures against which they usually spray chemical pesticides.[9] As a result, implicit costs may deter farmers from fully reaping off the benefits of crop diversification. Agri-food value chain – industrial and/or spatial – organization can also hinder adoption of diversified crop acreages and rotations by farmers. Such so-called socio-technical lock-ins – including lack of suitable extension services or insufficient local outlets for diversification crops – are often put forward for explaining this state of fact (*e.g.*, Magrini *et al* 2016, Meynard *et al* 2018, Mortensen and Smith 2020, Morel *et al* 2020). Yet, policy instruments aimed to address lock-in issues substantially differ from instruments aiming to overcome lack of profitability, whether real or

[8] Cropping system effects are mostly investigated through long run experiments in corn and soybean based systems in the US (*e.g.*, Davis *et al* 2012, Hunt *et al* 2017, Bowles *et al* 2020, Feng *et al* 2021) and in wheat based systems, with a specific focus on canola grain legumes, in Canada (*e.g.*, Zentner *et al* 2002, 2011; Gan *et al* 2015; Thiessen Martens *et al* 2015; Smith *et al* 2017; Liu *et al* 2019; Khakbazan *et al* 2017, 2020). Crop yield and return levels and are generally primary outcomes of interest. Experiments conducted in Europe mostly concern pre crop effects, with a particular focus on the effects of grain legumes on cereal yield and nitrogen fertilization levels (*e.g.*, Meynard *et al* 2013, Bues *et al* 2013, Preißel *et al* 2015, Reckling *et al* 2016, Zander *et al* 2016, Watson *et al* 2017, Hufnagel *et al* 2020). Agronomic experiments considering the effects of crop diversification on pesticide use levels are relatively rare and generally focus on herbicide use levels (*e.g.*, Liebman and Dyck 1993, Liebman and Staver 2001, Chikowo *et al* 2009, Hunt *et al* 2017, Colbach and Cordeaux 2018, Adeux *et al* 2019, Sharma *et al* 2021).

[9] Due to data availability, the effects of crop rotations on yield levels have been largely investigated, especially in the US. For instance, Seifert *et al* (2017) demonstrate that corn or soybean monocultures induce yield penalties when compared to soybean – corn rotations. Investigations of the effects of crop rotations on input use levels are rare, and usually rely on small and specific datasets. For instance, Nave *et al* (2013) showed that the French farmers they interviewed tend to downplay nitrogen surpluses left by legumes in their plots while cereal yields were significantly higher after legumes than after cereals or, even, oilseeds. Andert *et al* (2016) showed that crop sequence diversity tends to lower herbicide and fungicide uses in the German farms they observed.

perceived. Disentangling the main drivers of current crop choices of farmers (*e.g.*, distinguishing profitability and lock-in issues) is thus crucial from an agri-environmental policy perspective and assessing the pre crop and crop acreage diversity effects on farm crop production and on farmer choices is an important step toward this overall objective.

The main purpose of this study is therefore to assess pre crop and crop acreage diversity effects based on commercial farm data, which in turn enables us to investigate to what extent farmers make use of these effects. Our approach enables us to disentangle pre crop and crop acreage diversity effects on both yield and chemical input use levels. In particular, we investigate whether farmers relying on diversified crop acreages (and, likely, diversified crop rotations) tend to use less chemical inputs and whether farmers adjust their chemical inputs uses to the pre crop of the considered crops.

Agricultural economists who explicitly considered pre crops effects (generally on yield levels) in mathematical programming models aimed to optimize dynamic crop acreage choices (*e.g.*, El-Nazer and McCarl 1986, Hennessy 2006, Cai *et al* 2012, Akplogan *et al* 2013, Dury *et al* 2013, Livingston *et al* 2015, Liu *et al* 2016, Ridier *et al* 2016, Boyatbatli *et al* 2019) or investiged the drivers of farmers' acreage choice dynamic features based on econometric models (*e.g.*, Ozarem and Miranowski 1994, Thomas 2003, Hendricks *et al* 2014).

Others considered the effects of crop acreage diversity at the farm level on several types of outcomes. Most studies considered productivity effects of crop diversity. They measured the effects of crop acreage diversity indicators on crop production (value) aggregates (*e.g.*, Omer *et al* 2007, Di Falco and Chavas 2008, Di Falco *et al* 2010, Groom and Pereira Fontes 2021), on expected return measures or/and return risk measures (*e.g.*, Di Falco and Perrings 2005, Bozzola and Smale 2020). Our objective here is to assess pre crop and crop acreage diversity effects on a crop per crop basis in order to consider precisely defined agronomic effects and to circumvent the composition effects uncovered by Groom and Pereira Fontes (2021) when considering crop (value) aggregates.

Chavas and Kim (2007, 2010), Chavas (2009) and, Chavas and Di Falco (2012b) proposed to analyze the interest of crop diversification by relying on producer theory in various multi-output settings.[10] The analytical frameworks proposed by these authors provide theoretically grounded

[10] Chavas and Kim (2010) proposed the concept of economies of diversification as an extension of the concept of economies of scope of Panzar and Willig (1981) and Baumol *et al* (1982). Whereas economies of scope compare production diversification to complete production specialization based on production costs economies of diversification consider situations of partial specialization. Chavas and Kim (2007) and Chavas (2009) proposed measures of the effects of crop diversification in a primal framework. Kim *et al* (2012) and Chavas and Di Falco (2012a) provide applications of this theoretical framework. Chavas and Di Falco (2012b) proposed an analytical

measures of the benefits of crop diversification as well as useful decompositions of these measures. These decompositions highlight the effects of production complementarities across crops, which are closely related to the agronomic effects considered in this article, from other beneficial effects of crop diversification, which are linked to general production management.[11] These theoretical frameworks are however essentially static, while, by considering pre crop effects we aim at accounting for dynamic features of crop production underlying crop rotation effects.

The recent study of Bareille and Letort (2018) is the closest to ours. It measures the effects of crop acreage diversity, which is related to the crop acreage diversity effects considered in this article, on crop yield and chemical input use levels based on farm cost accounting data. They generally demonstrate positive effects of crop diversity on crop yield levels, and negative effects on chemical input uses and on yield variability. Yet, this study ignores pre crop effects. Indeed, most empirical analyses of crop diversity ignore pre crop effects, probably due to data lacking on crop sequence acreages.

To achieve our main objective, we organized a rich dataset by matching crop sequence acreage, weather and soil data to a cost accounting panel dataset covering 769 farms located in the Marne *département* and its neighborhood , which is a small district located 150 km east from Paris, from 2008 to 2014. This particular area counts among the most productive and the most diversified arable crop production areas in Europe. The Marne *département* provides local outlets to major grain crops (including grain legumes) but also to sugar beet, (starch and consumption) potatoes and alfalfa. The accountancy dataset reports the yearly crop acreages of the sampled farms but do not include information on acreages for pairs of current and previous crops. These acreages of crop sequences for the sampled farms were obtained by processing Integrated Administration and Control System (IACS), which enables to uncover the allocation of current crop acreages to the crops grown the previous year on the considered piece of land, hereafter crop sequence acreages..

We also developed purposely designed yield response and input use microeconometric models. These models feature pre crop and crop acreage diversity effects, thereby enabling us to investigate important (mostly dynamic) features of crop production. Considering crop yield

framework including risk management considerations, thereby adding risk spreading to the economic benefits of crop diversity.

[11] For instance, Chavas and Kim (2010) provide a decomposition of economies of diversification into four additive parts: a part measuring complementarity among outputs, a part reflecting economies of scale, a part reflecting convexity and a part reflecting the role of fixed costs.

response models together with chemical input demand models enable us to estimate the effects of pre crops and crop acreage diversity on both crop yield and chemical input use levels. Our models also incorporate random parameters for accounting for farm and farmer heterogeneity in crop yield and input use levels, and in input productivity levels (*e.g.,* Suri 2011, Koutchadé *et al* 2018). Importantly, the rich information content of our dataset and our considering random parameter systems enable us to control the well-known input use endogeneity issues that arise when considering the estimation of production functions (*e.g.*, Grilliches and Mairesse 1995, Ackerberg *et al* 2015).

The contributions of this article are thus threefold.

First, we provide a modelling framework that enables us to identify pre crop and crop acreage diversity effects on both yield and chemical input use levels. This modelling framework also (*i*) accounts for the effects of farms' and farmers' unobserved heterogeneity on yield, input use and productivity levels and (*ii*) controls for potential input use endogeneity in the considered econometric yield functions. We also consider extensions of standard crop acreage diversity measures that prove to be empirically useful when the number of grown crops vary significantly across observation units.

Second, our data and models enable us to obtain original empirical results on the effects of crop diversification on important agronomic features of crop production in commercial farms. Our estimation results demonstrate statistically significant pre crop and crop acreage diversity effects on crop yield levels and statistically significant crop acreage diversity effects on pesticide use levels, especially on herbicide use levels. The implied effects on crop returns are significant from a statistical viewpoint but rather limited from an economic viewpoint.

Third, our data and models enable us to obtain original empirical results on farmer choices regarding the effects of crop diversification. Our crop sequence acreage data demonstrate that farmers' crop sequence choices are rational from both agronomic and economic viewpoints. The considered farmers basically choose the best available pre crops for the major crops of their crop mix. This reduces the scope of the crop diversification effects that can be assessed based on farm data.

Taken together our results show that pre crop effects can be uncovered from farm data, but only for the most frequent crop sequences. They also suggest that pre crop and crop acreage diversity effects provide insufficient economic benefits to farmers, especially insufficient savings of chemical inputs, for leading them to adopt diversified crop acreages.[12]

The rest of the article is organized as follows. In section 2, we present the models we use for uncovering pre crop and crop diversity effects from cost accounting data. In section 3, we describe our estimation strategy, with special emphasis on the issues raised by input use endogeneity and random parameters. Section 4 presents the different datasets we use and how we combine them. Section 5 presents and discusses the estimation results while section 6 provides concluding remarks.

2. Modelling framework

Our primary interest lies in the magnitude of two types of effects on crop yield and input use levels: pre crop effects, i.e. the effects of previous crops of the crop grown on the same plot, on the one hand and the effect of crop acreage diversity at the farm level on the other hand. We c estimate these effects based on a panel data set describing the production choices and performances of a large sample of farmers, $i = 1,...,N$, over a short time period, $t = 1,...,T$. Term $\mathcal{K}$ denotes the set of crops that are potentially grown by the sampled farmers, with $\mathcal{K} = \{1,...,K\}$.

The yield level of crop *k* obtained by farmer *i* in year *t* is denoted by $y_{k,it}$. The corresponding use level of input *j* is denoted by $x_{j,k,it}$ for $j \in \mathcal{J}$. In our application, input set $\mathcal{J} = \{1,...,J\}$ includes nitrogen fertilizers, herbicides and other pesticides, which mostly include fungicides and insecticides.

Pre crop effects imply that the observed yield level of crop *k*, $y_{k,it}$, is a weighted average of the yield levels obtained for each previous crop after which crop *k* was grown by farmer *i* in year *t*. Let $y_{mk,it}$ denote the yield level of crop *k* when this crop is grown after crop *m* and let $z_{mk,it}$ denote the share of acreage of crop *k* grown after crop *m* (*i.e.*, $z_{mk,it}$ is the share of the acreage of crop *k*, which is grown in year *t*, that is grown on land on which crop *m* was grown in year $t-1$)The observed yield level of crop *k* is given by

$$y_{k,it} = \sum\nolimits_{m \in \mathcal{K}} z_{mk,it} y_{mk,it} \text{ for } k \in \mathcal{K} \qquad \text{(1a)}$$

[12] Moreover, these results are consistent with results obtained by Koutchadé *et al* (2021) in the considered area. These results tend to show that the considered farmers don't produce protein pea, which is a typical diversification crop for agronomists (*e.g.*, Bues *et al* 2013, Meynard *et al* 2018), mostly due to profitability issues. For instance, simulation results suggest that standard area based payments would significantly increase pea acreages in the Marne area, by leading producing farmers to increase their pea acreages but mostly by leading others to include pea in their crop rotations.

Similarly, accounting for potential pre crop effects on input use levels supposes to define input uses at the crop sequence levels. Let $x_{j,mk,it}$ denote the quantity of input j used by farmer i in year t for crop k when this crop is grown after crop m. The observed use level of input j for crop k is given by

$$x_{j,k,it} = \sum\nolimits_{m \in \mathcal{K}} z_{mk,it} x_{j,mk,it} \text{ for } k \in \mathcal{K} \text{ and } j \in \mathcal{J} \qquad \text{(1b)}$$

Crop yields and input uses being unobserved at the crop sequence level, we replace them by relatively simple models.

2.1. Yield and input use models at the crop sequence level

We define yield functions at the crop sequence level, with

$$y_{mk,it} = a_{mk,0}^{(y)} + \mu_{k,i}^{(y)} + \alpha_{k,t,0}^{(y)} + \mathbf{x}_{mk,it}' \boldsymbol{\beta}_{k,i} + \mathbf{c}_{it}' \boldsymbol{\lambda}_{k,0}^{(y)} + \mathbf{d}_{it}' \boldsymbol{\delta}_{k,0}^{(y)} + \varepsilon_{k,it}^{(y)} \text{ for } m \in \mathcal{K} \text{ and } k \in \mathcal{K} \qquad \text{(2a)}$$

for the yield of crop k when it is grown after crop m. Vector $\mathbf{x}_{mk,it} = (x_{j,mk,it}, j \in \mathcal{J})$ collects the input uses of farmer i for crop k after crop m in year t. We consider crop yield functions instead of crop supply functions for disentangling the effects of pre crops or of crop acreage diversity that directly impact yield levels from those that may impact yield levels through adjustments in input use levels $\mathbf{x}_{mk,it}$). Indeed, yield functions (2a) allow controlling the effects of the intensity in chemical inputs on yield levels when estimating the effects of crop diversity. Parameters $a_{mk,0}^{(y)}$ and $\boldsymbol{\delta}_{k,0}^{(y)}$ are our main interest parameters. Parameter $a_{mk,0}^{(y)}$ defines the pre crop effects of crop m on the yield of crop k. These are defined with respect to a reference pre crop (the mean of random parameter $\mu_{k,i}^{(y)}$ is left unconstrained). Indeed, we impose the normalization constraint stating that $a_{rk,0}^{(y)} = 0$ if crop r is the reference pre crop of crop k. Accordingly, parameter $a_{mk,0}^{(y)}$ defines the yield effect of using crop m instead of crop r as the pre crop of crop k.

Although these effects may vary across farms and years we specify these effects as fixed parameters due to data constraints. Uncovering the distribution of pre crop effects across farms and/or time requires crop sequence acreages to sufficiently vary across farms and time. As discussed below, crop sequence acreages reported in (or reconstructed from) farm datasets are likely to lack the variability needed to uncover year specific or the distribution of farm specific pre crop effects.

Vector $\mathbf{d}_{it}$ contains a set of crop acreage diversity indicators aimed to capture crop acreage diversity effects. These indicators combine grown crop numbers and Shannon indices. More precisely, vector $\mathbf{d}_{it}$ includes two subsets of variables. It includes a set of dummy variables, one for each number of crops grown observed in our data, for capturing the effect of the size of the crop set considered by farmers. Vector $\mathbf{d}_{it}$ also includes the cross products of these dummy variables with the corresponding crop acreage Shannon indices, for capturing the effects of the land allocation chosen by farmers.[13] Using this set of crop acreage diversity indicators has two main advantages. This allows estimating the effects of the number of grown crops without any parametric restriction on the one hand, and this allows circumventinga shortcoming of the Shannon index, explained in what follows, when the number of crops is variable on the other hand.

Let $s_{k,it}$ denote the share of the acreage of crop k in the arable land area of farmer i in year t. Provided that $s_{k,it} \in [0,1]$ for $k \in \mathcal{K}$ and $\sum_{k\in\mathcal{K}} s_{k,it} = 1$, the Shannon index of crop acreage $\mathbf{s}_{it} = (s_{k,it}, k \in \mathcal{K})$ is defined by $h(\mathbf{s}_{it}) = -\mathbf{s}'_{it} \ln \mathbf{s}_{it}$.[14] Function $h(\mathbf{s}_{it})$ is upper bounded by $\ln n(\mathbf{s}_{it})$ where $n(\mathbf{s}_{it}) \in \mathcal{K}$ is the number of crops actually grown in $\mathbf{s}_{it}$.[15] This implies that the Shannon index is a questionable measure of crop diversity when numbers of grown crops vary widely across farms, since the upper bound of this index, $\ln n(\mathbf{s}_{it})$, grows at a rate that decreases in the number of crops that are actually grown, $n(\mathbf{s}_{it})$. The set of indicators contained in $\mathbf{d}_{it}$ allows disentangling the effects of grown crop numbers and those of the crop acreage diversity given grown crop numbers.

Vector $\mathbf{c}_{it}$ contains control variables aimed to capture the effects of production conditions that impact farmers' crop production choices. We use a rich set of variables describing soil properties at the farm level and weather conditions at the municipality level.

Parameters $\boldsymbol{\beta}_{k,i}$ give the marginal productivity levels of the considered inputs. Like farm specific effects $\mu_{k,i}^{(y)}$, these parameters are assumed to be farm specific. Models featuring such random parameters allow to account for unobserved heterogeneity (*e.g.*, Wooldridge 2010, Arellano and Bonhomme 2011). In the case of agricultural production choices, this heterogeneity is due to unobserved characteristics of the sampled farmers (*e.g.*, skills, motivations) or farms (*e.g.*, spatial

[13] Shannon indices are centered at their sample means by crop number for facilitating the interpretation of the direct effects of the crop number indicators.

[14] Given that $s_{k,it} \ln s_{k,it}$ can be set at 0 if $s_{k,it} = 0$ by continuity extension, following the continuity of function $g(x) = x \ln x$ in $x \in \mathbb{R}_+^*$ and $\lim_{x\to 0^+} g(x) = 0$.

[15] Entropy function $h(\mathbf{s})$ achieves its (unique) maximum in $\mathbf{s} = (s_1,\ldots,s_K)$ at $h(\mathbf{s}) = \ln K$ and $h(\mathbf{s}) = \ln K$ if and only if $s_k = 1/K$ for $k \in \mathcal{K}$.

distribution of the plot, available machinery, unobserved soil or climate features) that do not vary or vary little over the considered time period (*e.g.*, Koutchadé *et al* 2018, 2021). For instance, they may capture the effects of farm specific factors (that are not controlled by $\mathbf{d}_{it}$) impacting pressures of pests, diseases or weeds. These parameters are expected to significantly vary across farmers and farms.

Year specific effects $\alpha^{(y)}_{k,t,0}$ capture the effects of large scale factors impacting all farms, such as weather driven pest and disease outbreaks or widely adopted (technological or agronomic) innovations.

The models of input use at the crop sequence level are defined similarly, with

$$x_{j,mk,it} = a^{(x)}_{j,mk,0} + \mu^{(x)}_{j,k,i} + \alpha^{(x)}_{j,k,t,0} + \mathbf{d}'_{it}\boldsymbol{\delta}^{(x)}_{j,k,0} + \mathbf{c}'_{it}\boldsymbol{\lambda}^{(x)}_{j,k,0} + \varepsilon^{(x)}_{j,k,it} \text{ for } m \in \mathcal{K},\ k \in \mathcal{K} \text{ and } j \in \mathcal{J} \quad \text{(2b)}$$

Parameter $a^{(x)}_{j,mk,0}$ is the pre crop effects of crop m on the use of input j for crop k and random term $\mu^{(x)}_{j,k,i}$ is a standard additively separable farm specific effect.[16] Year specific effects $\alpha^{(x)}_{j,k,t,0}$ capture the effects of large scale factors, such as weather driven pest and disease outbreaks, widely adopted innovations or economic factors, including prices or changes in the value chains.

Due to the limited time span of our dataset, the effects of prices are difficult to disentangle from those of unobserved (to the analyst) temporal shocks or trends that impact all farmers. The effects on chemical uses of crop and input prices, which mostly vary across years,[17] are expected to be captured by year specific terms $\alpha^{(x)}_{j,k,t,0}$. These price patterns also significantly impact our strategy for identifying the parameters of crop yield models (2a) since they basically prevent us from using prices as instrumental variables for input uses in the yield function equations we consider.

[16] Pre crop effect parameters $a^{(y)}_{mk,0}$ and $a^{(x)}_{j,mk,0}$ need to be normalized. They are set at 0 for the most frequent previous crop of crop k (*i.e.*, the reference pre crop of crop k), which is rapeseed for wheat and wheat for the other considered crops in our application.

[17] The intra-farm variance of output prices is does not exceed 20% of the total variance of crop prices in our sample. In our application, input prices are measured by price indices, which are supplied by the French ministry of agriculture, only vary in the time dimension.

2.2. Yield and input use models at the crop level

Combining equations (1) and (2) yields crop k yield model

$$y_{k,it} = \mu_{k,i}^{(y)} + \alpha_{k,t,0}^{(y)} + \mathbf{x}'_{k,it}\boldsymbol{\beta}_{k,i} + \mathbf{z}'_{k,it}\mathbf{a}_{k,0}^{(y)} + \mathbf{d}'_{it}\boldsymbol{\delta}_{k,0}^{(y)} + \mathbf{c}'_{it}\boldsymbol{\lambda}_{k,0}^{(y)} + \varepsilon_{k,it}^{(y)} \tag{3a}$$

and the corresponding input use models

$$x_{j,k,it} = \mu_{j,k,i}^{(x)} + \alpha_{j,k,t,0}^{(x)} + \mathbf{z}'_{k,it}\mathbf{a}_{j,k,0}^{(x)} + \mathbf{d}'_{it}\boldsymbol{\delta}_{j,k,0}^{(x)} + \mathbf{c}'_{it}\boldsymbol{\lambda}_{j,k,0}^{(x)} + \varepsilon_{j,k,it}^{(x)} \text{ for } j \in \mathcal{J} \tag{3b}$$

for $k \in \mathcal{K}$. We use here the fact that the elements of vector $\mathbf{z}_{k,it}$, that is to say the shares of crop k on its potential pre crops, sum to 1.

The yield function models given in equation system (3) are linear in input use vector $\mathbf{x}_{k,it}$, which is unusual and, thereby, deserves a few comments. Admittedly, the linearity in input uses of crop sequence yield models (2a) in crop sequence input use levels $\mathbf{x}_{mk,it}$ greatly facilitates the aggregation process of these models at the crop level as shown by equation (3a).[18] Yet, linear crop sequence yield models can be interpreted as first order Taylor expansion in $\mathbf{x}_{mk,it}$ of any (sufficiently smooth) model of $y_{mk,it}$. Importantly, the intercept and the coefficients of $\mathbf{x}_{mk,it}$ in the model of $y_{mk,it}$, which are collected in vector $\boldsymbol{\beta}_{k,i}$, are farm specific. Yield functions considered in equations (2a) and (3a) can thus be interpreted as farm specific approximates of the underlying "true" yield functions. Also, coefficient $\beta_{j,k,i}$ delivers a direct measure of the marginal productivity of input j for crop k in farm i.

3. Identification and estimation

Equations (3) define the production choice equations that we consider for estimation purpose. These are collected in the following equation system:

$$\begin{cases} y_{k,it} = \mu_{k,i}^{(y)} + \alpha_{k,t,0}^{(y)} + \mathbf{z}'_{k,it}\mathbf{a}_{k,0}^{(y)} + \mathbf{x}'_{k,it}\boldsymbol{\beta}_{k,i} + \mathbf{d}'_{it}\boldsymbol{\delta}_{k,0}^{(y)} + \mathbf{c}'_{k,it}\boldsymbol{\lambda}_{k,0}^{(y)} + \varepsilon_{k,it}^{(y)} \\ \mathbf{x}_{k,it} = \boldsymbol{\mu}_{k,i}^{(x)} + \boldsymbol{\alpha}_{k,t,0}^{(x)} + \mathbf{Z}_{it}\mathbf{a}_{k,0}^{(x)} + \mathbf{D}_{it}\boldsymbol{\delta}_{k,0}^{(x)} + \mathbf{C}_{k,it}\boldsymbol{\lambda}_{k,0}^{(x)} + \boldsymbol{\varepsilon}_{k,it}^{(x)} \end{cases} \tag{4}$$

Vectors $\boldsymbol{\mu}_{k,i}^{(x)}$, $\boldsymbol{\alpha}_{k,t,0}^{(x)}$ and $\boldsymbol{\varepsilon}_{k,it}^{(x)}$ are given by $\boldsymbol{\mu}_{k,i}^{(x)} = (\mu_{j,k,i}^{(x)} : j \in \mathcal{J})$, $\boldsymbol{\alpha}_{k,t,0}^{(x)} = (\alpha_{j,k,t,0}^{(x)} : j \in \mathcal{J})$ and $\boldsymbol{\varepsilon}_{k,it}^{(x)} = (\varepsilon_{j,k,it}^{(x)} : j \in \mathcal{J})$ while matrices $\mathbf{Z}_{it}$, $\mathbf{D}_{it}$ and $\mathbf{C}_{k,it}$ are defined by $\mathbf{Z}_{it} = \boldsymbol{\iota}_J \otimes \mathbf{z}'_{it}$, $\mathbf{D}_{it} = \boldsymbol{\iota}_J \otimes \mathbf{d}'_{it}$ and $\mathbf{C}_{k,it} = \boldsymbol{\iota}_J \otimes \mathbf{c}'_{k,it}$.

Estimating equation system (4) requires identification assumptions. Let vector $\boldsymbol{\gamma}_{k,i}$ collect the

[18] The same remark holds for the additive separability of the pre crop effects in the crop sequence level yield and input use models.

random parameters of model (4), with $\boldsymbol{\gamma}_{k,i} = (\boldsymbol{\mu}_{k,i}, \boldsymbol{\beta}_{k,i})$ and $\boldsymbol{\mu}_{k,i} = (\mu_{k,i}^{(y)}, \boldsymbol{\mu}_{k,i}^{(x)})$ and let vector $\boldsymbol{\varepsilon}_{k,it} = (\varepsilon_{k,it}^{(y)}, \boldsymbol{\varepsilon}_{k,it}^{(x)})$ collect its error terms. We assume that vectors $\boldsymbol{\gamma}_{k,i}$, $\boldsymbol{\varepsilon}_{k,it}$ and $\mathbf{w}_{k,it} = (\mathbf{z}_{k,it}, \mathbf{d}_{it}, \mathbf{c}_{it})$ are mutually independent and that the regressors collected in $\mathbf{w}_{k,it}$ are strictly exogenous in the considered equation system. Finally, we assume that error terms $\boldsymbol{\varepsilon}_{k,it}$ are serially uncorrelated. This last assumption makes use of the fact that farm specific random parameters are expected to capture the most persistent (unobserved) features of the dynamics of the considered crop production processes. Assuming that error terms $\boldsymbol{\varepsilon}_{k,it}$ and random parameters $\boldsymbol{\gamma}_{k,i}$ are independent is standard, and required for identifying the probability distribution of $\boldsymbol{\gamma}_{k,i}$.

3.1. Identification

The exogeneity assumption related to crop sequence acreage share vector $\mathbf{z}_{\ell,it}$ deserves some comments. These variables describe choices of farmers. Exogeneity of $\mathbf{z}_{\ell,it}$ is partly supported by the fact that crop sequence acreage decisions are taken prior to the occurrence of most random events impacting crop yield and input use levels. Yet, omitted variable biases may still arise. For instance, soils of farms with relatively large acreage shares of potatoes and/or sugar beet are generally deep and well structured. These soil properties have positive impacts on the production of most arable crops (*e.g.*, Carpentier and Letort 2014). In our models soil property effects are controlled for by a rich set of variables describing the soils of the sampled farms.[19]

Similar observations hold regarding crop acreage diversity indicator vector, $\mathbf{d}_{it}$. In our empirical application this vector is evaluated by considering previous year crop acreage shares, that is to say based on $\mathbf{s}_{it-1}$. This eliminates potential endogeneity issues related to error terms $\boldsymbol{\varepsilon}_{k,it}$.[20] Our results on the effects of crop acreage diversity are robust to alternative construction approaches for the diversity indicator set $\mathbf{d}_{it}$, that is to say based on current acreages, on whole crop acreage (observed) history of farmers or on one year lagged crop acreages (as in our application). This reflects the fact that farmers' crop acreages are relatively stable over time. This also provides support to our interpreting our empirical results on the effects of $\mathbf{d}_{it}$ as cropping system effects, at least to some extent. These are long run effects that are induced by the crop acreage history of the considered farm, which in turn determines the state of the farm agroecosystem. Importantly, the variables describing soil properties prevent our crop diversity indicators to

[19] The control variables describing farm soils include measures of soil depth, cationic exchange capacity, pH, water holding capacity as well as organic matter, clay, silt and sand contents.

[20] Even if the magnitude of these effects are likely to be limited.

capture the effects of soil quality. As discussed above, good soils enlarge the set of profitable arable crops for farmers. Failing to control for soil quality is likely to bias our empirical measure of crop acreage diversity effects through crop acreage diversity indicators $\mathbf{d}_{it}$.

We impose parametric distributional assumptions on random vectors $\boldsymbol{\gamma}_{k,i}$ and $\boldsymbol{\varepsilon}_{k,it}$, mostly for facilitating the estimation of the fixed parameters of the models and of the probability distribution of $\boldsymbol{\gamma}_{k,i}$ by Maximum Likelihood (ML). We assume that $\boldsymbol{\gamma}_{k,i}$ is multivariate normal, with $\boldsymbol{\gamma}_{k,i} \sim \mathcal{N}(\boldsymbol{\eta}_{k,0}, \boldsymbol{\Omega}_{k,0})$ and that error terms $\varepsilon_{k,it}^{(y)}$ and $\boldsymbol{\varepsilon}_{k,it}^{(x)}$ are normal, with $\varepsilon_{k,it}^{y} \sim \mathcal{N}(0, \psi_{kk,0}^{(y)})$ and $\boldsymbol{\varepsilon}_{k,it}^{(x)} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\psi}_{k,0}^{(x)})$. Of course, the correlation structure of $\mu_{k,i}^{(y)}$, $\mu_{k,i}^{(x)}$ and $\boldsymbol{\beta}_{k,i}$ is defined by variance-covariance matrix $\boldsymbol{\Omega}_{k,0}$.

Our last assumption concerns the status of the input use vector, $\mathbf{x}_{k,it}$, in the yield function model. This point is crucial as the endogeneity of input use in production function is a longstanding issue that has originated a considerable, and still lively, econometric literature (*e.g.*, Mundlak 1996 and 2001, Just and Pope 2001, Ackerberg *et al* 2015).[21] We assume that error terms $\boldsymbol{\varepsilon}_{k,it}^{(x)}$ and $\varepsilon_{k,it}^{y}$ are uncorrelated, implying input choices are assumed exogenous in the yield models conditionally on farm specific parameter $\boldsymbol{\gamma}_{k,i}$. This exogeneity assumption is admittedly restrictive, though common for panel data production function models (*e.g.*, Blundell and Bond 2000, Suri 2011).

Assuming that input uses $\mathbf{x}_{k,it}$ are exogenous with respect to $\varepsilon_{k,it}^{y}$ appears reasonable in our application, due to our using a rich set of control variables and our specifying farm specific random parameters. We basically assume that control variables $\mathbf{w}_{k,it}$, year specific effects $\alpha_{k,t,0}^{(y)}$ and farm specific random parameters $\mu_{k,i}^{(y)}$ and $\boldsymbol{\beta}_{k,i}$ capture most of the effects of the factors that simultaneously impact yield and input use levels. Importantly, the variance-covariance matrix, $\boldsymbol{\Omega}_{k,0}$, of random parameter vectors $\boldsymbol{\gamma}_{k,i}$ is left unrestricted.[22] Accordingly, input use levels $\mathbf{x}_{k,it}$ can be correlated with the random parts of the corresponding yield model, albeit only through correlations of the farm specific parameters of the yield model, $\mu_{k,i}^{(y)}$ and $\boldsymbol{\beta}_{k,i}$, and those of the input use equations, $\boldsymbol{\mu}_{k,i}^{(x)}$. As a matter of fact, the considered yield models accommodate a fairly rich set of input use endogeneity sources, albeit these only involve farm specific random

[21] See, *e.g.*, Ackerberg *et al* (2015). Mundlak (1996, 2001) and Just and Pope (2001) specifically consider agricultural production. Ackerberg *et al* (2015) state that the long history of production function estimation in applied economics cannot be deemed an unqualified success, as many issues hampering early estimations are still an issue today.

[22] Implying that the considered yield models are so-called correlated random coefficient (linear) models (*e.g.*, Wooldridge 2005a, Wooldridge 2005b, Suri 2011)

parameters.

3.2. Estimation

Equation (4) describes a recursive simultaneous equation system since input uses $\mathbf{x}_{k,it}$ are used as explanatory variables of yield levels $y_{k,it}$ while $y_{k,it}$ is not part of the models of $\mathbf{x}_{k,it}$. The input use and yield models featured in equation (4) rely on identical sets of exogenous variables, year specific dummy variables included. As argued above, we do not identify the parameters of our production choice models by relying on instrumental variables.[23] Our identification strategy relies on a full information approach. It combines the use of a rich set of control variables and the parametric specification of the multivariate probability distribution function of the random parameters of the considered models. Basically, we assume that the control variables and the random parameters of the model enable us to assume that error terms $\boldsymbol{\varepsilon}_{k,it}^{(x)}$ and $\varepsilon_{k,it}^{y}$ are uncorrelated conditionally on $\mathbf{w}_{k,it}$ and $\boldsymbol{\gamma}_{k,i}$. Then, we manage the issues raised by the endogeneity of $\mathbf{x}_{k,it}$ in the model of $y_{k,it}$ (which are due to random parameter vector $\boldsymbol{\gamma}_{k,i}$ in our modelling framework) by explicitly modelling (*i*) endogenous variable vector $\mathbf{x}_{k,it}$ and (*ii*) the correlation structure linking the farm specific random terms of the model of $\mathbf{x}_{k,it}$, $\boldsymbol{\mu}_{k,i}^{(x)}$, on the one hand and those of the model of $y_{k,it}$, $\mu_{k,i}^{(y)}$ and $\boldsymbol{\beta}_{k,i}$, on the other hand.

Although it is unusual, this approach is suitable given our data and objectives. As input use models (3b) are standard random parameter models, the estimation issues we face are mostly due to correlated random coefficient crop yield models (3a). Breitung and Salish (2021) and Woodridge (2019) recently proposed alternative approaches for estimating correlated random coefficient models. These approaches do not require any distribution assumption on the random terms of the considered equation. They make use of extensions of Mundlak's device (Mundlak 1978). This device relies on linear dependency assumptions across the elements of $\boldsymbol{\gamma}_{k,i}$ that are closely linked to those implicitly imposed by the joint normality of $\boldsymbol{\gamma}_{k,i}$ in equation systems (4). Also, the approaches proposed by Breitung and Salish (2021) and Woodridge (2019) primarily

[23] As a matter of fact, it is difficult to find suitable instrumental variables for input uses in crop production functions when crop and input prices do not display sufficient variations for suitably instrumenting input uses. Most exogenous factors, other than prices, that impact input uses do so because they also impact the crop production process, input uses being used for taking advantage or compensating the effects of the considered exogenous factors. As a result, it is difficult to find non-price exogenous factors (*e.g.*, weather effects, soil characteristics) that impact input uses without directly impacting yield levels.

focus on the estimation of random parameter means whereas we are also interested in there variance and covariance.

Since our models are fully parametric, we consider ML estimators of the parameters of equation systems (4). Apart from their being relatively large equation systems, two issues have to be dealt with when estimating these systems.

First, our models feature standard fixed parameters but also random coefficients, the parametric probability distribution of which is to be estimated. We circumvent this issue by using an Expectation-Maximization (EM) type algorithm (Dempster *et al* 1977, Wu 1983) for computing the ML estimators of the parameters of our models. EM type algorithms are particularly well suited for estimating models featuring unobserved variables, of which random parameters are prominent examples (*e.g.*, Lavielle 2014).[24] Importantly, the interaction terms $\mathbf{x}'_{k,it}\boldsymbol{\beta}_{k,i}$ featured in the yield functions and the random parameters appearing in the input use models imply that the equation system we consider involve products of random parameters, which raises non trivial estimation issues in our models. Relying on stochastic extensions to standard (deterministic) EM algorithms is necessary in such nonlinear settings. The conditional expectation that constitutes the E step of EM algorithm cannot be integrated either analytically or numerically and, thereby, requires simulation methods. We devised a Stochastic Approximation Expectation Maximization (SAEM) algorithm for estimating our models. SAEM algorithms were proposed by Delyon *et al* (1999). They make a more efficient use of simulations than competing stochastic EM type algorithms. The SAEM algorithm we used is presented in Appendix A.

Second, attrition is the rule rather than the exception in microeconomic panel data. Attrition is not an issue when units are missing at random, that is to say when the decision to drop out is not related to factors that are correlated with the response variables (*e.g.*, Wooldridge 2010). Our panel dataset is not balanced, for two reasons. First, farmers enter in and leave the customer base of the accountancy firm that made these data available to us. Also, data can be lost or observations can be incompletely recorded. The resulting attrition processes can be considered as random regarding the modelled processes. Second, farmers can decide not to produce some crops. In our application most sampled farmers produce the considered crops every year (wheat, barley or rapeseed) or do not produce them at all (sugar beet). Ignoring that observations are available depending on farmers' choice potentially raises endogenous sample selection issues

[24] These algorithms are easy to code for our models and have interesting robustness and global convergence properties, their main drawback being their linear convergence rate (even of computing time remains reasonable in our application).

when this choice depends on important unobserved factors that impact input use and yield levels.[25] Yet, accounting for sample selection is relevant when the objective of the study is to infer the features of a process for an entire population while the process is only observed for a specific sub-population. The objective of our study is much simpler. We aim to estimate pre crop and crop acreage diversity effects and to investigate how farmers use them in the sample that is available to us. We do not seek for results that can be extrapolated to situations in which the considered crops could be produced whereas they are not produced in our data.

4. Data

Our dataset is primarily based on a large sample of farm cost accounting data and combines information from different sources for supplementing these basic data. We used data recorded by the Integrated Administration and Control System (IACS) in France for uncovering the crop sequence acreages of the sampled farms. We also used data from the *GlobalSoilMap* initiative (*e.g.*, Arrouays *et al* 2020) for obtaining measures of the main characteristics of the soils of the sampled farms. Finally, we used data from Meteo France for obtaining detailed information on the weather conditions that prevailed in the considered area over the considered time span.

4.1. Farm cost accounting data

Our main dataset consists of an unbalanced panel accountancy dataset of 769 farms mostly located in the Marne *départment*, which provides a detailed description of farmers' choices in terms of acreages, crop yields as well as fertilizers and pesticides expenditures per crop. Aggregate fertilizers and pesticides volumes are computed from the corresponding expenditures by using price indices provided by the French ministry of agriculture at the regional level and expressed in constant 2010 euros per ha. Importantly, uses of the major nutrient elements – namely N, P and K – are also reported in kg for each crop.

We consider farms observed from 2008 to 2014 and displaying at least three consecutive years of observations. These farms mostly grow eight crops: (winter) wheat, (mostly spring) barley, (winter) rapeseed, corn, protein pea, alfalfa, sugar beet and (starch and consumption) potatoes. We aim at estimating the pre crop effects of these eight crops on the yield and input uses of the

[25] Following the pioneering work of Heckman (1976), agricultural production economists developed specific modelling frameworks for dealing with such issues when analyzing farmer production choices. See, *e.g.*, Lacroix and Thomas (2011) or Koutchadé *et al* (2021), for recent examples.

four major crops of the sample: wheat, barley, rapeseed and sugar beet. Tables 1 reports some descriptive statistics on farmers' production choices for these four crops and on farms' acreage diversification. Wheat appears to be the dominant crop in our sample, as it is grown every year by all farms and represents on average one-third of farms' acreage. As shown in table 1b, farms' acreages are quite diversified, with an average of more than five crops grown each year and most farmers (92% of them) growing at least four crops.

Table 1a: Descriptive statistics: yield and chemical input use levels

	Crops							
	Wheat		Barley		Rapeseed		Sugar beet	
Average yield (ton/ha)	8.65	(1.06)	7.00	(1.19)	3.88	(0.65)	93.0 2	(13.15)
Average output price (€/ton)	160	(33)	164	(35)	357	(71)	26	(4)
Average use of nitrogen (kg/ha)	217	(34)	147	(25)	214	(38)	137	(36)
Average use of herbicides (€/ha)	63	(19)	30	(12)	99	(31)	160	(53)
Average use of other pesticides (€/ha)	125	(36)	76	(25)	109	(38)	96	(31)
Average acreage share	0.34	(0.10)	0.21	(0.10)	0.14	(0.08)	0.12	(0.08)

Note: Sample standard deviation are in parentheses.

Table 1b: Descriptive statistics: crop acreage diversity

	Sample share	Average number of grown crops		Average Shannon index	
Farms growing 3 or less crops	0.08	2.85	(0.18)	1.09	(0.18)
Farms growing 4 crops	0.17	4.00	(-)	1.31	(0.10)
Farms growing 5 crops	0.37	5.00	(-)	1.48	(0.09)
Farms growing 6 crops	0.30	6.00	(-)	1.63	(0.08)
Farms growing 7 or more crops	0.08	7.04	(0.04)	1.76	(0.08)
Total sample		5.33	(1.02)	1.49	(0.21)

Note: Sample standard deviation are in parentheses.

4.2. IACS data

The IACS ensures the management of agricultural payments across EU countries[26]. It consists of several interconnected databases, which are updated on a yearly basis. We focus here on one particular database, the Land Parcel Identification System (LPIS). This database provides detailed information on crop acreages implemented on block of plots. Each block of plots is georeferenced, has a unique identifier and is associated to a unique farm identifier. We used the LPIS dataset for uncovering the crop sequence acreages of the farms of our sample. This dataset is very rich but, because farm and plot blocks identifiers vary from one year to the other, and because each block may contain more than one plot each year, specific data processing is required to extract information on farm crop sequences. For this purpose, we used the RPG explorer software developed by Martin *et al* (2017). By relying on established rules on how the crops match up from one year to the next, this software offers the possibility to recover crop sequence acreages shares at the farm level.[27] This was performed for all farms of the area from which the farms of our sample are drawn. These data were then matched to our cost accounting dataset using the farm level crop acreage seriesbserved in both datasets as matching criteria. This allowed us to perfectly match[28] two-thirds of the farms of sample of cost accounting data with a farm in the IACS data. More flexible matching criteria, combined with manual checks, then resulted in a matching rate of 78% of our initial sample.[29]

[26] More details can be found in European Commission (2019).

[27] These rules are based on the knowledge of the crop acreages declared in each block from one year to the next. A succession of 10 rules implemented one after the other can be used to determine the sequences of crops. Rule 1 (only one crop in the block in one year and the next) is considered as giving certain results, rules 2 (two crops per year, distributed over equal areas from one year to the next but different from each other) and 3 (one crop in one year is "broken down" into two crops in the next year with equal total acreage) are supported by solid hypotheses, from rule 4 onwards the probability of error in identifying the sequence increases. In our case, it hasn't been necessary for the software to frequently make use of rules beyond rule 3. More details on each rule can be found in Martin *et al* (2017).

[28] We consider a match as perfect when, for each the eight selected crops, the discrepancy of the acreages between the two datasets is less than 0.1 hectare

[29] It should be noted here that, although very unlikely, a farm in our sample may have been matched with the wrong farm in the IACS sample. This could happen if the two farms are the same size and have very similar acreages each year. However, this would not have a significant impact on our estimation results, since two farms with similar cropping patterns are expected to show similar effects of crop sequences and crop diversification on yields and input uses.

4.3. Soil and climate data

A significant part of the heterogeneity in yields and input uses among farms may be due to the heterogeneity in the soil and climatic conditions they face. To control for these heterogeneous factors in our econometric estimations, we also introduce soil and climate data in our dataset. We use weather indicators provided at the municipality level by *Meteo France*, the French National Weather Service, and soil quality indicators provided at the farm level[30] by the team of the "SoilServ" project funded by the French National Research Agency (ANR-16-CE32-0005). Statistics summing up these climate, respectively soil, indicators are reported in tables C1, respectively C2, of Appendix C.

4.4. Expert knowledge information

Expert knowledge information was gathered through interviews with three agricultural scientists and an extension agent of the considered area. These experts provided a list of unwarranted crop sequences, which are less likely to be chosen or never chosen by farmers and rankings of the effects of crop sequences on yield and input use levels. We use the information on the expected rankings of the effects on crop yield and input use levels to assess the consistency of our estimation results. The expected rankings of the effects of crop sequences on yields and input uses are reported in Table 2. Empty cells correspond to the crop sequences strongly unwarranted by the experts we have consulted.

Wheat yields are expected to be the highest when wheat is grown after pea, alfalfa or rapeseed, while growing wheat after wheat or barley is expected to lead to the lowest yields according to the experts. Growing barley after rapeseed or corn is expected to boost yield level for barley, while growing barley after barley is expected to penalize barley's yield level. In fact, growing a crop after the same crop is generally either unwarranted, or should lead to the lowest yield levels for that crop because this type of crop sequence favors the development of weed and/or pest pressures (corn being a notable exception in this respect).

Legumes fix significant amounts of atmospheric nitrogen that are made available for the following crops. Accordingly, the interviewed experts' rankings displayed in Table 2 show that growing cereals (wheat, barley or corn) after legumes (pea or alfalfa) is expected to lower fertilizer uses compared to growing cereals after cereals. Stated another way, a targeted output

[30] Soil quality indicators were actually first provided at the plot level and aggregated at the farm level by using the correspondence between farms and plots provided by the IACS data.

of cereals could be achieved with a lower level of fertilizers when using a legume-cereal sequence rather than a cereal-cereal sequence. The rankings displayed in table 2 also depend on the ability of crops to uptake fertilizers and, as a result, on the fertilizer surplus left by pre crops in soils. For instance, fertilizer uses are expected to be the highest after corn due to the efficiency of the use of soil nitrogen by these crops.

Experts' rankings regarding pesticide uses displayed in Table 2 mostly depend on the fact that monoculture tends to increase pressures of weeds, pests and diseases. Accordingly, crop sequences involving a single crop or crops belonging to similar botanic families are expected to induce higher pesticide use levels. Conversely, crop sequences involving different crops tend to reduce crop protection needs, according to so-called break crop effects.

Table 2: Rankings of the expected effects of pre crops on crop yield, fertilizer use and pesticide use levels per crop

		Current crop			
		Yield level rankings per crop			
		Wheat	Barley	Rapeseed	Sugar beet
Previous crop	*Wheat*	5	2	2	1
	Barley	6	3	2	1
	Rapeseed	2	1		2
	Corn	4	1		2
	Protein pea	1	3	1	
	Alfalfa	1	3		3
	Sugar beet	3	2		3
	Potatoes	3	2		2
		Fertilizer use level rankings per crop			
		Wheat	Barley	Rapeseed	Sugar beet
Previous crop	*Wheat*	1	1	1	1
	Barley	1	1	1	1
	Rapeseed	2	2		1
	Corn	1	1		1
	Protein pea	3	3	2	
	Alfalfa	3	3		2
	Sugar beet	2	2		1
	Potatoes	2	2		1
		Pesticide use level rankings per crop			
		Wheat	Barley	Rapeseed	Sugar beet
Previous crop	*Wheat*	1	1	1	1
	Barley	1	1	2	1
	Rapeseed	2	2		1
	Corn	2	1		1
	Protein pea	2	2	2	
	Alfalfa	2	2		1
	Sugar beet	2	2		1
	Potatoes	2	2		1

Note: 1 = highest expected level, 2 = second highest expected level, etc.

5. Results

Our application considers four crops: (winter) wheat, (spring) barley, (winter) rapeseed and sugar beet. These crops are the major crops in the considered area since they account for 82% of the arable crop acreage. We present here three sets of results. First, we briefly discuss the crop sequence acreages based on IACS data for our farm sample. Second, we present the estimation results of our equation systems composed of a yield equation and three inputs equations for nitrogen fertilizers, herbicides and other pesticides for each of the considered crops. We focus our discussion on the pre crop and crop acreage diversity effects. Third, we provide a set of results aimed to assess the economic value of the pre crop and crop acreage diversity effects that we uncover.

5.1. Crop sequence acreages

The average crop sequence acreage shares recovered from IACS data and matched to our data sample are reported in Table 3. These shares describe how farmers allocate the acreage of their current crops to plots with specific previous crops on average (*i.e.*, they correspond to the means of terms $z_{mk,it}$ over our sample). A striking feature of the results displayed in Table 3 is that farmers tend to rely on the most favorable crop sequences from an agronomic viewpoint. For instance, they avoid growing wheat after wheat (*i.e.*, the acreage share of wheat grown after wheat in the wheat acreage equals 0.06) and prefer growing wheat after rapeseed or sugar beet. Indeed, pea and rapeseed are considered as favorable pre crops for wheat by agronomists and our results show that land previously used to grow rapeseed or pea is mostly devoted to wheat production. The rapeseed – wheat sequence accounts for 39% of wheat crop acreage on average, the sugar beet – wheat sequence for 16%.

Conversely, the average acreage shares of many crop sequences are almost null, implying that these crop sequences are almost never observed in our data. Many of these unobserved crop sequences are strongly unwarranted from an agronomic viewpoint and thus (almost) never used by farmers. For instance, growing rapeseed after rapeseed foster pest and disease issues. These first results suggest that farmers' crop sequence acreage choices are particularly rational from an agronomic viewpoint and, as a result, from an economic viewpoint.

Crop sequence acreage share choices are also subject to constraints, such as the limited availability of favorable pre crops for the major crops of farmers' acreages. Of course, available previous crop acreages depend on famers' previous acreage choices. For instance, wheat and barley account for about half of the arable crop acreage in the considered area. The average acreage share of wheat amounts to 0.34 and that of barley to 0.21. This implies that wheat and barley are major pre crops in the area, according to purely "mechanical" effects. For instance, wheat and barley are the pre crops of 97% of rapeseed acreages and of 91% of sugar beet acreages, and wheat is the pre crop of 56% of barley acreages. Conversely, despite pea being among the most favorable previous crops for wheat and pea production being almost always followed by wheat production, the pea–wheat sequence only accounts for 6% of wheat crop acreage on average, because the average acreage share of pea only amounts to 0.02 in the area.

Farmers favoring the most profitable crop sequences and tending to avoid the least favorable ones significantly affects the econometric analysis of pre crop effects. First, the effects of pre crops involved in never or rarely used crop sequences are poorly identified, when they can be identified, because the corresponding crop sequence acreages display insufficient variability. Second, minor crops are generally grown on a few previous crops (which are often major crops[31]), if not on only one previous crop. Third, major crops are the only ones displaying allocations to pre crop acreages that significantly vary across farms. These observations sum up the main shortcoming of farm data (*i.e.*, of observed data as opposed to experimental data) for investigating the effects of crop sequences on crop yield and input use levels. Our estimation results on pre crop effects largely support the points made here.

Table 3a: Average allocation of the acreages of the major crops to previous crop acreages

		Current (major) crops				
		Wheat	Barley	Rapeseed	Sugar beet	Previous crop acreage shares
Previous crops	Wheat	0.06	0.56	0.38	0.59	0.35
	Barley	0.02	0.13	0.59	0.32	0.22
	Rapeseed	0.39	0.03	0.00	0.01	0.14
	Corn	0.06	0.03	0.00	0.00	0.03
	Protein pea	0.06	0.00	0.00	0.00	0.02
	Alfalfa	0.08	0.01	0.00	0.00	0.08
	Sugar beet	0.16	0.18	0.01	0.02	0.12
	Potatoes	0.05	0.02	0.00	0.02	0.02
	Other pre crops	0.10	0.03	0.01	0.03	0.02
Current crop acreage shares		0.34	0.21	0.14	0.12	

[31] Straw cereals in our application.

Table 3b: Frequency of crop production and crop sequences

		Current (major) crops				Previous crop frequency
		Wheat	Barley	Rapeseed	Sugar beet	
Previous crops	*Wheat*	0.30	0.81	0.60	0.62	1
	Barley	0.13	0.41	0.77	0.44	0.87
	Rapeseed	0.81	0.12	0.02	0.03	0.91
	Corn	0.21	0.10	0.00	0.01	0.36
	Protein pea	0.28	0.02	0.01	0.01	0.28
	Alfalfa	0.33	0.04	0.01	0.02	0.65
	Sugar beet	0.50	0.40	0.02	0.06	0.79
	Potatoes	0.16	0.05	0.01	0.03	0.19
	Other pre crops	0.50	0.23	0.09	0.10	-
Current crop frequency		1	0.87	0.91	0.79	

5.2. Crop input use and yield models: general results

Tables 4 display selected parameter estimates of the yield, nitrogen, herbicides and other pesticides equations for the four considered crops. Due to space limitation we focus here on the estimation results for our parameters of interest, that is to say the parameters capturing the effects of crop sequences (*i.e.*, fixed parameters $\mathbf{a}_{k,0}^{(y)}$ and $\mathbf{a}_{k,0}^{(x)}$) and crop acreage diversity (*i.e.*, fixed parameters $\boldsymbol{\delta}_{k,0}^{(y)}$ and $\boldsymbol{\delta}_{k,0}^{(x)}$) on yield and input use levels. Those characterizing the intensity of farmers' production practices (*i.e.*, the distribution of random parameters $\boldsymbol{\gamma}_{k,i}$) are also of special interest, as they allow investigating, to some extent, the rationality underlying farmers' chemical input choices. The other estimation results, the effects of the control variables in particular, are reported in Appendix C.[32]

Tables 4 display the estimates of the parameters characterizing the distribution of the model random parameters, that is to say the means and standard deviations of the elements of vectors $\boldsymbol{\gamma}_{k,i} = (\boldsymbol{\mu}_{k,i}, \boldsymbol{\beta}_{k,i})$, as well as general statistics. The reported simulated R^2 measures correspond to standard R^2 measures applied to models in which farm specific parameters are replaced by their estimates based on the estimated models and farm specific observations (*e.g.*, Koutchadé *et al*

[32] Tables C3-C6 mostly report estimation results of the effects of weather and soil property variables. Including these variables in our models appears to be significantly improve their estimation from a statistical viewpoint.

2018, 2021). These simulated R^2 demonstrate that our models provide a better fit to the yield data than to the chemical input use data. The estimated crop yield models explain from 63% to 70% of the observed yield variance. The pesticide use models explain from 50% to 65% of the observed herbicide and other pesticide use variances. The corresponding percentages drop down to 38% and 44% for the nitrogen fertilizer use models.

The estimates of the parameters characterizing the (multivariate normal) distribution of the farm specific parameters in the considered models are accurately estimated. The estimates of the standard deviations of these parameters demonstrate that farmers' choices and crop production processes are strongly impacted by farm specific unobserved factors (despite our controlling for the effects of soil characteristics at the farm level).

Table 4a: Selected parameter estimates of the crop yield models: random farm specific parameters and general statistics

	Yield models (t/ha)							
	Wheat		Barley		Rapeseed		Sugar beet	
Intercept, mean	8.60**	(0.07)	6.10**	(0.08)	0.50**	(0.04)	83.8**	(0.83)
Intercept, standard deviation	0.70**	(0.07)	0.50**	(0.09)	0.50**	(0.04)	8.40**	(1.04)
Nitrogen, mean (x100)	0.03	(0.03)	-0.06	(0.05)	0.08**	(0.01)	-0.40	(0.39)
Nitrogen, std deviation (x100)	0.21**	(0.03)	0.30**	(0.06)	0.15**	(0.01)	1.95**	(0.45)
Herbicides, mean (x100)	0.14**	(0.05)	0.02	(0.11)	0.04**	(0.02)	0.55	(0.32)
Herbicides, std deviation (x100)	0.38**	(0.07)	0.63**	(0.15)	0.22**	(0.02)	2.42**	(0.40)
Other pesticides, mean (x100)	0.34**	(0.03)	0.27**	(0.06)	0.13**	(0.02)	0.80	(0.61)
Other pesticides, Standard deviation (x100)	0.17**	(0.03)	0.37**	(0.07)	0.20**	(0.02)	5.39**	(0.80)
Average yield level	8.65		7.00		3.88		93.07	
Simulated R^2	0.68		0.63		0.64		0.70	
Observation number	3,982		3,327		3,530		3,085	
Farm number	769		654		692		607	

*Note: Symbol **, respectively *, indicates that the parameter is significantly estimated at the 5%, respectively 10%, level. Estimated standard deviations of the parameter estimates are in parentheses.*

Our estimates also show that random coefficients of the crop yield models – *i.e.*, elements of vector $\boldsymbol{\beta}_{k,i}$ – are statistically correlated with random parameters of the corresponding crop input use models – *i.e.*, elements of vector $\boldsymbol{\mu}_{k,i}^{(x)}$ – for all considered crops. This indicates that the considered crop yield equations really contain correlated random coefficients (see Appendix C8). Moreover, when the estimated correlations are negative when they are statistically non-null. This suggests that the crop yield functions that are approximated by our crop yield models display decreasing returns to input uses.

Table 4b: Selected parameter estimates of the input use models: random farm specific parameters and general statistics

	Fertilizer use models (kg/ha)							
	Wheat		Barley		Rapeseed		Sugar beet	
Intercept, mean	249.2**	(0.63)	151.1**	(0.56)	115.8*	(0.77)	356.2**	(0.87)
Intercept, Std deviation	13.46**	(0.54)	11.29**	(0.43)	15.92*	(0.62)	17.20**	(0.55)
Average use of N	217.95		147.19		215.19		138.55	
Simulated R^2	0.38		0.42		0.42		0.44	
	Herbicide use models (€/ha, 2010 prices)							
	Wheat		Barley		Rapeseed		Sugar beet	
Intercept, mean	171.6**	(0.42)	85.7**	(0.28)	285.6*	(0.75)	319.9**	(1.38)
Intercept, std deviation	10.0**	(0.29)	5.7**	(0.18)	16.8*	(0.54)	30.5**	(0.99)
Average herbicide use	63.08		30.47		99.27		160.55	
Simulated R^2	0.55		0.50		0.55		0.67	
	Other pesticide use models (€/ha, 2010 prices)							
	Wheat		Barley		Rapeseed		Sugar beet	
Intercept, mean	144.7**	(1.00)	143.7**	(0.66)	127.7**	(1.03)	109.8**	(0.79)
Intercept, std deviation	25.43**	(0.71)	14.72**	(0.46)	24.32**	(0.69)	16.86**	(0.55)
Average pesticide use	125.1		76.0		109.0		96.2	
Simulated R^2	0.65		0.55		0.60		0.55	
	Observation and farm numbers							
	Wheat		Barley		Rapeseed		Sugar beet	
Observation number	3,982		3,327		3,530		3,085	
Farm number	769		654		692		607	

*Note: Symbol **, respectively *, indicates that the parameter is significantly estimated at the 5%, respectively 10%, level. Estimated standard deviations of the parameter estimates are in parentheses.*

The farm specific coefficients of the input use variables in the crop yield models (*i.e.*, random parameters $\boldsymbol{\beta}_{k,i}$) give the marginal productivity of the considered chemical inputs at the farm level. Their means, which are reported in Table 4a, yield the average marginal productivity of these inputs. The estimated average marginal productivities of nitrogen fertilizers are of either sign and small in absolute value. Such results are common in the agricultural production economics literature, at least for conventional production practices. Responses of crop production to nitrogen uses are known to generally exhibit a plateau at high nitrogen use levels.[33] The estimated average marginal productivity levels are positive for pesticides, and small for herbicides. Farmers usually use herbicides for controlling weeds following a long run strategy (*e.g.*, Colbach and Cordeau 2018). Herbicides aim to control current weed populations as well as weed seed banks. Parameters $\beta_{j,k,i}$ capture the short run effects of input *j* on the yield level of crop *k*. They fail to capture their long run effects, which are expected to be positive for herbicides.

Let assume that input *j* is purchased at price $p_{j,k}^{(x)}$ and crop *k* is sold at price $p_{k}^{(y)}$. According to our crop yield models, the marginal net return of crop *k* to input *j* is given by $p_{k}^{(y)}\beta_{j,k,i} - p_{j,k}^{(x)}$ for farm *i*. Since input prices or price indices are close to one in our application this expression basically provides the net return to the last Euro of input *j* used for crop *k*. Table 5 reports the sample means and standard deviations of the estimated marginal net returns of crops to chemical inputs at the sample mean prices. According to these results, chemical inputs, nitrogen fertilizers and herbicides in particular, are used above their respective expected profit maximizing levels by most farmers. These results suggest that the farmers of our sample seek for relatively high yield levels, which supposes to rely on relatively high crop protection and fertilization levels. Yet, assessing the extent of the revealed overuses of chemical inputs would require assessing the concavity properties of the considered crop yield functions, which is out of the scope of this study.[34]

[33] See, *e.g.*, Tembo *et al* (2008) for a recent empirical analysis of this feature of the productivity of nitrogen fertilizers.

[34] If these overuse levels are significant they are unlikely to be "massive". As reminded above, crop yields are known to exhibit a plateau at high nitrogen use levels. Similarly, the marginal productivity of pesticides is known to sharply decrease in pesticide use levels (*e.g.*, Frisvold 2019).

Table 5: Estimated means and standard deviations of crop marginal net returns to chemical inputs (at average price levels, 2008–2014)

	Chemical input use models					
	Means of the estimated crop marginal net returns to inputs					
	Nitrogen fertilizers		Herbicides		Other pesticides	
Wheat	-0.95	(0.05)	-0.78	(0.08)	-0.46	(0.05)
Barley	-1.10	(0.08)	-0.97	(0.18)	-0.56	(0.10)
Rapeseed	-0.71	(0.04)	-0.86	(0.07)	-0.54	(0.07)
Sugar beet	-1.10	(0.10)	-0.86	(0.08)	-0.79	(0.16)
	Standard deviations of the estimated of crop marginal net returns to inputs					
	Nitrogen fertilizers		Herbicides		Other pesticides	
Wheat	0.34	(0.05)	0.61	(0.11)	0.27	(0.05)
Barley	0.49	(0.10)	1.03	(0.25)	0.61	(0.11)
Rapeseed	0.54	(0.04)	0.79	(0.07)	0.71	(0.10)
Sugar beet	0.51	(0.12)	0.63	(0.10)	1.40	(0.21)

Note: Estimated standard deviations of the parameter estimates are in parentheses

5.3. Pre crop effects on yield and input use levels

Tables 6 report the effect of pre crops on the outcome (yield, nitrogen, herbicide and other pesticide use levels) of the considered crops compared to that of a reference pre crop. The reference pre crop of a given crop is its most frequent one in our data, which is rapeseed for wheat and wheat for the other crops. As evidenced by the relatively large estimates of the standard deviation of the estimated effects reported in Table 6, previous crop effects are poorly identified in our models.[35] Previous crop effects on input uses are particularly poorly estimated. As discussed above, such results can partly be due to crop sequence acreage choices patterns. Farmers tend to select the most favorable pre crop for their major crops as well as to choose similar crop acreages across years. This implies that their crop sequence acreages display similar patterns.[36] The implied limited variability in crop sequence acreages prevents obtaining accurate estimates of the corresponding pre crop effects.

[35] Even if their signs are generally consistent with experts' views.

[36] Small pre crop effects in absolute value could also be due to the well-known attenuation biases induced by measurement errors (*e.g.*, Wooldridge 2010) since crop sequence acreage shares are reconstructed in our data, with a reconstruction process that may be prone to errors. Yet, attenuation biases are associated to downward biased estimates of the standard deviation of the estimated effects (*e.g.*, Wooldridge 2010). Taken together these observations suggest that our pre crop effect estimates are unlikely to be impacted by significant attenuation biases in our application.

Table 6a: Selected parameter estimates of the crop yield models: selected pre crop effects

	Yield models (t/ha)							
	Wheat		Barley		Rapeseed		Sugar beet	
Pre crop effects								
Wheat	-0.32**	(0.10)	0.00	(-)	0.00	(-)	0.00	(-)
Barley	-0.19	(0.16)	-0.16**	(0.07)	0.04	(0.03)	-0.25	(0.55)
Rapeseed	0.00	(-)	0.16	(0.20)			1.25	(3.03)
Protein pea	0.20**	(0.10)	0.17	(0.41)	0.05	(0.25)		
Alfalfa	-0.09	(0.08)	0.02	(0.35)			-8.51	(5.22)
Sugar beet	0.01	(0.06)	0.21**	(0.07)			-0.51	(1.69)

*Note: Symbol **, respectively *, indicates that the parameter is significantly estimated at the 5%, respectively 10%, level. Estimated standard deviations of the parameter estimates are in parentheses.*

As an illustration, the acreage share of the pea–barley sequence is almost null on average while the barley–barley one equals 0.13 (Table 3a). The estimated standard errors of the pre crop effects of pea are at least fivefold those of barley when going through the equations related to the yield or input use levels of barley (Tables 6). This comes to illustrate our concerns regarding the identification of crop rotation effects for rarely used crop sequences.

Unsurprisingly, the most accurate estimated pre crop effects are those of the wheat yield equation. They tend to show that growing wheat after rapeseed instead of after wheat increases expected yield levels by 0.32 t/ha while growing wheat after pea instead of after wheat increases expected yield levels by 0.52 t/ha (which amounts to 6% of the sample average wheat yield level). These results are in line with experimental results (*e.g.*, Meynard *et al* 2013, Jeuffroy *et al* 2015, Preißel *et al* 2015). The estimated pre crop effects on barley yield levels are also in the expected ranges (*e.g.*, Meynard *et al* 2013, Jeuffroy *et al* 2015, Reckling *et al* 2016).

Table 6b: Selected parameter estimates of the input use models: selected pre crop effects

	Fertilizer use models (kg/ha)							
	Wheat		Barley		Rapeseed		Sugar beet	
Pre crop effects								
Wheat	0.32	(3.79)	0.00	(-)	0.00	(-)	0.00	(-)
Barley	2.01	(6.32)	0.85	(1.91)	-1.66	(1.77)	-2.39	(1.91)
Rapeseed	0.00	(-)	-0.74	(4.53)			6.36	(7.93)
Protein pea	1.83	(3.37)	-5.19	(9.81)	-4.79	(18.50)		
Alfalfa	4.04	(3.27)	5.06	(8.08)			2.51	(13.00)
Sugar beet	2.01	(2.54)	-0.12	(1.58)			-5.73	(5.75)
	Herbicide use models (€/ha, 2010 prices)							
	Wheat		Barley		Rapeseed		Sugar beet	
Pre crop effects								
Wheat	-0.11	(2.29)	0.00	(-)	0.00	(-)	0.00	(-)
Barley	1.37	(4.13)	1.94**	(0.95)	-0.57	(1.44)	-2.57	(2.52)
Rapeseed	0.00	(-)	0.62	(2.46)			7.78	(11.21)
Protein pea	1.55	(2.38)	-5.17	(5.78)	5.52	(18.90)		
Alfalfa	0.58	(2.18)	1.62	(3.74)			9.24	(34.09)
Sugar beet	-1.35	(1.58)	-1.68*	(0.97)			8.41	(8.50)
	Other pesticide use models (€/ha, 2010 prices)							
	Wheat		Barley		Rapeseed		Sugar beet	
Pre crop effects								
Wheat	4.07	(4.08)	0.00	(-)	0.00	(-)	0.00	(-)
Barley	-15.63**	(6.55)	-0.50	(1.88)	1.10	(1.73)	-1.05	(1.55)
Rapeseed	0.00	(-)	-3.34	(4.93)			-2.23	(6.85)
Protein pea	-5.32	(3.52)	-5.64	(17.04)	-16.49	(20.27)		
Alfalfa	-2.05	(3.27)	8.48	(4.42)			-3.92	(13.05)
Sugar beet	-1.66	(2.50)	0.87	(1.91)			1.86	(5.90)

*Note: Symbol **, respectively *, indicates that the parameter is significantly estimated at the 5%, respectively 10%, level. Estimated standard deviations of the parameter estimates are in parentheses.*

Our results demonstrate very limited adjustments, if any, of farmers' chemical input uses to the pre crops of their crop acreages. In particular, we decided to focus on nitrogen uses instead of aggregated fertilizer uses for investigating the effects on nitrogen uses of legumes as pre crops. Our results tend to show that farmers do not reduce their nitrogen uses after legumes. These estimation results are consistent with the results obtained by Nave *et al* (2013) based on French farmers interviews. They are also consistent with our estimates of the marginal productivity of nitrogen fertilizers, at least to some extent. Farmers tend to overuse nitrogen fertilizers when they downplay legume nitrogen surpluses while deciding their uses of mineral nitrogen. Nitrogen surpluses are not lost, as they can induce higher yields, but total nitrogen applications exceed their economically optimal levels.

Three phenomena may underlie these results. First, data issues may prevent our obtaining accurate estimates of pre crop effects. As discussed above, our data may not contain sufficient information for uncovering pre crop effects on input uses. Moreover, recorded crop input use levels are likely to be less accurate than recorded yield levels. These data issues cannot be ruled out but they are unlikely to fully explain our low estimates of pre crop effects on input uses. As will be shown below, these data allow us to uncover relatively precise crop acreage diversity effects on pesticide uses, thereby suggesting that the sampled farmers adjust their pesticide uses, especially their herbicide uses, to the conditions prevailing in their fields.

Second, if farmers automatically reap off the benefits of pre crop effects on yield levels they need to be willing to adjust their chemical input uses for benefiting from the effects of pre crops on soil nutrient contents and/or on pest and weed pressures. Farmers are likely to be aware of nitrogen surpluses left by legumes or of the break effects of diversified crop sequences on pest and weed pressures but they may be reluctant to adjust their input uses. Nitrogen surpluses and break crop effects on pest and weed pressures are random. Assessing them is costly and may only yield limited savings in chemical input expenditures.

Third, pre crop effects on chemical inputs may be limited in our data. Indeed, our data enable us to uncover the effects of a few crop sequences only, those involving pre crops with sufficiently variable acreages for a given crop. These pre crops, those of wheat excepted, may not induce contrasted effects either on yield levels or on chemical input uses. For instance, wheat and barley are by far the most frequent pre crops of sugar beet in our sample. Despite wheat being mostly a winter crop and barley being mostly a spring crop in the considered area, these crops are both straw cereals sharing many agronomic features. As a matter of fact, barley and wheat are expected to have similar effects on sugar beet production by the experts we have consulted (Tables 2). Accordingly, wheat being the reference pre crop of sugar beet in our application, the absence of statistically significant pre crop effects of barley on sugar beet production is not particularly surprising. Finally, farmers' production practices may also induce limited pre crop and crop acreage diversity effects. Experimental results of Coulter *et al* (2011) regarding corn based cropping systems in the US suggest that high yielding cropping management practices attenuate the effects of crop diversity. Indeed, high yielding crop management practices are known to call for both high fertilization and high crop protection levels. High yields require high nutrient loads and high yielding crop cultural techniques (*e.g.*, high seeding densities, early sowing, high nitrogen fertilization) tend to enhance pest, weed and disease pressures.[37] These

[37] The most productive seeds are also often more susceptible to pests and diseases. High nitrogen fertilization levels also increase competition with weeds and increase the susceptibility of crops to diseases (and straw cereals to

effects of high yielding cropping management practices may swamp those of crop diversity.

5.4. Crop acreage diversity effects on yield and input use levels

Tables 7 report the effects of the number of grown crops, our main crop acreage diversity effects, on the outcomes of the considered crops. These effects are measured as differences with respect to effect of the reference number of grown crops, which is five (the most frequent number of grown crops in our data) in our empirical application. The "Crop diversity effects: Shannon index per crop number" sub-panels report the effects of the crop acreage Shannon index interacted with the grown crop number dummy variables. These effects measure the effects of crop acreage diversity holding fixed the number of crops actually grown.

Crop diversity is expected by agronomists (*e.g.*, Meynard *et al* 2013, Duru *et al* 2015) to increase crop yield levels (*e.g.*, by decreasing pest and weed pressures that cannot be controlled by pesticides, by impacting soil structure at various depth levels), to decrease pesticide use levels (by decreasing pest and weed pressures that can be chemically controlled) and, to a lesser extent, to decrease fertilizer use levels (*e.g.*, by improving soil properties that in turn enhance nutrient efficiency of crops). Our estimation results tend to support these hypotheses. Yield levels increase and pesticide use levels decrease as the grown crop number and the related Shannon index increase. Yet, the estimated effects are non-null from a statistical viewpoint only for yield and herbicide use levels.

According to our results, wheat yield levels are 0.20 t/ha higher when wheat is grown in a 7 crop farm than in a 5 crop farm, and wheat yield levels are 0.39 t/ha higher when wheat is grown in a 7 crop farm than in a 3 crop farm. Moreover, crop acreage diversity as measured by the Shannon index also tends to increase wheat yield levels holding constant the number of grown crops. Other crops display similar patterns regarding crop acreage diversity effects.[38] Such results are fully consistent with agronomists' views and experimental results (e.g., Lin 2011, Kremen and Miles 2012, Meynard et al 2013, Hufnagel et al 2020).

lodging). Early sowing increases the exposure of crops to pests and diseases while dense uniform sowing may foster the occurrence and the severity of pest and disease outbreaks. Such effects were discussed and documented by Loyce and Meynard (1997) and Loyce *et al* (2008, 2012) in the case of winter wheat.

[38] According to our results, sugar beet yield levels are 7.67 t/ha lower when wheat is grown in a 5 crops farm than in a 3 crops farm. Yet, this estimated effect is very inaccurate, the related estimation standard deviation being estimated at 4.39 t/ha. Indeed, farmers producing sugar beet rarely grow less than three other crops. Most of them also grow wheat, barley and rapeseed.

Table 7a: Selected parameter estimates of the crop yield models: crop acreage diversity effects

	Yield models (t/ha)							
	Wheat		Barley		Rapeseed		Sugar beet	
	Crop diversity effects: crop number							
3 crops or less	-0.19**	(0.07)	-0.35**	(0.13)	0.01	(0.07)	-7.67	(4.39)
4 crops	-0.10*	(0.05)	-0.19**	(0.07)	-0.04	(0.04)	-1.08	(1.29)
5 crops	0.00	(-)	0.00	(-)	0.00	(-)	0.00	(-)
6 crops	0.06	(0.04)	0.02	(0.05)	0.06*	(0.03)	1.38**	(0.61)
7 crops or more	0.20*	(0.07)	0.15*	(0.08)	0.18**	(0.04)	1.90*	(0.93)
	Crop diversity effects: Shannon index per crop number							
3 crops x *Shannon index*	-0.13	(0.41)	0.69	(0.62)	-0.26	(0.36)	-13.27	(29.80)
4 crops x *Shannon index*	0.72**	(0.27)	1.33**	(0.47)	0.21	(0.20)	6.57	(6.89)
5 crops x *Shannon index*	0.73**	(0.31)	0.88**	(0.36)	0.33	(0.20)	9.79**	(4.58)
6 crops x *Shannon index*	0.28	(0.33)	0.40	(0.41)	0.59**	(0.23)	14.38**	(4.42)
7 crops x *Shannon index*	1.44**	(0.58)	0.87	(0.64)	0.93**	(0.30)	15.73**	(6.48)

*Note. Symbol **, respectively *, indicates that the parameter is significantly estimated at the 5%, respectively 10%, level. Estimated standard deviations of the parameter estimates are in parentheses.*

Our results also tend to demonstrate that crop acreage diversity significantly impacts herbicide uses, although with less accurate estimates than for crop yields. Overall, these results are consistent with agronomists' experimental results (e.g., Liebman and Dyck 1993, Liebman and Staver 2001, Smith and Gross 2007, Chikowo et al 2009, Adeux et al 2019, Sharma et al 2021). Andert et al (2016) obtained similar results for a (small) sample of (large) German farms. For instance, farms growing 5 crops use 4.7 €/ha (at the 2010 price levels) less herbicides on wheat than farms growing 3 crops, farms spending 63.1 €/ha on herbicides for wheat on average. Similarly, farms growing 5 crops use 11.1 €/ha less herbicides on rapeseed than farms growing 3 crops, farms spending 99.3 €/ha on herbicides for rapeseed on average.

Table 7b: Selected parameter estimates of the input use models: crop acreage diversity effects

	Fertilizer use models (kg/ha)							
	Wheat		Barley		Rapeseed		Sugar beet	
	Crop diversity effects: crop number							
3 crops or less	-0.38	(3.20)	-1.41	(4.31)	-2.01	(4.82)	6.08	(24.09)
4 crops	0.40	(1.64)	0.69	(1.63)	-1.59	(2.28)	3.27	(4.41)
5 crops	0.00	(-)	0.00	(-)	0.00	(-)	0.00	(-)
6 crops	1.55	(1.40)	0.54	(1.12)	3.45*	(1.68)	-0.44	(1.91)
7 crops or more	2.65	(2.19)	1.37	(2.04)	3.72	(2.48)	-3.03	(2.60)
	Crop diversity effects: Shannon index per crop number							
3 crops x *Shannon index*	-3.74	(17.91)	-13.71	(26.74)	-12.25	(19.33)	-83.64	(107.95)
4 crops x *Shannon index*	10.54	(9.13)	-6.55	(10.83)	-3.94	(14.56)	1.24	(24.56)
5 crops x *Shannon index*	-12.98	(11.09)	-12.00	(8.20)	-13.53	(13.49)	-36.25**	(16.84)
6 crops x *Shannon index*	-1.56	(11.34)	-4.22	(8.88)	12.62	(12.46)	1.78	(13.29)
7 crops x *Shannon index*	-3.28	(20.36)	-7.39	(17.68)	0.22	(22.09)	-25.68	(21.83)
	Herbicide use models (€/ha, 2010 prices)							
	Wheat		Barley		Rapeseed		Sugar beet	
	Crop diversity effects: crop number							
3 crops or less	4.66**	(1.54)	3.56	(2.02)	11.05**	(3.63)	12.11	(59.26)
4 crops	1.93	(1.03)	1.20	(0.84)	8.14**	(1.88)	4.21	(3.53)
5 crops	0.00	(-)	0.00	(-)	0.00	(-)	0.00	(-)
6 crops	-1.64*	(0.88)	-1.37**	(0.58)	-2.42	(1.49)	-1.41	(2.39)
7 crops or more	-2.37	(1.74)	-1.34	(0.99)	-3.29	(2.48)	-5.30	(4.27)
	Crop diversity effects: Shannon index per crop number							
3 crops x *Shannon index*	1.99	(8.68)	-12.01	(11.14)	15.37	(23.84)	-38.16	(372.78)
4 crops x *Shannon index*	-9.35	(5.15)	-10.32**	(4.98)	-8.71	(11.66)	-31.32	(18.48)
5 crops x *Shannon index*	-4.12	(6.13)	-8.88**	(3.68)	-12.98	(10.83)	-4.11	(19.37)
6 crops x *Shannon index*	-7.27	(8.17)	-3.05	(5.66)	-23.70*	(12.69)	3.41	(18.70)
7 crops x *Shannon index*	7.57	(15.25)	-0.67	(9.88)	-18.79	(20.45)	-11.79	(30.71)

Table 7b: (Continued)

	Other pesticide use models (€/ha, 2010 prices)							
	Wheat		Barley		Rapeseed		Sugar beet	
Crop diversity effects: crop number								
3 crops or less	-3.73	(3.28)	-2.44	(3.33)	-0.82	(4.15)	3.11	(18.21)
4 crops	-3.17	(2.07)	0.14	(1.66)	2.94	(2.37)	0.92	(2.53)
5 crops	0.00	(-)	0.00	(-)	0.00	(-)	0.00	(-)
6 crops	-0.25	(1.76)	-0.72	(1.32)	-1.35	(1.89)	1.00	(1.62)
7 crops or more	1.90	(2.89)	-2.16	(2.22)	0.75	(3.10)	-1.50	(2.79)
Crop diversity effects: Shannon index per crop number								
3 crops x *Shannon index*	5.99	(14.46)	1.52	(25.08)	-16.66	(28.23)	55.79	(73.47)
4 crops x *Shannon index*	1.83	(10.94)	-1.28	(8.37)	-1.55	(12.14)	-10.12	(13.18)
5 crops x *Shannon index*	-13.95	(11.38)	-6.53	(8.91)	-29.88**	(13.92)	-26.92**	(12.69)
6 crops x *Shannon index*	1.58	(13.52)	-5.49	(11.55)	23.23	(14.91)	3.80	(12.42)
7 crops x *Shannon index*	5.31	(17.92)	-1.52	(17.93)	4.22	(19.47)	10.15	(21.19)

*Note: Symbol **, respectively *, indicates that the parameter is significantly estimated at the 5%, respectively 10%, level. Estimated standard deviations of the parameter estimates are in parentheses.*

The estimated effects of the crop acreage Shannon index per grown crop number also suggest that crop acreage diversity tends to lower weed pressures. Yet, the related estimates are generally inaccurate and lack statistical significance. In the same vein, the estimated effects of the crop acreage diversity indicators on sugar beet herbicide use levels have expected signs. They are also relatively large, but, these effects are estimated too inaccurately for being meaningful from a statistical viewpoint. Indeed, herbicide uses on sugar beet are both relatively large (sugar beet is a root crop) and heterogeneous across farms. Their sample average amounts to 160.6 €/ha and their between-farm standard deviation to 30.5 €/ha. This may be explained by heterogeneous tillage practices, which significantly impact weed control, across our sample.

Also, the effects of crop acreage diversification on herbicide uses may not solely be due to agro-ecological weed regulation effects. For instance, in our sample most farms growing at most 3 crops do not produce sugar beet or potatoes, implying that comparing farms growing 3 crops (or less) and farms growing at least 4 crops largely consists of comparing farms not growing sugar beet to farms growing sugar beet or potatoes. As these root crops require high level weed control, the effects of crop acreage diversity on herbicide use on grain crops may be due to carry-over effects of the chemical weed control implemented for protecting root crops.[39]

It is worth noting that our results on crop acreage diversity effects in the yield and herbicide equations are not driven by farm size (at least in our sample, which mostly contains relatively large farms), as the inclusion of the farm size among the control variables turns out to be statistically insignificant regardless the equation in which it is included. Also, our results are not driven by soil quality effects. Our including a rich set of soil property measures in our models controls for the well-known fact that good soils both widen the scope of profitable crops (*e.g.*, root crops require deep and suitably structured soils) and enhance crop profitability.[40] Yet, the fact that farmers using more diversified crop acreages may be more skilled from a technical viewpoint cannot be ruled out.

Finally, measuring crop acreage diversity by the usual Shannon index yields results pointing to the absence of crop diversity effects, whatever the considered crop. These results suggest crop mix diversity and crop acreage evenness given crop mix are features of crop acreages (and rotations) that need to be distinguished for uncovering the agro-ecolological effects of crop diversity.

5.5. Economic assessment of pre crop and crop acreage diversity effects

In order to assess the economic value of the pre crop and crop acreage diversity effects uncovered by our modelling framework, we compute the effects of changes in pre crops or in crop acreage diversity on farmers' crop returns to chemical inputs. We compute these effects for an "average farmer" and at the mean prices of our sample. Appendix B provides the related technical details.

[39] This comes to illustrate the point recently made by Colbach *et al* (2020) on the analysis of farm versus experimental data when considering crop rotations, weed populations and their effects on crop yields, and herbicide uses.

[40] Notwithstanding our data covering a limited geographical area.

Table 8a: Economic assessment of selected pre crop effects (€/ha), average effects at average price levels (2008–2014)

	Economic value of the effect of a pre crop, *versus* the considered crop reference pre crop (€/ha)									
	Yield value		Nitrogen fertilizer cost		Herbicide cost		Other pesticide cost		Return to chemical inputs	
	(1)		(2)		(3)		(4)		(1) - (2) - (3) - (4)	
Wheat (reference pre crop: rapeseed)										
Wheat	-48.9**	(15.9)	0.1	(1.7)	-0.1	(2.3)	4.1	(4.1)	-53.1**	(16.0)
Protein pea	30.0*	(17.2)	0.8	(1.6)	1.5	(2.4)	-5.3	(3.5)	32.9*	(16.8)
Yield value or input cost sample mean	1,377		240		63		125		949	
Barley (reference pre crop: wheat)										
Barley	-27.1**	(11.5)	0.6	(1.3)	1.9**	(0.9)	-0.5	(1.9)	-29.1**	(11.9)
Corn	-46.6**	(20.1)	-0.1	(2.8)	-2.1	(1.5)	-7.4**	(3.3)	-37.0	(20.5)
Sugar beet	34.6**	(11.5)	-0.1	(1.1)	-1.7	(1.0)	0.9	(1.9)	35.5**	(11.8)
Yield value or input cost sample mean	1,141		181		30		76		854	

*Note: Symbol **, respectively *, indicates that the parameter is significantly estimated at the 5%, respectively 10%, level. Estimated standard deviations of the parameter estimates are in parentheses.*

Table 8a reports the effects of changing the pre crop of wheat and barley from their respective reference pre crop to pre crops that have significant effects according to our estimation results. Growing wheat after wheat rather than after rapeseed entail an average loss of 53 €/ha, which amounts to 4.6% of the average wheat return to chemical inputs. On the contrary, growing wheat after protein pea rather than after rapeseed increases wheat crop return by 33 €/ha on average. Most of these effects on wheat return are due to pre crop effects on wheat yield levels, as pre crop effects on input uses are fairly limited in general.

Changing the pre crop of barley to corn or barley entails losses while changing to sugar beet implies gains of around 35€/ha. As in the case of wheat, these effects on barley return are mostly due to pre crop effects on barley yield levels. Their magnitude is limited as they represent around 4% of the average barley return to chemical inputs.

Table 8b reports the average effects of crop acreage diversity, as measured here by the number of grown crops, on crop returns to chemical inputs. Farmers growing wheat as part of a 7 crops acreage improves wheat return by 31.8 €/ha on average compared to growing wheat as part of a 5 crop acreage. Similarly, growing wheat as part of a 3 crops acreage instead of a 5 crop one entails an average loss of 32.1 €/ha.

Comparable results are obtained for the other considered crops. For instance, the return of barley is improved by 85.2 €/ha on average when the number of grown crops increases from 3 to 7. Increasing the number of grown crops from 5 to 7 leads to average return increases of 67.2 €/ha for rapeseed and of 57.7 €/ha for sugar beet.

Table 8b: Economic assessment of crop diversity effects (€/ha), average effects at average price levels (2008–2014)

	Economic value of the number of grown crops, *versus* 5 grown crops (€/ha)									
	Yield value		Nitrogen fertilizer cost		Herbicide cost		Other pesticide cost		Return to chemical inputs	
	(1)		(2)		(3)		(4)		(1) - (2) - (3) - (4)	
	Wheat (reference: 5 crops)									
3 crops or less	-31.4**	(12.1)	-0.2	(1.5)	4.7**	(1.5)	-3.7	(3.3)	-32.1**	(12.7)
4 crops	-17.8**	(8.5)	0.2	(0.8)	1.9*	(1.0)	-3.2	(2.1)	-16.8**	(8.7)
6 crops	9.2	(6.9)	0.7	(0.6)	-1.6*	(0.9)	-0.3	(1.8)	10.4	(6.7)
7 crops or more	32.5**	(11.3)	1.2	(1.0)	-2.4	(1.7)	1.9	(2.9)	31.8**	(11.7)
Sample mean	1,377		240		63		125		948	
	Barley (reference: 5 crops)									
3 crops or less	-58.1**	(21.0)	-1.0	(2.9)	3.6	(2.0)	-2.4	(3.3)	-58.4**	(21.2)
4 crops	-31.6**	(11.7)	0.5	(1.1)	1.2	(0.8)	0.1	(1.7)	-33.3**	(11.9)
6 crops	3.0	(8.4)	0.4	(0.8)	-1.4**	(0.6)	-0.7	(1.3)	4.8	(8.4)
7 crops or more	24.1*	(12.6)	0.9	(1.4)	-1.3	(1.0)	-2.2	(2.2)	26.8**	(12.5)
Sample mean	1,141		181		30		76		854	
	Rapeseed (reference: 5 crops)									
3 crops or less	4.5	(24.8)	-0.9	(2.2)	11.1**	(3.6)	-0.8	(4.2)	-4.6	(24.6)
4 crops	-10.4	(13.3)	-0.7	(1.1)	8.1**	(1.9)	2.9	(2.4)	-20.6	(13.4)
6 crops	21.9**	(9.8)	1.6**	(0.8)	-2.4	(1.5)	-1.3	(1.9)	23.6**	(9.6)
7 crops or more	66.9**	(15.9)	1.7	(1.2)	-3.3	(2.5)	0.8	(3.1)	67.2**	(15.6)
Sample mean	1,381		233		99		109		940	
	Sugar beet (reference: 5 crops)									
3 crops or less	-198.8	(104.3)	4.4	(17.4)	12.1	(59.3)	3.1	(18.2)	-217.9	(153.1)
4 crops	-27.9	(34.1)	2.4	(3.2)	4.2	(3.5)	0.9	(2.5)	-35.1	(34.3)
6 crops	36.1**	(15.9)	-0.3	(1.4)	-1.4	(2.4)	1.0	(1.6)	36.8**	(16.6)
7 crops or more	48.9**	(24.3)	-2.2	(1.9)	-5.3	(4.3)	-1.5	(2.8)	57.7**	(25.5)
Sample mean	2,424		294		161		96		1,874	

Note. Symbol **, respectively *, indicates that the parameter is significantly estimated at the 5%, respectively 10%, level. Estimated standard deviations of the parameter estimates are in parentheses.

As in the case of pre crop effects, crop acreage diversity effects are mostly due to effects on yield levels. Crop acreage diversity also significantly impacts herbicide uses from a statistical viewpoint although the related economic effects are limited. For instance, increasing the number of grown crops from 3 to 5 leads to savings in herbicide expenses on rapeseed of 11 €/ha on average, which equals to 11% of herbicide costs on rapeseed on average.

6. Concluding remarks

The main objective of this article is to estimate effects of crop diversity on yields and input uses. Because usually available datasets lack information regarding crop sequence acreages, we combine farm accounting data with IACS data, enriched with soil quality and weather data, and devise statistical models of yields and input uses. These models, which are defined as simultaneous equation systems, account for both input use endogeneity and unobserved heterogeneity of farms and farmers. In our application considering major arable crops in the Marne area, pre crops effects on yield levels are estimated relatively accurately and are generally consistent with the rankings provided by crop production experts. Estimated pre crop effects on input uses are small, suggesting that farmers tend to downplay them when deciding their chemical input use levels. Our results also show that crop acreage diversity, at least when described by a suitable set of indicators, increases yield levels and reduces pesticide uses, herbicide uses in particular. Taken together our results uncover statistically significant albeit economically limited effects of pre crops and crop acreage diversity on crop gross margins, at least in the economic context prevailing from 2008 to 2014.

Crop sequence acreages in our dataset are highly concentrated on the most profitable ones. This demonstrates that farmers' crop sequence acreages are economically rational but this also underlies an important drawback of farm data for estimating pre crop effects. Farmers' crop sequence choice patterns imply that pre crop effects can only be estimated for a limited number of previous crops and only for major crops. We interpret the fact that estimated effects on input uses are small as a consequence of farmers' neglecting these effects. Yet, other explanations can be put forward, including measurement errors in crop sequence acreages.

Although our application reveals statistically significant crop acreage diversity effects on both crop yield and herbicide use levels, our approach does not enable us to disentangle (long run) cropping system effects from (current) spatial crop diversity effects. Our constructing the crop acreage diversity indicators that we use based on lagged acreage and results obtained by using the farm crop acreage histories suggest, but do not prove, that our estimated crop acreage diversity effects mostly capture cropping system effects. More generally, our approach identifies crop diversity effects by comparing the production choices and performances of farms characterized by heterogeneous crop acreages. Although we control for confounding factors by relying on detailed soil property measures, we cannot control for farmer skill heterogeneity that may impact both crop level production choices and crop acreage choices.

Our modelling framework accounts for significant unobserved heterogeneity effects in crop input demand and yield function models. However, it also relies on simplifying assumptions that can impact our empirical results to some extent. For instance, our crop yield models allow for heterogeneous productivity effects of chemical inputs but they assume homogenous pre crop and crop acreage diversity effects. Our crop sequence yield models are linear in input uses and entail additively separable pre crop effects. Control variable effects are assumed not to depend on the considered pre crop. These features of the crop sequence yield models we consider are convenient for aggregating them at the crop level but investigating their impacts on our estimation results is worthy albeit challenging.

Our empirical results tend to show that crop diversification positively impacts the yield levels of major crops, that is to say of the crops that contribute the most to farmers' revenue– *i.e.*, straw cereals, rapeseed and sugar beet in our application. They also suggest that crop diversification has limited effects on chemical input uses on these major crops. Despite their being significant from a statistical viewpoint, the agronomic effects revealed by our study have relatively small impacts on the returns of major crops. This may explain why EU farmers keep on using relatively specialized crop rotations and crop acreages. Typical diversification crops such as grain legumes are minor crops in the UE, mostly due to their insufficient profitability in comparison to that of major crops (*e.g.*, Bues *et al* 2013, Magrini *et al* 2016, Zander *et al* 2016, Watson *et al* 2017). The positive effects of crop diversity on the economic returns of major arable crops are unlikely to suffice for covering the opportunity cost of inserting typical diversification crops in otherwise specialized crop mixes (*e.g.*, Carpentier *et al* 2021).

Given our results, policy measures aimed to foster crop diversification are unlikely to significantly reduce chemical input uses on major crops if they are not supplemented by measures specifically aimed to reduce the uses of these inputs. Significant increases in the prices of pesticides and chemical fertilizers may partly solve this issue. First, this would increase the value of the chemical input use reductions on the major crops permitted by crop diversification and, as a result, could lead farmers to pay more attention to these reductions. Second, this would reduce the impact of the opportunity cost of inserting legumes in farmers' crop mixes since these typical diversification crops don't require nitrogen fertilization. Setting incentive taxes on chemical inputs would, however, significantly impacts arable crop producers' income. This calls for specific measures aimed to neutralize, at least partly, the income effects of the considered taxing scheme, even if only for acceptability purpose.

Despite the limitations of our modelling framework and of the information content of our dataset we are confident in the internal validity of our empirical measures of the pre crop and crop acreage diversity effects on yield and chemical input use levels in the arable crop sector of the Marne area. The external validity of our results is, however, more debatable since our case study displays salient specific features. The Marne area counts among the most productive arable crop production basin in the EU and farmers in this area rely on both relatively high yielding – and, thus, intensive in chemical inputs – cropping practices and relatively diversified cropping systems. In particular, results obtained by Coulter *et al* (2011) related to corn based cropping systems in the US tend to demonstrates that high yielding cropping practices attenuate the effects of crop rotation diversification. This may explain why farmers downplay pre crop effects such as legume nitrogen surpluses or break crop effects on biotic pressures. These effects may induce too limited chemical input use savings for farmers to put much effort for valuing them. Also, pre crop effects, break crop ones in particular, may be less pronounced in diversified crop rotations than they are in specialized ones. Of course, further investigations, by economists and agronomists, are required for supporting or refuting these hypotheses.

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Appendix A. Sketch of the SAEM algorithm

The crop yield and input use models considered in our study is a simultaneous equations model featuring both fixed and random parameters:

(A.1) $$\begin{cases} y_{it} - \mathbf{x}_{it}'\boldsymbol{\beta}_i = \mu_i^{(y)} + \mathbf{w}_{it}'\mathbf{a}_0^{(y)} + \varepsilon_{it}^{(y)} \\ \mathbf{x}_{it} = \boldsymbol{\mu}_i^{(x)} + \mathbf{W}_{it}^{(x)}\mathbf{a}_0^{(x)} + \boldsymbol{\varepsilon}_{it}^{(x)} \end{cases}$$

where $\mathbf{W}_{it}^{(x)} = \boldsymbol{\iota}_J \otimes \mathbf{w}_{it}'$. Equation system (A.1) is a typical recursive (linear) simultaneous equation system. Dependent variable $\mathbf{x}_{it}$ appears in the structural equation of y_{it} while dependent variable y_{it} does not appear in the structural equation of $\mathbf{x}_{it}$.

We assume that $\boldsymbol{\gamma}_i = (\mu_i^{(y)}, \boldsymbol{\mu}_i^{(x)}, \boldsymbol{\beta}_i) \sim \mathcal{N}(\boldsymbol{\eta}_0, \boldsymbol{\Omega}_0)$, $\varepsilon_{it}^{(y)} \sim \mathcal{N}(0, \psi_0^{(y)})$ and $\boldsymbol{\varepsilon}_{it}^{(x)} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\psi}_0^{(x)})$. Random terms $\boldsymbol{\gamma}_i$, $\boldsymbol{\varepsilon}_i^{(y)} = (\varepsilon_{it}^{(y)} : t = 1,\ldots,T)$ and $\boldsymbol{\varepsilon}_i^{(x)} = (\boldsymbol{\varepsilon}_{it}^{(x)} : t = 1,\ldots,T)$ are assumed mutually independent and independent of $\mathbf{w}_i = (\mathbf{w}_{it} : t = 1,\ldots,T)$. Terms $\varepsilon_{it}^{(y)}$ and $\mathbf{x}_i = (\mathbf{x}_{it} : t = 1,\ldots,T)$ are assumed independent. These assumptions imply that equation system (A.1) only contains regression equations conditionally on $\mathbf{w}_{it}$ and $\boldsymbol{\gamma}_i$, which is the main statistical feature of the so-called seemingly unrelated regression (SUR) systems of Zellner (1962). Finally, terms $\varepsilon_{it}^{(y)}$ and $\boldsymbol{\varepsilon}_{it}^{(x)}$ are assumed serially uncorrelated.

We consider the following compact form:

(A.2) $\mathbf{B}_i \mathbf{q}_{it} = \boldsymbol{\mu}_i + \mathbf{W}_{it}\mathbf{a}_0 + \boldsymbol{\varepsilon}_{it}$,

where $\boldsymbol{\mu}_i = (\mu_i^{(y)}, \boldsymbol{\mu}_i^{(x)})$, $\mathbf{q}_{it} = (y_{it}, \mathbf{x}_{it})$, $\mathbf{W}_{it} = \boldsymbol{\iota}_{J+1} \otimes \mathbf{w}_{it}'$, $\mathbf{a}_0 = (\mathbf{a}_0^{(y)}, \mathbf{a}_0^{(x)})$, $\boldsymbol{\varepsilon}_{it} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\psi}_0)$, and

(A.3) $\mathbf{B}_i = \begin{bmatrix} 1 & -\boldsymbol{\beta}_i \\ \mathbf{0} & \mathbf{I}_J \end{bmatrix}$ and $\boldsymbol{\psi}_0 = \begin{bmatrix} \psi_0^{(y)} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\psi}_0^{(x)} \end{bmatrix}$.

The considered model being fully parametric, estimation of its parameters is considered in the ML estimation framework. EM type algorithms are convenient for computing ML estimators for models featuring random parameters (*e.g.*, Dempster *et al* 1977, Lavielle 2014). We proceed in two steps for presenting the computation procedure we employ for estimating our models. First, we present how a classical (*i.e.*, deterministic) EM algorithm could be designed for estimating our models in theory. This enables us to present the main concepts underlying the design of EM type algorithm. Second, we explain why a stochastic version EM algorithm is needed in our case and present the stochastic approximate EM (SAEM) we use. SAEM algorithms were proposed by Delyon *et al* (1999) and further developed afterwards (*e.g.*, Kuhn and Lavielle 2005, Lavielle 2014).

Let $\boldsymbol{\theta}_0 = \left(\mathbf{a}_0, \psi_0^{(y)}, vech(\boldsymbol{\psi}_0^{(x)}), \boldsymbol{\gamma}_0, vech(\boldsymbol{\Omega}_0)\right)$ be the vector of parameters to be estimated. Let define vectors $\mathbf{q}_i = (\mathbf{q}_{it} : t \in \mathcal{H}_i)$ and $\mathbf{w}_i = (\mathbf{w}_{it} : t \in \mathcal{H}_i)$ where set $\mathcal{H}_i \subseteq \{1,\ldots,T\}$ denotes the time span on which farm i is observed. The observed data are given by $(\mathbf{q}_i,\mathbf{w}_i)$ for $i=1,...,N$. The complete data are given by $(\mathbf{q}_i,\mathbf{w}_i,\boldsymbol{\gamma}_i)$ and $i=1,...,N$. Let function $\varphi(\mathbf{u};\boldsymbol{\Xi})$ denote the probability distribution function of $\mathcal{N}(\mathbf{0},\boldsymbol{\Xi})$ at $\mathbf{u}$. The contribution of observation i to the sample likelihood function at $\boldsymbol{\theta}$ (conditional on exogenous variables $\mathbf{w}_i$) is given by

(A.4) $$\ell_i(\boldsymbol{\theta})=\int\left(\prod\nolimits_{t\in\mathcal{H}_i}\varphi(\mathbf{Bq}_{it}-\boldsymbol{\mu}-\mathbf{W}_{it}\mathbf{a};\boldsymbol{\psi})\right)\varphi(\boldsymbol{\gamma}-\boldsymbol{\eta};\boldsymbol{\Omega})d\boldsymbol{\gamma},$$

which is difficult to integrate due to the dimension of $\boldsymbol{\gamma}$. Note, however, that

(A.5) $$\ln\varphi(\mathbf{Bq}_{it}-\boldsymbol{\mu}+\mathbf{W}_{it}\mathbf{a};\boldsymbol{\psi})=\ln\varphi(y_{it}-\mathbf{x}_{it}'\boldsymbol{\beta}-\mu^{(y)}-\mathbf{w}_{it}'\mathbf{a}_0^{(y)};\psi^{(y)})+\ln\varphi(\mathbf{x}_{it}-\boldsymbol{\mu}^{(x)}-\mathbf{W}_{it}^{(x)}\mathbf{a}_0^{(x)};\boldsymbol{\psi}^{(x)})$$

since $\mathbf{x}_{it}$ is exogenous in the model of y_{it} conditionally on $\boldsymbol{\gamma}_i$. The contribution of observation i to the complete sample log-likelihood function at $\boldsymbol{\theta}$ (conditional on exogenous variables $\mathbf{w}_i$) is given by

(A.6) $$\ln\ell_i^c(\boldsymbol{\theta};\boldsymbol{\gamma}_i)=\sum\nolimits_{t\in\mathcal{H}_i}\ln\varphi(\mathbf{B}_i\mathbf{q}_{it}-\boldsymbol{\mu}_i-\mathbf{W}_{it}\mathbf{a};\boldsymbol{\psi})+\ln\varphi(\boldsymbol{\gamma}_i-\boldsymbol{\eta};\boldsymbol{\Omega}),$$

Implying that the complete data log-likelihood function is given by

(A.7) $$\ln L^c(\boldsymbol{\theta})=\sum\nolimits_{i=1}^N\ln\ell_i^c(\boldsymbol{\theta};\boldsymbol{\gamma}_i)=\sum\nolimits_{i=1}^N\sum\nolimits_{t\in\mathcal{H}_i}\ln\varphi(\mathbf{B}_i\mathbf{q}_{it}-\boldsymbol{\mu}_i-\mathbf{W}_{it}\mathbf{a};\boldsymbol{\psi})+\sum\nolimits_{i=1}^N\ln\varphi(\boldsymbol{\gamma}_i-\boldsymbol{\eta};\boldsymbol{\Omega})$$

or, equivalently, by

(A.8) $$\begin{aligned}\ln L^c(\boldsymbol{\theta})=cst&-\tfrac{1}{2}\sum\nolimits_{i=1}^N\sum\nolimits_{t\in\mathcal{H}_i}\left\{\ln\det(\boldsymbol{\psi})+(\mathbf{B}_i\mathbf{q}_{it}-\boldsymbol{\mu}_i-\mathbf{W}_{it}\mathbf{a})'\boldsymbol{\psi}^{-1}(\mathbf{B}_i\mathbf{q}_{it}-\boldsymbol{\mu}_i-\mathbf{W}_{it}\mathbf{a})\right\}\\&-\tfrac{1}{2}\sum\nolimits_{i=1}^N\left\{\ln\det(\boldsymbol{\Omega})+(\boldsymbol{\gamma}_i-\boldsymbol{\eta})'\boldsymbol{\Omega}^{-1}(\boldsymbol{\gamma}_i-\boldsymbol{\eta})\right\}\end{aligned}$$

or

(A.9) $$\begin{aligned}\ln L^c(\boldsymbol{\theta})=cst&-\tfrac{1}{2}\sum\nolimits_{i=1}^N\sum\nolimits_{t\in\mathcal{H}_i}\left\{\ln\det(\boldsymbol{\psi})+tr\left(\boldsymbol{\psi}^{-1}(\mathbf{B}_i\mathbf{q}_{it}-\boldsymbol{\mu}_i-\mathbf{W}_{it}\mathbf{a})(\mathbf{B}_i\mathbf{q}_{it}-\boldsymbol{\mu}_i-\mathbf{W}_{it}\mathbf{a})'\right)\right\}\\&-\tfrac{1}{2}\sum\nolimits_{i=1}^N\left\{\ln\det(\boldsymbol{\Omega})+tr\left(\boldsymbol{\Omega}^{-1}(\boldsymbol{\gamma}_i-\boldsymbol{\eta})(\boldsymbol{\gamma}_i-\boldsymbol{\eta})'\right)\right\}\end{aligned}.$$

Let function $\pi(\boldsymbol{\gamma}\,|\,\mathbf{q},\mathbf{w};\boldsymbol{\theta})$ denote the probability distribution function of $\boldsymbol{\gamma}_i$ at $\boldsymbol{\gamma}$ conditionally on $\mathbf{q}_i=\mathbf{q}$ and $\mathbf{w}_i=\mathbf{w}$ when $\boldsymbol{\theta}_0=\boldsymbol{\theta}$. In our setting, the EM algorithm consists of iterating a sequence composed of two steps until numerical convergence. Let term $\boldsymbol{\theta}^{(n)}$ denote the estimate of $\boldsymbol{\theta}_0$ obtained at the end of iteration n. At iteration $n+1$ the expectation (E) consists of computing the expectation of the complete data log-likelihood function at $\boldsymbol{\theta}$, $\ln L^c(\boldsymbol{\theta})$, conditionally on the observed data (*i.e.*, on $(\mathbf{q}_i,\mathbf{w}_i)$ for $i=1,...,N$) assuming that $\boldsymbol{\theta}_0=\boldsymbol{\theta}^{(n)}$. The resulting conditional expectation is given by $\mathcal{L}(\boldsymbol{\theta}\,|\,\boldsymbol{\theta}^{(n)})=\sum\nolimits_{i=1}^N\int\ln\ell_i^c(\boldsymbol{\theta};\boldsymbol{\gamma})\pi(\boldsymbol{\gamma}\,|\,\mathbf{q}_i,\mathbf{w}_i;\boldsymbol{\theta}^{(n)})d\boldsymbol{\gamma}$. The corresponding maximization (M) step consists of computing $\boldsymbol{\theta}^{(n+1)}=\arg\max_{\boldsymbol{\theta}}\mathcal{L}(\boldsymbol{\theta}\,|\,\boldsymbol{\theta}^{(n)})$ for updating the ML estimate of $\boldsymbol{\theta}_0$. Due to the interaction term $\mathbf{x}_{it}'\boldsymbol{\beta}_i$ in the yield function, density function $\pi(\boldsymbol{\gamma}\,|\,\mathbf{q},\mathbf{w};\boldsymbol{\theta})$ is not standard in our case.

Monte Carlo or stochastic versions of the EM algorithm can be used for managing the expectation integration issue raised above (*e.g.*, McLachlan and Peel 2007, Lavielle 2014). As their competing counterparts, SAEM algorithms involve integration with simulation methods. They, however, make a more efficient use of simulation draws by recycling past draws for constructing a stochastic approximate of the sample log-likelihood function (Lavielle *et al* 2014). SAEM algorithms proceed by iterating a sequence composed of three steps until numerical convergence: a simulation (S) step, a stochastic approximation (SA) step and a maximization (M) step.

At iteration $n+1$ the S step consists of drawing $R_{(n)}$ simulations of $\boldsymbol{\gamma}_i$ from the density $\pi(\boldsymbol{\gamma}_i \,|\, \mathbf{q}_i, \mathbf{w}_i; \boldsymbol{\theta}^{(n)})$, for $i=1,...,N$. Let term $\tilde{\boldsymbol{\gamma}}_{i,r}^{(n)}$ denote these draws for $r=1,...,R_{(n)}$ and $i=1,...,N$. Simulation numbers vary in the course of the algorithm. They need to be small (10 in our case) at the beginning, for exploring the parameter space, and large (100 in our case) near the end of the iterative procedure, for speeding up the convergence process. To perform the S step, we rely on a MCMC sampler that has $\pi(\boldsymbol{\gamma} \,|\, \mathbf{q}_i, \mathbf{w}_i; \boldsymbol{\theta}^{(n)})$ as its stationary distribution density at iteration n for farm i. Specifically, we use a Metropolis-Hasting sampler with a normal random walk kernel. We draw $R_{(n)}$ simulations $\tilde{\boldsymbol{\gamma}}_{i,r}^{(n)}$ ($r=1,...,R_{(n)}$) after "burning" the first fifty draws for each sampled farm. The transition kernel distribution used for drawing $\tilde{\boldsymbol{\gamma}}_{i,r}^{(n)}$ is given by $\mathcal{N}(\tilde{\boldsymbol{\gamma}}_{i,r-1}^{(n)}, \boldsymbol{\Phi}^{(n)})$ where $\boldsymbol{\Phi}^{(n)}$ is a diagonal matrix that is adaptively adjusted for reaching acceptance rates between 0.24 and 0.4. The acceptance probability is given by $\tau_{i,r}^{(n)} = \min\{1, \ell_i^c(\boldsymbol{\theta}; \tilde{\boldsymbol{\gamma}}) \ell_i^c(\boldsymbol{\theta}; \tilde{\boldsymbol{\gamma}}_{i,r-1}^{(n)})^{-1}\}$ when is $\tilde{\boldsymbol{\gamma}}$ a candidate for $\tilde{\boldsymbol{\gamma}}_{i,r}^{(n)}$, that is to say $\tilde{\boldsymbol{\gamma}}$ is accepted (and, thus, $\tilde{\boldsymbol{\gamma}}_{i,r}^{(n)} = \tilde{\boldsymbol{\gamma}}$) with probability $\tau_{i,r}^{(n)}$, and a new value of $\tilde{\boldsymbol{\gamma}}$ is drawn otherwise.

The SA step consists of updating the stochastic approximate of the sample log-likelihood function based on the following recursive formula:

(A.10) $$Q_{(n)}(\boldsymbol{\theta}) = (1-\lambda_{(n)}) Q_{(n-1)}(\boldsymbol{\theta}) + \lambda_{(n)} \sum_{i=1}^{N} R_{(n)}^{-1} \sum_{r=1}^{R_{(n)}} \log \ell_i^c(\boldsymbol{\theta}; \tilde{\boldsymbol{\gamma}}_{i,r}^{(n)})$$

where weight parameter $\lambda_{(n)} > 0$ needs to decrease in n provided that $\lambda_{(1)} = 1$, $\sum_{n=1}^{+\infty} \lambda_{(n)} = +\infty$ and $\sum_{n=1}^{+\infty} \lambda_{(n)}^2 < +\infty$. We follow Kuhn and Lavielle (2005) and define $\lambda_{(n)}$ as

(A.11) $$\lambda_{(n)} = \begin{cases} 1 \text{ for } n_1 \geq n \geq 1 \\ (n-n_1+1)^{3/4} \text{ for } n > n_1 \end{cases}.$$

for implementing the SAEM algorithm in our application.

Finally, the M step consists of updating the estimate of $\boldsymbol{\theta}_0$ from $\boldsymbol{\theta}^{(n)}$ to according to $\boldsymbol{\theta}^{(n+1)} = \operatorname{argmax}_{\boldsymbol{\theta}} Q_{(n)}(\boldsymbol{\theta})$. Parameter n_1 needs to be chosen such that $\boldsymbol{\theta}^{(n)}$ for $n \geq n_1$ lies in the neighborhood of the solution to the considered optimization process, that is say as soon as

$\boldsymbol{\theta}^{(n+1)} \simeq \boldsymbol{\theta}^{(n)}$ while the elements of $\boldsymbol{\theta}^{(n)}$ don't demonstrate any specific trend as n grows.

SAEM algorithms are particularly well suited when the complete data likelihood function belongs to the exponential family. In this case, the SA step consists of updating sufficient statistics while the M step only involve simple analytical computations. In our setting, the SA step at iteration n just consists of applying the following recursive formulas:

(A.12)

$$\begin{cases} \mathbf{s}_{\gamma,i}^{(n)} = (1-\lambda_{(n)})\mathbf{s}_{\gamma,i}^{(n-1)} + \lambda_{(n)} R_{(n)}^{-1} \sum_{r=1}^{R_{(n)}} \tilde{\boldsymbol{\gamma}}_{i,r}^{(n)}, \text{ for } i = 1,\ldots,N \\ \mathbf{S}_{\gamma\gamma,i}^{(n)} = (1-\lambda_{(n)})\mathbf{S}_{\gamma\gamma,i}^{(n-1)} + \lambda_{(n)} R_{(n)}^{-1} \sum_{r=1}^{R_{(n)}} \tilde{\boldsymbol{\gamma}}_{i,r}^{(n)} (\tilde{\boldsymbol{\gamma}}_{i,r}^{(n)})', \text{ for } i = 1,\ldots,N \\ \mathbf{s}_{q,it}^{(n)} = (1-\lambda_{(n)})\mathbf{s}_{q,it}^{(n-1)} + \lambda_{(n)} R_{(n)}^{-1} \sum_{r=1}^{R_{(n)}} (\tilde{\mathbf{B}}_{i,r}^{(n)} \mathbf{q}_{it} - \tilde{\boldsymbol{\mu}}_{i,r}^{(n)}), \text{ for } t \in \mathcal{H}_i \text{ and } i = 1,\ldots,N \\ \mathbf{S}_{q,it}^{(n)} = (1-\lambda_{(n)})\mathbf{S}_{qq,it}^{(n-1)} + \lambda_{(n)} R_{(n)}^{-1} \sum_{r=1}^{R_{(n)}} (\tilde{\mathbf{B}}_{i,r}^{(n)} \mathbf{q}_{it} - \tilde{\boldsymbol{\mu}}_{i,r}^{(n)} - \mathbf{W}_{it}\mathbf{a}^{(n)})(\tilde{\mathbf{B}}_{i,r}^{(n)} \mathbf{q}_{it} - \tilde{\boldsymbol{\mu}}_{i,r}^{(n)} - \mathbf{W}_{it}\mathbf{a}^{(n)})', \text{ for } t \in \mathcal{H}_i \text{ and } i = 1,\ldots,N \end{cases}$$

while the corresponding M step just consists of applying the following recursive formulas:

$$\text{(A.13)} \quad \begin{cases} \boldsymbol{\eta}^{(n)} = N^{-1} \sum_{i=1}^{N} \mathbf{s}_{\gamma,i}^{(n)} \\ \boldsymbol{\Omega}^{(n)} = N^{-1} \mathbf{S}_{\gamma\gamma,i}^{(n)} - \boldsymbol{\eta}^{(n)} \boldsymbol{\eta}^{(n)\prime} \\ \mathbf{a}^{(n)} = \left(\sum_{i=1}^{N} \sum_{t\in\mathcal{H}_i} \mathbf{W}_{it}' (\boldsymbol{\Psi}^{(n-1)})^{-1} \mathbf{W}_{it} \right)^{-1} \sum_{i=1}^{N} \sum_{t\in\mathcal{H}_i} \mathbf{W}_{it}' (\boldsymbol{\Psi}^{(n-1)})^{-1} \mathbf{W}_{it} \mathbf{s}_{q,it}^{(n)} \\ \boldsymbol{\Psi}^{(n)} = M^{-1} \sum_{i=1}^{N} \sum_{t\in\mathcal{H}_i} \left(\mathbf{S}_{qq,it}^{(n)} - \mathbf{W}_{it}\mathbf{a}^{(n)} \mathbf{s}_{q,it}^{(n)\prime} - \mathbf{s}_{q,it}^{(n)} \mathbf{a}^{(n)\prime} \mathbf{W}_{it}' + \mathbf{W}_{it}\mathbf{a}^{(n)} \mathbf{a}^{(n)\prime} \mathbf{W}_{it}' \right) \end{cases}$$

where $M = \sum_{i=1}^{N} H_i$ is the number of observations in the considered sample, term H_i being the cardinality of set $\mathcal{H}_i$ (*i.e.*, the number of observations related to farm *i* in the sample).

Appendix B. Economic value of pre crop and crop diversity effects

Let rewrite the model of the use of input j for crop k as:

(B.1) $$x_{j,mk,it}=\mu^{(y)}_{j,k,i}+\alpha^{(x)}_{j,k,t,0}+a^{(x)}_{j,mk,0}+\delta^{(x)}_{j,n,k,0}+\mathbf{v}'_{j,k,it}\boldsymbol{\zeta}^{(x)}_{j,k,0}+\varepsilon^{(x)}_{j,k,it}$$

when crop m is the pre crop and the number of grown crops, $\kappa_{i,t-1}$, equals n. Vector $\mathbf{v}_{j,k,it}$ collects the control variables of the model (dummy variables indicating year t and $\kappa_{i,t-1}=n$ excepted). Parameter $a^{(x)}_{j,mk,0}$ defines the effect of pre crop m on the use of input j for crop k given that crop $r(k)$ is the reference crop of crop k (*i.e.*, $a^{(x)}_{j,r(k)k,0}=0$). It corresponds to $x_{j,mk,it}-x_{j,ref(k)k,it}$ and it is value at

(B.2) $$\Delta^{(x)}_{pre,j,k}(m)=p^{(x)}_{j,k}a^{(x)}_{j,mk,0}$$

when input j is purchased at price $p^{(x)}_{j,k}$.

Parameter $\delta^{(x)}_{j,n,k,0}$ defines the effect of growing n crops on the use of input j for crop k given that growing 5 crops is the reference situation (*i.e.*, $\delta^{(x)}_{j,5,k,0}=0$). The effect of growing crop k as part of n crop set rather than a 5 crop set on the use of input j is valued at

(B.3) $$\Delta^{(x)}_{div,j,k}(n)=p^{(x)}_{j,k}\delta^{(x)}_{j,n,k,0}.$$

Let rewrite the yield function crop k as:

(B.4) $$y_{mk,it}=\mu^{(y)}_{k,i}+\alpha^{(y)}_{k,t,0}+a^{(y)}_{mk,0}+\delta^{(y)}_{n,k,0}+\sum\nolimits_{j\in\mathcal{J}}\beta_{j,k,i}x_{j,mk,it}+\mathbf{v}'_{k,it}\boldsymbol{\zeta}^{(y)}_{k,0}+\varepsilon^{(y)}_{k,it}$$

when crop m is the pre crop and the number of grown crops, $\kappa_{i,t-1}$, equals n. Vector $\mathbf{v}_{k,it}$ collects the control variables of the model (dummy variables indicating year t and $\kappa_{i,t-1}=n$ excepted). Parameter $a^{(y)}_{mk,0}$ defines the direct effect of pre crop m on the yield of crop k given that crop $r(k)$ is the reference crop of crop k (*i.e.*, $a^{(y)}_{r(k)k,0}=0$). The effect of pre crop m on the yield of crop k that pass through adjustments in input uses is given by $\sum_{j\in\mathcal{J}}\beta_{j,k,i}a^{(x)}_{j,mk,0}$. Accordingly, the total effect of pre crop m on the yield of crop k (given that crop $r(k)$ is the reference crop of crop k) is given by $y_{mk,it}-y_{ref(k)k,it}=a^{(y)}_{mk,0}+\sum_{j\in\mathcal{J}}\beta_{j,k,i}a^{(x)}_{j,mk,0}$. It is valued at

(B.5) $$\Delta^{(y)}_{pre,k}(m)=p^{(y)}_{k}a^{(y)}_{mk,0}+p^{(y)}_{k}\sum\nolimits_{j\in\mathcal{J}}\beta_{j,k,0}a^{(x)}_{j,mk,0}$$

when crop k is sold at price $p^{(y)}_{k}$ and parameter $\boldsymbol{\beta}_{k,i}=(\beta_{j,k,i}:j\in\mathcal{J})$ is set at its mean value, $\boldsymbol{\beta}_{k,0}=E[\boldsymbol{\beta}_{k,i}]$ with $\boldsymbol{\beta}_{k,0}=(\beta_{j,k,0}:j\in\mathcal{J})$. The corresponding effect on crop k return to chemical inputs is given by

(B.6) $$\Delta^{(\pi)}_{pre,k}(m)=\Delta^{(y)}_{pre,k}(m)-\sum\nolimits_{j\in\mathcal{J}}\Delta^{(x)}_{pre,j,k}(m)=p^{(y)}_{k}a^{(y)}_{mk,0}+\sum\nolimits_{j\in\mathcal{J}}(p^{(y)}_{k}\beta_{j,k,0}-p^{(x)}_{j,k})a^{(x)}_{j,mk,0}.$$

Parameter $\delta^{(y)}_{n,k,0}$ defines the direct effect of growing n crops on the yield of crop k given that growing 5 crops is the reference situation (*i.e.*, $\delta^{(y)}_{5,k,0}=0$) while term $\sum_{j\in\mathcal{J}}\beta_{j,k,i}\delta^{(x)}_{j,n,0}$ gives the effect that pass through adjustments in input uses. The total effect of growing n crops instead of 5 crops on the yield of crop k is valued at

(B.7) $\Delta^{(y)}_{div,k}(n)=p^{(y)}_k\delta^{(y)}_{j,n,0}+p^{(y)}_k\sum_{j\in\mathcal{J}}\beta_{j,k,0}\delta^{(x)}_{j,n,0}$

when crop k is sold at price $p^{(y)}_k$ and $\boldsymbol{\beta}_{k,i}=\boldsymbol{\beta}_{k,0}$. The congruent effect on crop k return to chemical inputs is given by

(B.8) $\Delta^{(\pi)}_{div,k}(n)=\Delta^{(y)}_{div,k}(n)-\sum_{j\in\mathcal{J}}\Delta^{(x)}_{div,j,k}(n)=p^{(y)}_k\delta^{(y)}_{n,0}+\sum_{j\in\mathcal{J}}(p^{(y)}_k\beta_{j,k,0}-p^{(x)}_{j,k})\delta^{(x)}_{j,n,0}$.

The economic values of pre crop or acreage diversity effects on input use, yield or crop return levels presented above – *i.e.*, terms $\Delta^{(x)}_{pre,j,k}(m)$, $\Delta^{(y)}_{pre,k}(m)$, $\Delta^{(\pi)}_{pre,k}(m)$, $\Delta^{(x)}_{div,j,k}(n)$, $\Delta^{(y)}_{div,k}(n)$ and $\Delta^{(\pi)}_{div,k}(n)$ – are defined as functions of fixed parameters – *i.e.*, parameters $a^{(y)}_{mk,0}$, $\mathbf{a}^{(x)}_{mk,0}=(a^{(x)}_{j,mk,0}:j\in\mathcal{J})$, $\delta^{(y)}_{n,0}$, $\boldsymbol{\delta}^{(x)}_{n,0}=(\delta^{(x)}_{j,n,0}:j\in\mathcal{J})$ and $\boldsymbol{\beta}_{k,0}$ – and of chosen price levels – *i.e.*, $p^{(y)}_k$ and $\mathbf{p}^{(x)}_k=(p^{(x)}_{j,k}:j\in\mathcal{J})$. Let collect the involved parameters in vector $\boldsymbol{\xi}_0=(a^{(y)}_{mk,0},\mathbf{a}^{(x)}_{mk,0},\delta^{(y)}_{n,0},\boldsymbol{\delta}^{(x)}_{n,0},\boldsymbol{\beta}_{k,0})$.

Consistent estimates of economic values of pre crop or acreage diversity effects are obtained by replacing $\boldsymbol{\xi}_0$ by its ML estimator $\hat{\boldsymbol{\xi}}_M$, which is $M^{1/2}$ consistent (*i.e.*, asymptotically normal in M). The approximate asymptotic distribution of these value estimates can easily be obtained from that of $\hat{\boldsymbol{\xi}}_M$ by using the so-called delta method (*e.g.*, Wooldridge 2010), which is based on the following well-known result. If term $\hat{\boldsymbol{\xi}}_M$ is a $M^{1/2}$ consistent estimator of $\boldsymbol{\xi}_0$ with $M^{1/2}(\hat{\boldsymbol{\xi}}_M-\boldsymbol{\xi}_0)\xrightarrow[M\to+\infty]{D}\mathcal{N}(\mathbf{0},\boldsymbol{\Upsilon}_0)$ and function $g(\boldsymbol{\xi})$ is continuously differentiable in $\boldsymbol{\xi}$ on the support of $\hat{\boldsymbol{\xi}}_M$ then term $g(\hat{\boldsymbol{\xi}}_M)$ is a $M^{1/2}$ consistent estimator of $g(\boldsymbol{\xi}_0)$ with $M^{1/2}\{g(\hat{\boldsymbol{\xi}}_M)-g(\boldsymbol{\xi}_0)\}\xrightarrow[M\to+\infty]{D}\mathcal{N}(\mathbf{0},\mathbf{g}_0'\boldsymbol{\Upsilon}_0\mathbf{g}_0)$ where $\mathbf{g}_0=\frac{\partial}{\partial\boldsymbol{\xi}}g(\boldsymbol{\xi}_0)$. If $\hat{\boldsymbol{\Upsilon}}_M$ is a consistent estimator of $\boldsymbol{\Upsilon}_0$ then the variance of $g(\hat{\boldsymbol{\xi}}_M)$ can be approximated by $M^{-1}\frac{\partial}{\partial\boldsymbol{\xi}'}g(\hat{\boldsymbol{\xi}}_M)\hat{\boldsymbol{\Upsilon}}_M\frac{\partial}{\partial\boldsymbol{\xi}}g(\hat{\boldsymbol{\xi}}_M)$.

Appendix C. Supplementary results

Climate is an important driver of agricultural output. We gathered several weather variables provided by *Meteo France,* the French National Weather Service, at the municipality level and used them to build different weather indicators, which were matched to our farm accountancy data through the municipality codes lying in the two datasets. Our weather indicators include a rainfall indicator, which corresponds to the total rainfall, measured in meters, during the growing season of each crop ; an evapotranspiration[41] indicator, which is computed as the difference between the actually measured average evapotranspiration level during the growing season and a potential evapotranspiration level of the season; a growing degree-days (in thousands) indicator which is useful to predict when a certain plant stage will occur, for instance when a crop will reach maturity; a cumulative visible radiation indicator (which is divided by 10^5 for rescaling purpose), and an average temperature indicator.

Table C1: Summary statistics on weather indicators

	Crops			
	Wheat	Barley	Rapeseed	Sugar beet
Rainfall (a)	0.61	0.33	0.60	0.74
	(0.08)	(0.12)	(0.07)	(0.07)
Evapotranspiration	-1.39	-0.66	-1.30	-2.26
	(0.47)	(0.37)	(0.35)	(0.47)
Growing degree days (b)	1.55	0.92	1.52	2.27
	(0.08)	(0.13)	(0.13)	(0.14)
Visible radiation (c)	3.13	2.08	2.92	3.97
	(0.29)	(0.32)	(0.30)	(0.32)
Average temperature	9.25	10.70	8.76	10.53
	(0.49)	(1.41)	(0.59)	(0.68)

a: in meters; b: Growing degree-days (in thousands); c: divided by 10^5 for rescaling purposes.

[41] Evapotranspiration is the process by which water is transferred from the land to the atmosphere by evaporation from the soil and by transpiration from plants.

Table C2: Soil quality indicators

	Mean	Std dev.	Min.	Max.
Organic carbon content (a)	15.03	1.60	10.57	23.12
Clay content (b)	2.61	0.27	1.57	3.72
Cation exchange capacity (c)	13.13	1.01	10.65	21.00
pH	7.84	0.28	6.58	8.14
Soil depth (d)	10.68	2.34	5.21	21.96
Water holding capacity (e)	13.78	1.32	10.85	18.44
Sand content (b)	1.92	0.47	0.71	3.74
Silt content (b)	5.09	0.42	3.28	6.91

*(a): in g/kg; (b): in hg/kg; (c): in 10^(-2)*mol/kg; (d): in meters; (e): in millimeters.*

Table C3: Other control variable estimates for yield equations

	Wheat	Barley	Rapeseed	Sugar beet
Soil quality				
Organic carbon	0.09***	0.07**	0.04*	1.96***
	(0.03)	(0.03)	(0.02)	(0.51)
Clay	-0.24	-0.07	0.02	-7.81**
	(0.19)	(0.23)	(0.14)	(3.12)
Cation exch. cap	-0.09***	-0.04	-0.08***	-0.80
	(0.03)	(0.03)	(0.02)	(0.52)
pH	0.43***	0.28	0.11	4.14*
	(0.14)	(0.18)	(0.10)	(2.39)
Soil depth	-0.04**	-0.02	-0.02**	-2.03***
	(0.02)	(0.02)	(0.01)	(0.30)
Water holding cap	0.13***	0.11***	0.09***	1.57***
	(0.03)	(0.03)	(0.02)	(0.49)
Sand	0.08	0.01	-0.09	3.61**
	(0.10)	(0.11)	(0.06)	(1.51)
Silt	0.20**	0.08	0.09	5.66***
	(0.09)	(0.11)	(0.06)	(1.38)
Weather conditions				
Rainfall	-3.26***	-3.48***	-0.40	-20.39**
	(0.69)	(0.78)	(0.42)	(9.53)
Evapotranspiration	0.19	0.67***	-0.09	9.06***
	(0.13)	(0.21)	(0.10)	(1.74)
Growing degree days	-1.95	1.41*	-4.69***	80.96***
	(1.37)	(0.79)	(1.01)	(19.72)
Visible radiation	-0.12	-0.19	-0.23**	6.27***
	(0.13)	(0.26)	(0.10)	(1.75)
Average temp.	-0.00	-0.26***	1.07***	-24.03***
	(0.29)	(0.05)	(0.21)	(5.28)
Year dummies				
2008	-1.07***	-0.03	-0.74***	18.52***
	(0.18)	(0.14)	(0.12)	(4.27)
2009	-0.04	0.51***	0.20***	24.96***
	(0.11)	(0.10)	(0.07)	(2.93)
2011	-0.07	-1.35***	0.42***	35.81***
	(0.05)	(0.16)	(0.05)	(4.70)
2012	-0.60***	0.26*	-0.23***	19.19***
	(0.16)	(0.14)	(0.08)	(3.16)
2013	-0.14	-0.06	-0.73***	15.66***
	(0.17)	(0.21)	(0.15)	(2.97)
2014	0.95***	0.15	-0.53**	36.42***
	(0.30)	(0.10)	(0.22)	(6.35)

** p<0.1; ** p<0.05; *** p<0.01: standard errors are in parentheses below the estimated coefficients.*

Table C4: Other control variable estimates for nitrogen equations

	Wheat	Barley	Rapeseed	Sugar beet
Soil quality				
Organic carbon	-0.52	-0.04	0.76	-2.26
	(0.93)	(0.89)	(1.19)	(1.78)
Clay	18.72***	16.64***	17.39**	11.57
	(6.10)	(5.93)	(7.37)	(10.94)
Cation exch. cap	-3.31***	-2.48***	-2.86***	-2.60*
	(0.89)	(0.89)	(1.08)	(1.51)
pH	4.02	-1.10	7.67	-13.18*
	(5.06)	(5.03)	(6.09)	(7.51)
Soil depth	-1.36**	-0.96*	-0.97	-1.25
	(0.57)	(0.56)	(0.74)	(1.08)
Water holding cap	0.38	-0.94	-0.95	0.10
	(0.99)	(0.94)	(1.18)	(1.70)
Sand	1.45	4.52	7.08*	-2.88
	(3.81)	(3.53)	(4.01)	(6.54)
Silt	4.82	6.70**	9.05**	0.45
	(3.22)	(3.16)	(3.61)	(5.57)
Weather conditions				
Rainfall	0.79	10.78	10.21	-48.35
	(25.21)	(25.28)	(30.33)	(37.22)
Evapotranspiration	3.24	-5.47	-7.55	15.30**
	(5.26)	(6.71)	(6.88)	(6.62)
Growing d-d	71.06	9.94	41.29	54.72
	(50.27)	(20.10)	(66.20)	(71.20)
Visible radiation	-13.04**	-16.05**	-8.67	1.13
	(5.09)	(6.96)	(6.68)	(6.38)
Average temp.	-15.78	-0.59	-8.36	-11.12
	(11.06)	(1.60)	(14.24)	(18.98)
Year dummies				
2008	4.51	-6.94*	6.59	-3.54
	(7.07)	(4.22)	(8.45)	(14.73)
2009	-3.40	-3.99	7.64	-3.99
	(4.74)	(2.95)	(4.93)	(10.14)
2011	0.11	-1.79	4.63	6.23
	(2.09)	(4.28)	(3.05)	(15.86)
2012	-0.07	-7.46**	-4.66	-4.88
	(6.19)	(3.61)	(5.15)	(10.92)
2013	-3.87	-3.86	2.07	4.40
	(6.01)	(6.06)	(10.01)	(10.65)
2014	9.93	2.26	5.27	-1.93
	(11.13)	(2.58)	(14.33)	(22.41)

** p<0.1; ** p<0.05; *** p<0.01: standard errors are in parentheses below the estimated coefficients.*

Table C5: Other control variable estimates for herbicides equations

	Wheat	Barley	Rapeseed	Sugar beet
Soil quality				
Organic carbon	-4.55^{***}	-2.78^{***}	-4.87^{***}	-7.84^{***}
	(0.61)	(0.45)	(1.05)	(2.33)
Clay	24.72^{***}	11.28^{***}	29.35^{***}	49.51^{***}
	(3.96)	(2.75)	(6.93)	(15.25)
Cation exch. cap	0.94^{*}	-0.15	0.28	-1.84
	(0.56)	(0.40)	(0.88)	(2.16)
pH	-12.84^{***}	-5.72^{***}	-14.54^{***}	-33.42^{***}
	(2.75)	(1.96)	(4.60)	(11.32)
Soil depth	0.33	-0.48^{*}	0.08	-0.22
	(0.34)	(0.26)	(0.58)	(1.35)
Water holding cap	-0.95	0.13	-1.45	1.39
	(0.64)	(0.42)	(1.12)	(2.34)
Sand	1.36	0.98	2.55	18.27^{**}
	(1.96)	(1.50)	(3.56)	(8.62)
Silt	-1.91	0.38	-3.07	7.48
	(1.87)	(1.41)	(3.09)	(7.52)
Weather conditions				
Rainfall	-11.86	25.06^{**}	-38.91^{*}	15.25
	(15.20)	(10.35)	(22.61)	(43.47)
Evapotranspiration	0.44	-6.70^{**}	13.57^{**}	-1.70
	(3.09)	(2.88)	(5.32)	(7.91)
Growing d-d	12.26	-38.05^{***}	86.85^{*}	74.81
	(29.80)	(9.21)	(50.46)	(84.14)
Visible radiation	9.50^{***}	6.38^{**}	3.36	-17.71^{**}
	(2.70)	(2.63)	(4.64)	(7.04)
Average temp.	-4.98	0.85	-17.23	-9.75
	(6.30)	(0.65)	(10.96)	(22.14)
Year dummies				
2008	-3.75	0.11	-9.21	9.66
	(3.99)	(1.62)	(6.13)	(17.37)
2009	2.14	4.70^{***}	-11.33^{***}	-5.42
	(2.63)	(1.28)	(3.87)	(12.05)
2011	4.35^{***}	5.70^{***}	-5.20^{**}	21.26
	(1.24)	(2.07)	(2.59)	(18.70)
2012	14.98^{***}	8.06^{***}	-5.79	20.41
	(3.56)	(1.48)	(4.22)	(12.70)
2013	12.07^{***}	4.72^{*}	20.60^{***}	40.14^{***}
	(3.47)	(2.44)	(7.06)	(12.76)
2014	17.34^{***}	10.96^{***}	28.15^{***}	66.51^{**}
	(6.57)	(1.31)	(10.87)	(26.24)

* p<0.1; ** p<0.05; *** p<0.01: standard errors are in parentheses below the estimated coefficients.

Table C6: Other control variable estimates for other pesticides equations

	Wheat	Barley	Rapeseed	Sugar beet
Soil quality				
Organic carbon	-4.37***	-1.48	-5.31***	-0.86
	(1.20)	(1.00)	(1.40)	(1.27)
Clay	25.17***	8.02	24.01***	14.83*
	(8.64)	(6.53)	(8.95)	(8.25)
Cation exch. cap	-0.20	0.00	-1.18	0.35
	(1.18)	(0.83)	(1.28)	(1.30)
pH	-1.63	-4.13	-6.94	-14.79**
	(6.28)	(5.04)	(7.19)	(6.08)
Soil depth	-0.39	-0.33	-1.46*	-1.39*
	(0.69)	(0.51)	(0.75)	(0.72)
Water holding cap	0.82	0.51	2.03	-1.81
	(1.37)	(1.04)	(1.41)	(1.30)
Sand	3.35	-0.23	1.32	-1.51
	(4.51)	(3.10)	(4.50)	(4.36)
Silt	5.69	-2.96	2.57	4.80
	(4.32)	(3.38)	(4.49)	(4.10)
Weather conditions				
Rainfall	-16.12	-24.00	-5.55	-37.48
	(25.89)	(21.78)	(25.61)	(27.46)
Evapotranspiration	2.15	-2.30	6.57	4.09
	(5.31)	(6.47)	(5.66)	(5.14)
Growing d-d	113.61*	26.46	112.70*	-160.8***
	(58.75)	(21.95)	(63.39)	(51.01)
Visible radiation	-14.8***	-11.37*	10.43*	1.37
	(5.08)	(6.23)	(5.93)	(4.56)
Average temp.	-18.86	-1.90	-17.89	47.64***
	(12.29)	(1.38)	(13.75)	(13.35)
Year dummies				
2008	29.83***	8.60**	-8.73	-23.62**
	(7.42)	(3.91)	(7.80)	(10.18)
2009	17.04***	13.81***	9.12**	-18.45***
	(4.39)	(3.09)	(4.54)	(6.98)
2011	-2.84	-7.77*	-1.06	-36.49***
	(2.30)	(4.37)	(3.02)	(10.82)
2012	1.69	1.59	8.52	-4.98
	(6.94)	(3.73)	(5.75)	(7.79)
2013	19.69***	14.37***	29.36***	1.14
	(7.01)	(5.52)	(9.95)	(7.98)
2014	35.14***	7.22**	25.39*	-26.93*
	(12.97)	(3.00)	(14.35)	(15.82)

** p<0.1; ** p<0.05; *** p<0.01: standard errors are in parentheses below the estimated coefficients.*

Table C7: Variance-covariance estimates of the distribution error terms

	Yield	Nitrogen	Herbicides	Other pesticides	Yield	Nitrogen	Herbicides	Other pesticides
	Wheat				Barley			
Yield	0.43***				0.60***			
	(0.01)				(0.01)			
Nitrogen		643.26***	5.43	37.47***		378.04***	5.90*	22.68***
		(8.47)	(5.35)	(9.97)		(5.71)	(3.09)	(5.97)
Herbicides		5.43	183.27***	27.17***		5.90*	80.25***	14.51***
		(5.35)	(2.30)	(3.58)		(3.09)	(0.87)	(2.07)
Other pesticides		37.47***	27.17***	542.95***		22.68***	14.51***	333.10***
		(9.97)	(3.58)	(8.78)		(5.97)	(2.07)	(3.51)
	Rapeseed				Sugar beet			
Yield	0.18***				62.84***			
	(0.00)				(1.18)			
Nitrogen		815.82***	-4.23	35.67**		745.03***	14.98	15.90
		(13.56)	(11.30)	(14.37)		(11.74)	(16.79)	(10.20)
Herbicides		-4.23	505.50***	52.06***		14.98	1,072.63***	59.84***
		(11.30)	(4.60)	(7.72)		(16.79)	(12.34)	(11.38)
Other pesticides		35.67**	52.06***	696.06***		15.90	59.84***	451.78***
		(14.37)	(7.72)	(9.97)		(10.20)	(11.38)	(6.81)

** p<0.1; ** p<0.05; *** p<0.01: standard errors are in parentheses below the estimated variances.*

Table C8: Variance-covariance matrix of the random parameters

	Intercept Yield	Intercept Nitrogen	Intercept Herbicide	Intercept Other Pest.	Nitrogen Coeff.	Herbicide Coeff.	Other Pest. Coeff.
Wheat							
Intercept Yield	0.49*	0.03*	0.01	0.05*	-0.08*	-0.03	-0.04
	(0.09)	(0.01)	(0.01)	(0.02)	(0.03)	(0.06)	(0.03)
Intercept Nitrogen	0.03*	0.02*	0.00	0.01*	-0.00	0.00	-0.01
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Intercept Herbicide	0.01	0.00	0.01*	0.01*	-0.01*	-0.01*	0.00
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Intercept Other Pest.	0.05*	0.01*	0.01*	0.06*	0.01	-0.02	-0.02*
	(0.02)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Nitrogen Coeff.	-0.08*	-0.00	-0.01*	0.01	0.05*	-0.01	-0.01
	(0.03)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.01)
Herbicide Coeff.	-0.03	0.00	-0.01*	-0.02	-0.01	0.15*	-0.00
	(0.06)	(0.01)	(0.01)	(0.01)	(0.02)	(0.05)	(0.02)
Other Pest. Coeff.	-0.04	-0.01	0.00	-0.02*	-0.01	-0.00	0.03*
	(0.03)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.01)
Barley							
Intercept Yield	0.20*	0.03*	-0.01	0.02	-0.02	0.02	-0.06
	(0.08)	(0.01)	(0.00)	(0.01)	(0.04)	(0.09)	(0.05)
Intercept Nitrogen	0.03*	0.01*	0.00	0.01*	-0.01	0.00	-0.00
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.01)
Intercept Herbicide	-0.01	0.00	0.00*	0.00*	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Intercept Other Pest.	0.02	0.01*	0.00*	0.02*	0.01	0.01	-0.03*
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.01)
Nitrogen Coeff.	-0.02	-0.01	-0.00	0.01	0.09*	-0.01	-0.07*
	(0.04)	(0.01)	(0.00)	(0.01)	(0.03)	(0.06)	(0.03)
Herbicide Coeff.	0.02	0.00	0.00	0.01	-0.01	0.40*	-0.03
	(0.08)	(0.02)	(0.01)	(0.02)	(0.06)	(0.19)	(0.07)
Other Pest. Coeff.	-0.06	-0.00	0.00	-0.03*	-0.07*	-0.03	0.14*
	(0.05)	(0.01)	(0.00)	(0.01)	(0.03)	(0.07)	(0.05)
Rapeseed							
Intercept Yield	0.22*	0.00	0.00	0.06*	-0.03*	-0.04*	-0.04*
	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Intercept Nitrogen	0.00	0.03*	0.00*	0.01*	0.00	0.00	0.00
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept Herbicide	-0.00	0.00	0.03*	0.01*	0.00	0.00	-0.01*
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Intercept Other Pest.	0.06*	0.01*	0.01*	0.06*	0.00	-0.02*	-0.01*
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Nitrogen Coeff.	-0.03*	0.00	0.00	0.00	0.02*	0.00	-0.01*
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Herbicide Coeff.	-0.04*	0.00	0.00	-0.02*	0.00	0.05*	0.00

	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
Other Pest. Coeff.	-0.04*	0.00	-0.01*	-0.01*	-0.01*	0.00	0.04*
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Sugar beet							
Intercept Yield	69.87*	-1.96	-4.13	1.60	-0.02	3.49	-34.97*
	(17.45)	(1.77)	(2.65)	(1.55)	(4.08)	(0.38)	(10.61)
Intercept Nitrogen	-1.96	2.96*	0.69*	0.48*	1.16	1.08	-1.50
	(1.77)	(0.19)	(0.27)	(0.20)	(0.72)	(0.09)	(1.54)
Intercept Herbicide	-4.13	0.69*	9.31*	1.64*	-2.19	0.89	0.59
	(2.65)	(0.27)	(0.60)	(0.26)	(1.37)	(0.11)	(2.33)
Intercept Other Pest.	1.60	0.48*	1.64*	2.84*	-0.60	2.11*	-0.94
	(1.55)	(0.20)	(0.26)	(0.19)	(0.79)	(0.06)	(1.08)
Nitrogen Coeff.	-0.02	1.16	-2.19	-0.60	3.80*	0.07	-2.07
	(4.08)	(0.72)	(1.37)	(0.79)	(1.77)	(0.15)	(3.05)
Herbicide Coeff.	3.49	1.08	0.89	2.11*	0.07	5.84*	-4.88(*)
	(3.80)	(0.86)	(1.09)	(0.62)	(1.48)	(0.19)	(2.84)
Other Pest. Coeff.	-34.97*	-1.50	0.59	-0.94	-2.07	-4.88(*)	29.02*
	(10.61)	(1.54)	(2.33)	(1.08)	(3.05)	(0.28)	(8.62)

*Note: Symbol *, respectively (*), indicates that the parameter is tested non null at the 5%, respectively 10%, level. Estimated standard deviations of the parameter estimators are in parentheses below the parameter estimates.*

Table 4a: Selected parameter estimates of the crop yield models

	Yield models (t/ha)							
	Wheat		Barley		Rapeseed		Sugar beet	
Farm specific intercepts								
Intercept, mean	8.6*	(0.07)	6.1*	(0.08)	0.5*	(0.04)	83.8*	(0.83)
Intercept, std dev	0.7*	(0.07)	0.5*	(0.09)	0.5*	(0.04)	8.4*	(1.04)
Farm specific input use coefficients (x 10^2)								
Nitrogen, mean	0.03	(0.03)	-0.06	(0.05)	0.08*	(0.01)	-0.40	(0.39)
Nitrogen, standard deviation	0.21*	(0.03)	0.30*	(0.06)	0.15*	(0.01)	1.95*	(0.45)
Herbicides, mean	0.14*	(0.05)	0.02	(0.11)	0.04*	(0.02)	0.55	(0.32)
Herbicides, standard deviation	0.38*	(0.07)	0.63*	(0.15)	0.22*	(0.02)	2.42*	(0.40)
Other pesticide, mean	0.34*	(0.03)	0.27*	(0.06)	0.13*	(0.02)	0.80	(0.61)
Other pesticides, standard deviation	0.17*	(0.03)	0.37*	(0.07)	0.20*	(0.02)	5.39*	(0.80)
Pre crop effects								
Wheat	-0.32*	(0.10)	ref	(-)	ref	2	ref	(-)
Barley	-0.19	(0.16)	-0.16*	(0.07)	0.04	(0.03)	-0.25	(0.55)
Rapeseed	ref	(-)	0.16	(0.20)			1.25	(3.03)
Corn	-0.06	(0.13)	-0.26*	(0.12)			-3.81	(4.29)
Protein pea	0.20(*)	(0.10)	0.17	(0.41)	0.05	(0.25)		
Alfalfa	-0.09	(0.08)	0.02	(0.35)			-8.51	(5.22)
Sugar beet	0.01	(0.06)	0.21*	(0.07)			-0.51	(1.69)
Potatoes	-0.02	(0.11)	0.23	(0.22)			2.79	(3.62)
Other pre crops	-0.02	(0.10)	0.36*	(0.14)	-0.03	(0.18)	-0.98	(2.17)
Crop diversity effects: crop number								
3 crops or less	-0.19*	(0.07)	-0.35*	(0.13)	0.01		-7.67	(4.39)
4 crops	-0.10(*)	(0.05)	-0.19*	(0.07)	-0.04	(0.18)	-1.08	(1.29)
5 crops	ref	(-)	ref	(-)	ref	(-)	ref	(-)
6 crops	0.06	(0.04)	0.02	(0.05)	0.06(*)	(0.03)	1.38*	(0.61)
7 crops or more	0.20*	(0.07)	0.15(*)	(0.08)	0.18*	(0.04)	1.90(*)	(0.93)
Crop diversity effects: Shannon index per crop number								
3 crops x Shannon index	-0.13	(0.41)	0.69	(0.62)	-0.26	(0.36)	-13.27	(29.80)
4 crops x Shannon index	0.72*	(0.27)	1.33*	(0.47)	0.21	(0.20)	6.57	(6.89)
5 crops x Shannon index	0.73*	(0.31)	0.88*	(0.36)	0.33	(0.20)	9.79*	(4.58)
6 crops x Shannon index	0.28	(0.33)	0.40	(0.41)	0.59*	(0.23)	14.38*	(4.42)
7 crops x Shannon index	1.44*	(0.58)	0.87	(0.64)	0.93*	(0.30)	15.73*	(6.48)
General statistics								
Average yield level	8.65		7.00		3.88		93.07	
Simulated R^2	0.68		0.63		0.64		0.70	
Observation number	3982		3327		3530		3085	
Farm number	769		654		692		607	

Note. Symbol "", respectively "(*)", indicates that the parameter is tested non null at the 5%, respectively 10%, level. Estimated standard deviations of the parameter estimators are in parentheses below the parameter estimates.*

Table 4b: Selected parameter estimates of the nitrogen use models

	Fertilizer use models (kg/ha)							
	Wheat		Barley		Rapeseed		Sugar beet	
Farm specific intercepts								
Intercept, mean	249.2*	(0.63)	151.1*	(0.56)	115.8*	(0.77)	356.2*	(0.87)
Intercept, standard deviation	13.46*	(0.54)	11.29*	(0.43)	15.92*	(0.62)	17.20*	(0.55)
Pre crop effects								
Wheat	0.32	(3.79)	ref	(-)	ref	(-)	ref	(-)
Barley	2.01	(6.32)	0.85	(1.91)	-1.66	(1.77)	-2.39	(1.91)
Rapeseed	ref	(-)	-0.74	(4.53)			6.36	(7.93)
Corn	-1.96	(4.56)	-0.11	(4.19)			8.99	(28.49)
Protein pea	1.83	(3.37)	-5.19	(9.81)	-4.79	(18.50)		
Alfalfa	4.04	(3.27)	5.06	(8.08)			2.51	(13.00)
Sugar beet	2.01	(2.54)	-0.12	(1.58)			-5.73	(5.75)
Potatoes	4.68	(4.10)	-2.50	(4.98)			7.58	(7.10)
Other pre crops	-1.36	(3.54)	1.25	(3.97)	11.30	(9.28)	1.03	(5.69)
Crop diversity effects: crop number								
3 crops or less	-0.38	(3.20)	-1.41	(4.31)	-2.01	(4.82)	6.08	(24.09)
4 crops	0.40	(1.64)	0.69	(1.63)	-1.59	(2.28)	3.27	(4.41)
5 crops	ref	(-)	ref	(-)	ref	(-)	ref	(-)
6 crops	1.55	(1.40)	0.54	(1.12)	3.45*	(1.68)	-0.44	(1.91)
7 crops or more	2.65	(2.19)	1.37	(2.04)	3.72	(2.48)	-3.03	(2.60)
Crop diversity effects: Shannon index per crop number								
3 crops x Shannon index	-3.74	(17.91)	-13.71	(26.74)	-12.25	(19.33)	-83.64	(107.95)
4 crops x Shannon index	10.54	(9.13)	-6.55	(10.83)	-3.94	(14.56)	1.24	(24.56)
5 crops x Shannon index	-12.98	(11.09)	-12.00	(8.20)	-13.53	(13.49)	-36.25*	(16.84)
6 crops x Shannon index	-1.56	(11.34)	-4.22	(8.88)	12.62	(12.46)	1.78	(13.29)
7 crops x Shannon index	-3.28	(20.36)	-7.39	(17.68)	0.22	(22.09)	-25.68	(21.83)
General statistics								
Average use of N	217.95		147.19		215.19		138.55	
Simulated R^2	0.38		0.42		0.42		0.44	
Observation number	3982		3327		3530		3085	
Farm number	769		654		692		607	

*Note: Symbol *, respectively (*), indicates that the parameter is tested non null at the 5%, respectively 10%, level. Estimated standard deviations of the parameter estimators are in parentheses below the parameter estimates.*

Table 4c: Selected parameter estimates of the herbicide use models

	Herbicide use models (€/ha, 2010 prices)							
	Wheat		Barley		Rapeseed		Sugar beet	
Farm specific intercepts								
Intercept, mean	171.6*	(0.42)	85.7*	(0.28)	285.6*	(0.75)	319.9*	(1.38)
Intercept, standard deviation	10.0*	(0.29)	5.7*	(0.18)	16.8*	(0.54)	30.5*	(0.99)
Pre crop effects								
Wheat	-0.11	(2.29)	ref	(-)	ref	(-)	ref	(-)
Barley	1.37	(4.13)	1.94*	(0.95)	-0.57	(1.44)	-2.57	(2.52)
Rapeseed	ref	(-)	0.62	(2.46)			7.78	(11.21)
Corn	-1.98	(2.19)	-2.08	(1.50)			-5.82	(22.55)
Protein pea	1.55	(2.38)	-5.17	(5.78)	5.52	(18.90)		
Alfalfa	0.58	(2.18)	1.62	(3.74)			9.24	(34.09)
Sugar beet	-1.35	(1.58)	-1.68(*)	(0.97)			8.41	(8.50)
Potatoes	-2.05	(1.87)	-1.39	(2.43)			-4.36	(11.18)
Other pre crops	2.87	(1.85)	1.55	(1.96)	5.70	(7.32)	6.86	(6.43)
Crop diversity effects: crop number								
3 crops or less	4.66*	(1.54)	3.56	(2.02)	11.05*	(3.63)	12.11	(59.26)
4 crops	1.93	(1.03)	1.20	(0.84)	8.14*	(1.88)	4.21	(3.53)
5 crops	ref	(-)	ref	(-)	ref	(-)	ref	(-)
6 crops	-1.64(*)	(0.88)	-1.37*	(0.58)	-2.42	(1.49)	-1.41	(2.39)
7 crops or more	-2.37	(1.74)	-1.34	(0.99)	-3.29	(2.48)	-5.30	(4.27)
Crop diversity effects: Shannon index per crop number								
3 crops x Shannon index	1.99	(8.68)	-12.01	(11.14)	15.37	(23.84)	-38.16	(372.78)
4 crops x Shannon index	-9.35	(5.15)	-10.32*	(4.98)	-8.71	(11.66)	-31.32	(18.48)
5 crops x Shannon index	-4.12	(6.13)	-8.88*	(3.68)	-12.98	(10.83)	-4.11	(19.37)
6 crops x Shannon index	-7.27	(8.17)	-3.05	(5.66)	-23.7(*)	(12.69)	3.41	(18.70)
7 crops x Shannon index	7.57	(15.25)	-0.67	(9.88)	-18.79	(20.45)	-11.79	(30.71)
General statistics								
Average herbicide use	63.08		30.47		99.27		160.55	
Simulated R^2	0.55		0.50		0.55		0.67	
Observation number	3982		3327		3530		3085	
Farm number	769		654		692		607	

*Note: Symbol *, respectively (*), indicates that the parameter is tested non null at the 5%, respectively 10%, level. Estimated standard deviations of the parameter estimators are in parentheses below the parameter estimates.*

Table 4d: Selected parameter estimates of the other pesticides (mostly fungicides and insecticides) use models

	Other pesticide use models (€/ha, 2010 prices)							
	Wheat		Barley		Rapeseed		Sugar beet	
Farm specific intercepts								
Intercept, mean	144.7*	(1.00)	143.7*	(0.66)	127.7*	(1.03)	109.8*	(0.79)
Intercept, standard deviation	25.43*	(0.71)	14.72*	(0.46)	24.32*	(0.69)	16.86*	(0.55)
Pre crop effects								
Wheat	4.07	(4.08)	ref	(-)	ref	(-)	ref	(-)
Barley	-15.63*	(6.55)	-0.50	(1.88)	1.10	(1.73)	-1.05	(1.55)
Rapeseed	ref	(-)	-3.34	(4.93)			-2.23	(6.85)
Corn	-7.80	(4.16)	-7.44*	(3.33)			7.74	(14.76)
Protein pea	-5.32	(3.52)	-5.64	(17.04)	-16.49	(20.27)		
Alfalfa	-2.05	(3.27)	8.48	(4.42)			-3.92	(13.05)
Sugar beet	-1.66	(2.50)	0.87	(1.91)			1.86	(5.90)
Potatoes	1.27	(3.81)	-4.99	(5.98)			1.22	(8.93)
Other pre crops	0.89	(3.53)	-2.45	(4.49)	-6.33	(15.74)	-1.07	(3.91)
Crop diversity effects: crop number								
3 crops or less	-3.73	(3.28)	-2.44	(3.33)	-0.82	(4.15)	3.11	(18.21)
4 crops	-3.17	(2.07)	0.14	(1.66)	2.94	(2.37)	0.92	(2.53)
5 crops	ref	(-)	ref	(-)	ref	(-)	ref	(-)
6 crops	-0.25	(1.76)	-0.72	(1.32)	-1.35	(1.89)	1.00	(1.62)
7 crops or more	1.90	(2.89)	-2.16	(2.22)	0.75	(3.10)	-1.50	(2.79)
Crop diversity effects: Shannon index per crop number								
3 crops x Shannon index	5.99	(14.46)	1.52	(25.08)	-16.66	(28.23)	55.79	(73.47)
4 crops x Shannon index	1.83	(10.94)	-1.28	(8.37)	-1.55	(12.14)	-10.12	(13.18)
5 crops x Shannon index	-13.95	(11.38)	-6.53	(8.91)	-29.88*	(13.92)	-26.92*	(12.69)
6 crops x Shannon index	1.58	(13.52)	-5.49	(11.55)	23.23	(14.91)	3.80	(12.42)
7 crops x Shannon index	5.31	(17.92)	-1.52	(17.93)	4.22	(19.47)	10.15	(21.19)
General statistics								
Average pesticide use	125.1		76.0		109.0		96.2	
Simulated R^2	0.65		0.55		0.60		0.55	
Observation number	3982		3327		3530		3085	
Farm number	769		654		692		607	

*Note. Symbol *, respectively (*), indicates that the parameter is tested non null at the 5%, respectively 10%, level. Estimated standard deviations of the parameter estimators are in parentheses below the parameter estimates.*

Table 6: Selected parameter estimates of the crop yield and input use models: selected pre crop effects

	Yield models (t/ha)							
	Wheat		Barley		Rapeseed		Sugar beet	
Pre crop effects								
Wheat	-0.32*	(0.10)	0	(-)	0	(-)	0	(-)
Barley	-0.19	(0.16)	-0.16*	(0.07)	0.04	(0.03)	-0.25	(0.55)
Rapeseed	0	(-)	0.16	(0.20)			1.25	(3.03)
Corn	-0.06	(0.13)	-0.26*	(0.12)			-3.81	(4.29)
Protein pea	0.20(*)	(0.10)	0.17	(0.41)	0.05	(0.25)		
Alfalfa	-0.09	(0.08)	0.02	(0.35)			-8.51	(5.22)
Sugar beet	0.01	(0.06)	0.21*	(0.07)			-0.51	(1.69)
Potatoes	-0.02	(0.11)	0.23	(0.22)			2.79	(3.62)
Other pre crops	-0.02	(0.10)	0.36*	(0.14)	-0.03	(0.18)	-0.98	(2.17)
	Fertilizer use models (kg/ha)							
	Wheat		Barley		Rapeseed		Sugar beet	
Pre crop effects								
Wheat	0.32	(3.79)	0	(-)	0	(-)	0	(-)
Barley	2.01	(6.32)	0.85	(1.91)	-1.66	(1.77)	-2.39	(1.91)
Rapeseed	0	(-)	-0.74	(4.53)			6.36	(7.93)
Corn	-1.96	(4.56)	-0.11	(4.19)			8.99	(28.49)
Protein pea	1.83	(3.37)	-5.19	(9.81)	-4.79	(18.50)		
Alfalfa	4.04	(3.27)	5.06	(8.08)			2.51	(13.00)
Sugar beet	2.01	(2.54)	-0.12	(1.58)			-5.73	(5.75)
Potatoes	4.68	(4.10)	-2.50	(4.98)			7.58	(7.10)
Other pre crops	-1.36	(3.54)	1.25	(3.97)	11.30	(9.28)	1.03	(5.69)
	Herbicide use models (€/ha, 2010 prices)							
	Wheat		Barley		Rapeseed		Sugar beet	
Pre crop effects								
Wheat	-0.11	(2.29)	0	(-)	0	(-)	0	(-)
Barley	1.37	(4.13)	1.94*	(0.95)	-0.57	(1.44)	-2.57	(2.52)
Rapeseed	0	(-)	0.62	(2.46)			7.78	(11.21)
Corn	-1.98	(2.19)	-2.08	(1.50)			-5.82	(22.55)
Protein pea	1.55	(2.38)	-5.17	(5.78)	5.52	(18.90)		
Alfalfa	0.58	(2.18)	1.62	(3.74)			9.24	(34.09)
Sugar beet	-1.35	(1.58)	-1.68(*)	(0.97)			8.41	(8.50)
Potatoes	-2.05	(1.87)	-1.39	(2.43)			-4.36	(11.18)
Other pre crops	2.87	(1.85)	1.55	(1.96)	5.70	(7.32)	6.86	(6.43)
	Other pesticide use models (€/ha, 2010 prices)							
	Wheat		Barley		Rapeseed		Sugar beet	
Pre crop effects								
Wheat	4.07	(4.08)	0	(-)	0	(-)	0	(-)
Barley	-15.63*	(6.55)	-0.50	(1.88)	1.10	(1.73)	-1.05	(1.55)

Rapeseed	0	(-)	-3.34	(4.93)			-2.23	(6.85)
Corn	-7.80	(4.16)	-7.44*	(3.33)			7.74	(14.76)
Protein pea	-5.32	(3.52)	-5.64	(17.04)	-16.49	(20.27)		
Alfalfa	-2.05	(3.27)	8.48	(4.42)			-3.92	(13.05)
Sugar beet	-1.66	(2.50)	0.87	(1.91)			1.86	(5.90)
Potatoes	1.27	(3.81)	-4.99	(5.98)			1.22	(8.93)
Other pre crops	0.89	(3.53)	-2.45	(4.49)	-6.33	(15.74)	-1.07	(3.91)

*Note. Symbol *, respectively (*), indicates that the parameter is tested non null at the 5%, respectively 10%, level. Estimated standard deviations of the parameter estimators are in parentheses below the parameter estimates.*

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